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Sentiment-Adjusted Equilibrium Valuation and Predictability of Prices of Commercial Real Estate

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

INTRODUCTION

In 2023, the IPF Research Programme launched its second 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. This time, an appraisal of proposals received by the deadline of 31 August 2023 resulted in the provision of grants to six 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 Colin Lizieri, Nick Mansley and Zilong Wang, University of Cambridge.

Richard Gwilliam
Chair IPF Research Steering Group
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Executive Summary

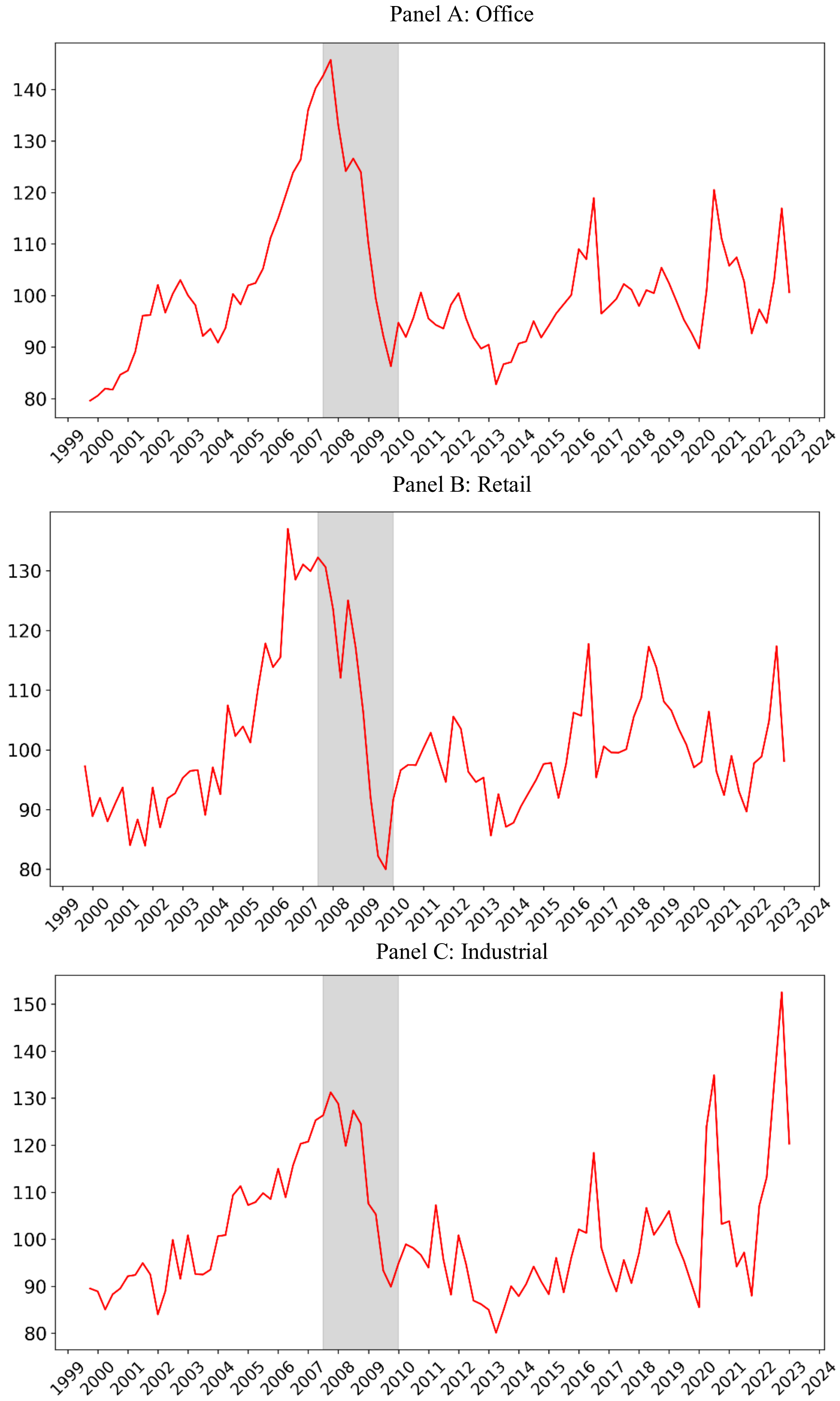
Forecasting commercial real estate (CRE) returns and providing reliable indicators of market risk is challenging. Previous research has not produced a reliable set of predictive indicators supported by theory. In addition, forecasts based on surveys of market experts do not show good track records, particularly for major downturns. Theory suggests that cap rates should be an important predictor of excess returns of CRE but again empirical evidence has yielded inconsistent results. These shortcomings are the motivation for this paper which develops and tests a Valuation Stress Index (VSI) that incorporates economic theory and sentiment to predict future CRE capital values.

The price of the property equals the present value of the expected future rental income. Assuming a constant growth rate of the rent, based on the Gordon Growth Model (1962), the price of the property equals the rent divided by the cap rate. We model rents for each of the three traditional property sectors (office, retail, and industrial) based on supply (the stock of floorspace) and a demand proxy for each sector. We model cap rates as a function of real risk-free returns, expected rental growth and sentiment. Once we have an equilibrium rent and an equilibrium cap rate, we calculate sentiment-adjusted equilibrium capital values and compare them with actual capital values. The deviation of the current value from the equilibrium value yields VSI, which is useful for predicting future price movements.

Figure 1 shows the pattern of VSI. A value above 100 indicates overvaluation whilst a value below 100 indicates undervaluation. Panel A, B, and C show the VSI for office, retail, and industrial property, respectively. The grey shaded areas indicate the global financial crisis period (GFC) period. VSI clearly showed overvaluation before the global financial crisis period (GFC). The VSI then fell sharply during the GFC as values moved back in line and then below sentiment-adjusted equilibrium capital values.

To assess the real-time predictive power of the VSI, we conducted out-of-sample analyses using only information available up to each forecast point. Comparing the VSI's forecast accuracy against other models, the VSI demonstrates superior out-of-sample performance. Furthermore, the VSI proves effective in providing timely warning signals prior to GFC, successfully predicting substantial negative returns. Overall, the results suggest that our model for sentiment-adjusted equilibrium capital value and VSI has significant predictive power for the future price movement of commercial real estate.

Figure 1: VSI over time



Notes: The figure plots VSI. The grey shaded areas indicate the GFC period.

Sentiment-Adjusted Equilibrium Valuation and Predictability of Prices of Commercial Real Estate

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Abstract:

We use an economic theory-based equilibrium capital value model augmented with sentiment adjustments to construct a Valuation Stress Index (VSI) for UK commercial real estate (CRE). The VSI serves as a quantitative measure of market overvaluation or undervaluation. We show that VSI has robust predictive power for future CRE capital value changes, both in-sample and out-of-sample across office, retail, and industrial sectors. Notably, VSI signalled large negative returns before the global financial crisis, highlighting its potential for providing an early warning signal. Our results underscore the significant value of our sentiment-adjusted equilibrium capital value model for forecasting CRE capital value changes.

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1. Introduction

Commercial real estate (CRE) is an important asset class in the multi-asset portfolio of institutional investors such as pension funds, life insurance companies, or sovereign wealth funds. During the asset allocation process, knowledge of the return and risk characteristics of assets is crucial. In addition, if an investor has some forecasting ability, the investor's welfare can be improved (Allen et al., 2019). Surprisingly, the literature on forecasting CRE returns is scarce. Although there is a large body of literature on whether residential real estate returns are predictable, only a few papers focus on the predictability of CRE returns.

Previous research on CRE return predictability has not produced a consistent set of predictive variables. This is mainly due to three issues. First, the choice of the predictive variables is often not derived from theory. For example, Krystalogianni et al. (2004) use 25 leading economic indicators to forecast the UK CRE cycle phases. Van de Minne et al. (2022) use 80 granular commercial property price indexes to derive factors to forecast US CRE prices. Second, predictions based on theory have only proved partially satisfactory. Analogous to the predictive power of dividend yield on stock returns, the cap rate should be an important predictor of excess returns of CRE. However, empirical evidence shows inconsistent prediction results across different property types. For example, Plazzi et al. (2010) show that cap rates can forecast returns for retail and industrial properties, but not for offices. They demonstrate a large noise component which is not based on fundamentals. Investors may not be fully rational and non-fundamental factors such as sentiment could influence asset prices. Investment in CRE could be especially sensitive to sentiment, due to specific characteristics of the real estate market, including high information asymmetry, individual agency in decision-making, limits to arbitrage and lags inherent in the asset allocation and investment decision-making process. Gallimore and Gray (2002) found that investors are aware of the importance of sentiment for their own decisions. Dietzel et al. (2014) and Beracha et al. (2019) suggest that sentiment in real estate conveys valuation information that can help predict CRE returns. Third, forecasts based on surveys of market experts do not show good track records. For example, McAllister et al. (2008), Bond and Mitchell (2011), Papastamos et al. (2015) and McAllister and Nase (2020) investigate the Investment Property Forum (IPF) Consensus Forecasts[1] in the UK CRE market. Market experts tend to be conservative in their forecasts and forecasts tend to fail to capture the large changes in times of market volatility.

To address this gap in the literature, we develop a Valuation Stress Index (VSI) based on economic theory and sentiment adjustment to forecast the future capital values of CRE. From an asset pricing perspective, the price of the property equals the present value of its future rents. Assuming a constant growth rate of the rent, based on the Gordon Growth Model (1962), the price of the property equals the rent divided by the cap rate. We model rent based on supply and demand for CRE space. We model cap rate as a function of expected returns, expected rental growth and sentiment. Once we have equilibrium rent and cap rate, we calculate sentiment-adjusted equilibrium capital values and compare them with

[1] The IPF Consensus Forecasts are quarterly surveys that collect predictions from leading UK real estate professionals on key metrics like rental growth, capital value growth, and total return for different CRE sectors.

actual capital values. The deviation of the current value from the equilibrium value yields VSI, which could be useful for predicting future price movements.

Based on data for the three traditional property sectors (office, retail, and industrial)[2] in the UK, we find that VSI has good predictive power for future price changes across different horizons (from one quarter to 20 quarter horizons). VSI clearly showed overvaluation before the global financial crisis (GFC) and the subsequent collapse in CRE value. Subsequent analysis is focused on a three-year forecasting horizon. Compared with a set of commonly used predictors, the forecasting power of VSI is much higher. We also show that VSI provides significant predictive information beyond that which is captured by these commonly used predictors. Those results hold for all three property types for in-sample analysis. In addition, cap rate shows significant predictive power for retail property and CRE sentiment shows significant predictive power for industrial property. We conduct several robustness checks, and our results remain the same.

In order to test the predictive power of VSI in real time, out-of-sample analyses are performed. Out-of-sample R^2 and encompassing tests are used to evaluate the predictive power. Out-of-sample R^2 compares the out-of-sample forecast accuracy compared to a naïve forecast using historical average value. VSI show good out-of-sample performance. They have higher out-of-sample R^2 than other predictive variables. In addition, VSI contains relevant information beyond that contained in other variables, although the cap rate has predictive power for future capital returns for retail, and CRE sentiment also appears to have predictive power for industrial properties. We further verify whether VSI can provide useful warning signals before crises. VSI predicted large negative returns before the crisis. For all three property types, we find that the predictive power decreased substantially after the Covid pandemic. This may be evidence of one or more structural breaks that are making it difficult to evaluate equilibrium capital values. Finally, we show that it is important to adjust sentiment in equilibrium cap rate and valuation. Out-of-sample R^2 reduced after excluding CRE sentiment in the cap rate model across all different types of property and different forecasting horizons.

We contribute to the literature by showing that sentiment-adjusted equilibrium valuation is a strong predictor of CRE prices. We utilise economic theories to justify this valuation approach. While the cap rate should theoretically be useful in forecasting future returns, empirical findings across property types and countries are inconsistent. For example, Plazzi et al. (2010) show that cap rate can forecast total returns for retail and industrial properties in the US, but not for offices. We find that cap rate can forecast capital return for retail properties in the UK, but not for office and industrial properties. In addition, we contribute to the literature by showing that adjusting for sentiment in equilibrium valuation can enhance predictive accuracy.

The rest of the paper is organised as follows: Section 2 reviews the relevant literature. Section 3 describes the data and Section 4 sets out our methods. Section 5 shows in-sample and out-of-sample analysis. Section 6 concludes.

[2] While the allocation to the traditional sectors (office, retail and industrial) has fallen relative to alternatives, the traditional sectors have the longest robust time series of data amongst UK CRE market segments.

2. Related Literature

Prior research has tried to predict future total returns, capital value returns, risk premia and rental growth of CRE. One branch of literature utilises a large number of variables (including macroeconomic indicators) to forecast CRE cyclical movement. Krystalogianni et al. (2004) use 25 leading economic indicators to predict the cyclical pattern of UK commercial real estate prices. Probit models are used to identify turning points in the capital value. The forecast performance shows satisfactory results. Tsolacos et al. (2014) use information from the Conference Board leading indicator and other predictive variables to forecast rental growth in the US. A probit model and a Markov-switching model are used in the study. The model can produce advance signals for forthcoming falls and rises in rents up to eight quarters ahead. Van de Minne et al. (2022) use a dynamic factor model (DFM) based on 80 granular commercial property indexes in the US. DFM can summarise a large number of time series variables into a few common factors. They show that a combination of DFM and an Autoregressive Distributed Lag (ARDL) model can predict the crisis and subsequent recovery.

Forecasting models based on a large number of variables are data-driven approaches. One drawback of such an approach is the lack of theoretical foundation and economic intuition. Based on Campbell and Shiller's (1988) present value model,[3] cap rates should forecast either future returns or future rental growth. Ghysels et al. (2007) test the predictive power of cap rates on CRE returns for 21 metropolitan areas. They find that cap rates predicted yearly returns in 17 out of 21 regions. Plazzi et al. (2010) extend the study by testing the predictive power of cap rates using different property types. They find that cap rates can forecast expected returns for apartment, retail, and industrial properties, but not offices. Offices have a relatively large noise component compared to the other property types in their study. In addition, cap rates marginally forecast office rental growth, but not rental growth for apartments, retail property, and industrial properties. However, those studies do not test the out-of-sample forecasting power of cap rates nor whether cap rates could be used as an early warning indicator.

In addition to the fundamental predictive variables, several studies investigate the role of sentiment in CRE. Ling et al. (2014) show that positive investor sentiment can lead to higher subsequent total returns in CRE. It is also useful for forecasting long-horizon total returns. Tsolacos (2012) show that economic sentiment indicators are useful for predicting rental growth turning points. Dietzel et al. (2014) use Google search intensity as a proxy for sentiment. They find that adding sentiment to the model with macroeconomic variables improves forecasting power. Marcato and Nanda (2016) show that sentiment measures are useful in explaining residential real estate prices, but not the non-residential sector. Beracha et al. (2019) find that the ex-ante risk premium of CRE is affected by sentiment as well as fundamental determinants. In addition, studies have shown that investor sentiment can affect the valuation of CRE by influencing cap rates. Clayton et al. (2008) show that investor sentiment helps to explain the time-series variation in cap rates. Heinig et al. (2020) find that a model with sentiment can better forecast cap rates.

Forecasting models based on econometrics can be mis-specified and subject to structural breaks (Hendry and Clement, 2003). Several studies investigate the predictive accuracy of market experts based on surveys. Ling (2005) utilises the RERC survey to investigate the US

[3] This model has been widely used in the residential real estate research (see, among others, Campbell et al., 2009; Ambrose et al., 2013)

market. Tsolacos (2006), McAllister et al. (2008), Bond and Mitchell (2011), Papastamos et al. (2015), Papastamos et al. (2018) and McAllister and Nase (2020) use IPF's Consensus Forecasts to investigate the UK market. Tsolacos (2006) show that a simple regression model with interest rates outperforms the consensus forecasts at one-year and two-year forecasting horizons. Bond and Mitchell (2011) compare the forecasting power between real estate derivative prices and IPF consensus estimates. They find that derivative prices provide more accurate forecasts in the short run. However, for forecasting horizons over a year, IPF consensus estimates provide better forecasts. Papastamos et al. (2018) compare the forecast accuracy of CRE returns and a variety of macroeconomic series by using consensus estimates. The results show that forecasters tend to be more accurate in the case of macroeconomic series than capital and total returns of CRE. McAllister et al. (2008) and McAllister and Nase (2020) show a large error in forecasting capital growth and total return. In general, the predictive accuracy of market experts in the CRE market is limited. Papastamos et al. (2015) argue that forecasts tend to underestimate growth rates during strong market conditions and overestimate them during poor market conditions. Market experts tend to be conservative in their forecasts to try to avoid large misses and anchor on past forecasts. In addition, there is a potential indication of herding bias among forecasting organisations. The large forecasting error could be due to the difficulty in forecasting yield (Papastamos et al., 2015; McAllister and Nase, 2020).

3. Methods

3.1. Modelling for Equilibrium Rent

Following Hendershott et al. (2002a) and Hendershott et al. (2002b), we model equilibrium rent as a reflection of supply and demand. Many other studies followed the same approach.[4] The long-run equation takes the following form:

$$\begin{aligned} Ln(Real\ Rental\ Value_t) \\ &= \beta_0 + \beta_1 Ln(Demand\ Proxy_t) + \beta_2 \mathrm{Ln}\big((1 - v_t) \times Stock_t\big) \\ &+ \beta_3 t + \beta_4 t^2 + \varepsilon_t \end{aligned} \tag{1}$$

where $(1 - v_t) \times Stock_t$ is the supply of occupied space, v is the vacancy rate and *Stock* is the current stock of floor space. $Demand\ Proxy$ is real GDP for office and industrial properties and is internet sales-adjusted real consumer spending for retail property[5]. We also fit the model with a non-linear time trend by including t and t^2 which are time and time squared. The reasons for including time trend are: 1) Cardozo et al. (2017) found that a trend-based approach to estimate equilibrium rent was effective. This indicates that there could be unobserved time trend factors that affect the rent; 2) Demand and supply proxies show clear trends: including a time trend can potentially avoid spurious regression problems; 3) we found a stable cointegration relationship by including the time trend. The estimated

[4] See, among others, Mouzakis and Richards (2007), Englund et al. (2008), Brounen and Jennen (2009a,
2009b), Adams and Fuss (2012), Ibanez and Pennington-Cross (2013), Chau and Wong (2016), and Crosby et al., (2022).

[5] (1-proportion of internet sales) × real consumer spending

coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ can be interpreted as the effect of demand and supply on real rent by using detrended variables (Woodbridge, 2016, p. 334).

We use market rent as the measure of nominal rent and calculate the real rental value by deflating nominal rent using the GDP deflator.

3.2. Modelling for the Sentiment-adjusted Equilibrium Cap Rate

Derived from the Gordon Growth Model (1962), the cap rate is determined by the risk-free interest rate, r_f, expected long-run inflation rate, i, and a return premium that can reflect both risk and liquidity, π, and the expected long-run rental growth rate, g (Bialkowski et al., 2023). Given that we do not have a good measure of the risk premium for UK commercial real estate, we assume a constant risk premium in our analysis. IFA surveys suggest a risk premium of c.3.5%. Building on previous research demonstrating the importance of sentiment in determining cap rates (Clayton et al.,2008; Heinig et al., 2020), we include sentiment measures in our model and posit that cap rates are a function of sentiment, s. We discuss the importance of including sentiment in the cap rate modelling in CRE in Section 3.4, below. The long-run relationship takes the following form:

$$Cap\ Rate_t = \alpha + r_{f,t} + i_t + f(s_t) - g_t \quad (2)$$

where g is the nominal growth rate in rental income, which can be characterised as a real rental growth rate plus the inflation rate. Following Bialkowski et al. (2023), we assume that inflation is neutral, that is, the real rental growth rate, the real risk-free rate, and the risk premium are unaffected by the rate of inflation, hence the inflation rate term in the equation above and in the rental growth rate cancel out, which implies that inflation does not directly affect the cap rate. In particular, we estimate the following long-run relationship:

$$Cap\ Rate_t = \alpha + \gamma_1(rr_{f,t}) + \gamma_2(s_t) + \gamma_3(rg_t) + \varepsilon_t \quad (3)$$

where $Cap\ Rate$ is measured by the equivalent yield. rr is the real risk-free rate which is proxied by the real yield of the 10-year UK government bond. s is the sentiment. Based on the conditions regarding demand, availability, and incentives in the Royal Institution of Chartered Surveyors (RICS) UK Property Monitor, we use Principal Component Analysis (PCA) to generate a CRE sentiment index. A higher value indicates a higher sentiment. rg is the expected real rental growth rate. Duca and Ling (2018) used survey questions to capture the expected long-term rental growth rate for US commercial real estate. Bialkowski et al. (2023) used the average growth rate over the previous three years to measure the expected rental growth rate. In this study, we use the rental expectation survey question from the RICS UK Property Monitor.[6] We assume that the rent expectation formation is not affected by inflation. In the survey, the answer to the question regarding rental expectation is highly correlated with the answers to the other three questions (demand, availability, and incentives). Thus, we run a regression of rental expectation on those three variables and use

[6] The expectation of long-run rental growth rate would be more appropriate. However, we do not have such measure. We assume long-run rental growth expectation is correlated with the short-run rental growth expectation.

the residual as the proxy for the expected real rental growth rate. In this way, our measure of the expected real rental growth rate is orthogonal to the sentiment.

3.3. Forecasting for Capital Growth

Based on the Gordon Growth Model (1962), the capital value of the property, CV, can be expressed as follows:[7]

$$CV = \frac{Rent}{Cap\ Rate} \tag{4}$$

Given the real equilibrium rent, we can adjust for inflation using the GDP deflator to calculate the nominal equilibrium rent. This is done by simply multiplying the real equilibrium rent by the GDP deflator. Combined with the equilibrium cap rate, we can derive the equilibrium capital value, CV_e. Based on the observed nominal market rent and cap rate, we can derive the actual capital value, CV_a. To determine the percentage of overvaluation or undervaluation, we define VSI as the ratio between actual capital value and equilibrium capital value. A value above 100 indicates overvaluation, and a value under 100 indicates undervaluation. In particular, VSI can be expressed as follows:

$$VSI_t = \frac{CV_a}{CV_e} \times 100 \tag{5}$$

VSI is our main predictor of capital growth at horizon h. In particular, we estimate the following equation for forecasting:

$$CG_{t+h} = \alpha + \beta VSI_t + \varepsilon_{t+h} \tag{6}$$

where $CG_{t+h} = \sum_{i=1}^{h} CG_{t+i}$ is the log capital value growth from time t to t+h. Given that we are using an overlapping sample and the error terms are autocorrelated, we use Newey and West (1987) t-statistics with h+4 lags.

3.4. The Importance of Adjusting Sentiment in Forecasting CRE returns.

In this section, following the arguments of Ling et al. (2014), we analyse overvaluation and undervaluation scenarios separately and use some numerical examples to demonstrate the importance of adjusting for sentiment in forecasting CRE returns.

During a period of overvaluation (when investor sentiment is high), due to the inability to short sell in the private CRE market, arbitrageurs cannot enter the market to counteract mispricing. This leads to slower and less substantial downward adjustments towards true equilibrium value. For example, consider an asset with a true equilibrium value of 75, but currently priced at 100 due to overvaluation. Without taking sentiment into account, we would expect the price to drop by 25% of current pricing to reach equilibrium. However, if we factor in positive investor sentiment, the sentiment-adjusted equilibrium cap rate should be lower than the unadjusted case. This implies that sentiment-adjustment equilibrium

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[7] UK commercial leases typically have five yearly rent review clauses and hence individual property yields reflect reversionary potential. As we are analysing aggregated returns using adjusted yields, we do not consider this explicitly.

capital value is higher, say 90. This indicates that our prediction would be a drop of value of 10% in the future if sentiment stays positive. The magnitude of price correction is less in the sentiment-adjusted case if sentiment stays the same.

During the period of undervaluation (when investor sentiment is low), perceived risk levels in the CRE market tend to rise. This higher risk perception leads investors to demand greater compensation for holding assets, which translates to higher required rates of return. In addition, given that CRE are often highly leveraged and real estate investors often face credit constraints in down markets, investors are less able to take long positions to counteract mispricing when assets are perceived to be undervalued. The combination of increased risk perception and limited access to capital leads to slower and less substantial upward adjustments towards true equilibrium value. For example, consider the true equilibrium value of 75, but currently priced at 50 due to undervaluation. Without taking sentiment into account, we would expect the price to increase by 50% to reach equilibrium. However, if we factor in negative investor sentiment, the sentiment-adjusted equilibrium cap rate should be higher than for the unadjusted case. This implies that the sentiment-adjustment equilibrium capital value is lower, say 60. This indicates that our prediction would be for an increase of value of 20% in the future. The magnitude of price correction is less in the sentiment-adjusted case.

Overall, given the specific characteristics of the CRE market we discussed, it is important to consider sentiment in price correction, as it will help us make more accurate predictions of future values.[8] Empirical evidence on the importance of sentiment is analysed in Sections 5.5.7 and 5.5.8.

4. Data

4.1. Commercial Real Estate Data

This study focuses on the three 'traditional' commercial property sectors in the UK: office, retail, and industrial.[9] For each property type, we collect equivalent yield[10], market rental value index, asset value growth index, and vacancy rate (in terms of floorspace) from MSCI. The data are available from 1987. We use the MSCI monthly series and convert them to quarterly frequency. The data on the overall stock of floor space is from the Valuation Office Agency with construction orders used to create a longer time series as outlined in Crosby et al. (2022).

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[8] To validate our argument in this section, sentiment must be persistent. Appendix A confirms this persistence across all three property types using AR(1) models. Specifically, the coefficient of lagged sentiment is positive, significant, and close to 1, indicating a strong tendency for sentiment to remain stable over time.

[9] In the UK, in contrast to the US and some other European markets, institutional investors tended to avoid residential rental investment although this has become an increasingly important focus particularly in the period after the GFC. The more recent shift to a "beds and sheds" focus in investment allocations might itself be indicative of the role of sentiment in commercial real estate.

[10] The equivalent yield takes into account both the initial income generated by the property and the potential for future income growth. The equivalent yield adjusts rental yields for the reversionary income caused by the pattern of rent reviews in leases.

4.2. Survey data

4.2.1. Commercial Real Estate Survey

We use survey data from the RICS UK Commercial Property Monitor. The survey is updated quarterly. Respondents are asked to compare conditions over the last three months with the previous three months as well as the outlook. The earliest data from the survey are available from the third quarter of 1998, but the questions asked varied. Questions with the longest time series are demand, availability, incentives, and rental expectations[11]. The survey results are presented in terms of the net balance. Net balance is the proportion of respondents reporting a rise in a variable minus those reporting a fall. For example, if 40% reported a rise and 10% reported a fall, the net balance will be 30%. Thus, net balance can take values from -100 to +100. A positive number indicates an overall increase while a negative number indicates an overall decline.

4.2.2 Economics Survey

We use a large set of survey questions regarding general economic conditions from the Confederation of British Industry (CBI). The CBI surveys conditions regarding business sentiment and confidence, sector specific data (e.g. manufacturing, retail), investment plans, employment trends, sales and orders, and pricing trends. In addition, we use the GfK consumer confidence index. These survey questions are mainly used to create synthetic commercial real estate sentiment for the period before 1999 as discussed in model detail in Section 5.4, below.

4.3. Macroeconomic data

Real and nominal yields of 10-year gilts are collected from the Bank of England. Internet sales data is from the Office for National Statistics (ONS). Other macroeconomic variables are obtained from DataStream. Those variables include the yield on the three-month Treasury Bill, real gross domestic product (GDP), real consumption, unemployment rate, the savings ratio, retail sales, FTSE all share index, new construction orders, and the GDP deflator as a proxy for inflation.

5. Empirical Results

5.1. Summary Statistics

We compare the predictive power of VSI for future capital value growth with a broad set of key economic variables as well as other indicators. The variables are the three-month Treasury Bill yield, the term spread (the difference in yields between a 10-year gilt and the three-month T-bill), real GDP growth, real consumption growth, change in the unemployment rate, saving ratio, retail sales volumes growth, stock return, new construction order, cap rate, and CRE sentiment. In Table 1, we provide summary statistics for VSI of office, retail, and industrial properties as well as these macroeconomic variables.

Figure 1 shows the pattern of VSI. Panel A, B, and C show VSI for office, retail, and industrial property, respectively. The grey shaded areas indicate the global financial crisis period (GFC) period. We define GFC period as running from July 2007 to December 2009. VSI clearly showed overvaluation before the GFC, then substantial decline during the GFC.

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[11] Rent expectations are available from the third quarter of 1999.

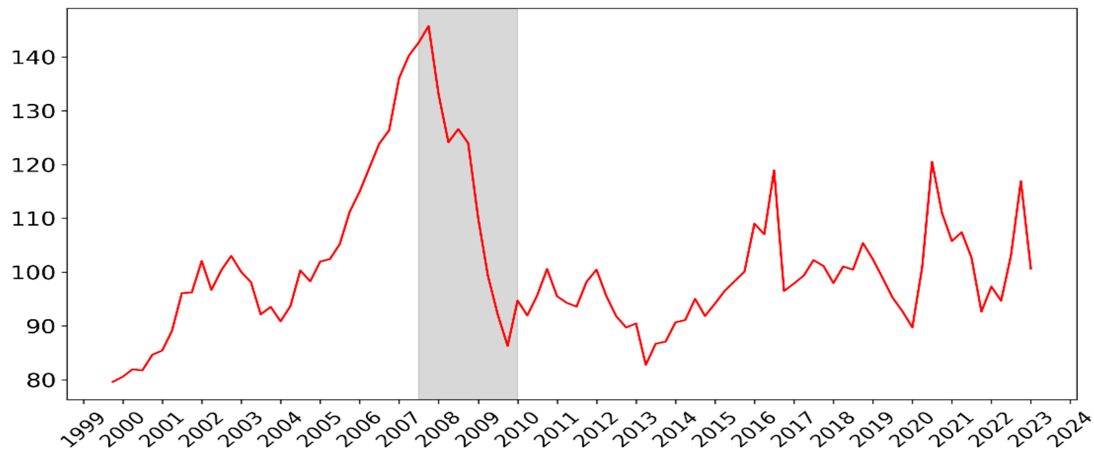
Table 1: Summary Statistics of Predictive Variables

Variable	Transformation	Mean	SD
VSI (office)	Level	101.4	13.72
VSI (retail)	Level	101.2	12.09
VSI (industrial)	Level	101.4	13.97
Yield of three-month bond (%)	Δ	-0.01	0.46
Term spread (%)	Level	0.93	1.16
Real GDP (%)	Δln	0.42	3.03
Real consumption (%)	Δln	0.40	3.66
Unemployment rate (%)	Δ	-0.02	0.23
Savings ratio (%)	Level	8.43	3.27
Retail sales volumes (%)	Δln	0.51	2.35
FTSE all share index (%)	Δln	0.35	7.78
New construction orders (%)	Δln	-0.13	13.55
Cap rate (office)	Level	7.23	1.12
Cap rate (retail)	Level	6.67	0.81
Cap rate (industrial)	Level	7.37	1.55
CRE sentiment (office)	Level	0.00	1.63
CRE sentiment (retail)	Level	0.00	1.68
CRE sentiment (industrial)	Level	0.00	1.65

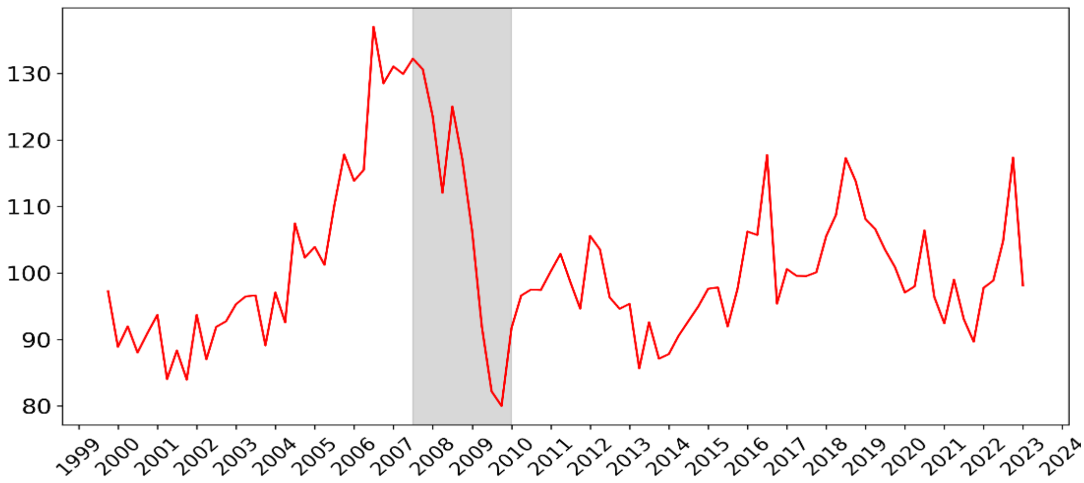
Notes: The table shows summary statistics of VSI for office, retail, industrial properties and macroeconomic variables. For each variable, we report the mean and standard deviation (SD). The table also shows how the variables have been transformed to ensure stationarity. The transformation codes are as follows: Level, no transformation; Δ, first-difference; Δln, log first-difference. The sample period is 1999 Q3 – 2022 Q4.

Figure 1: VSI over time

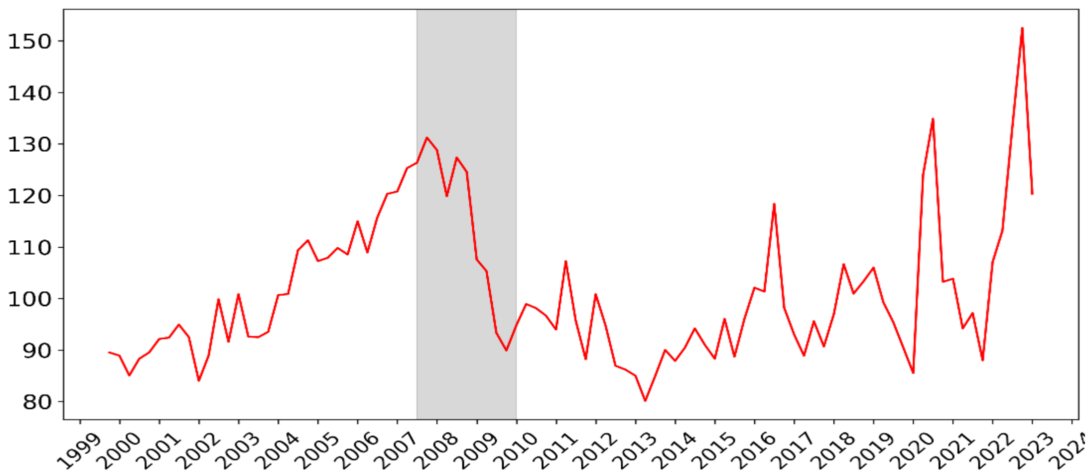
Panel A: Office



Panel B: Retail



Panel C: Industrial

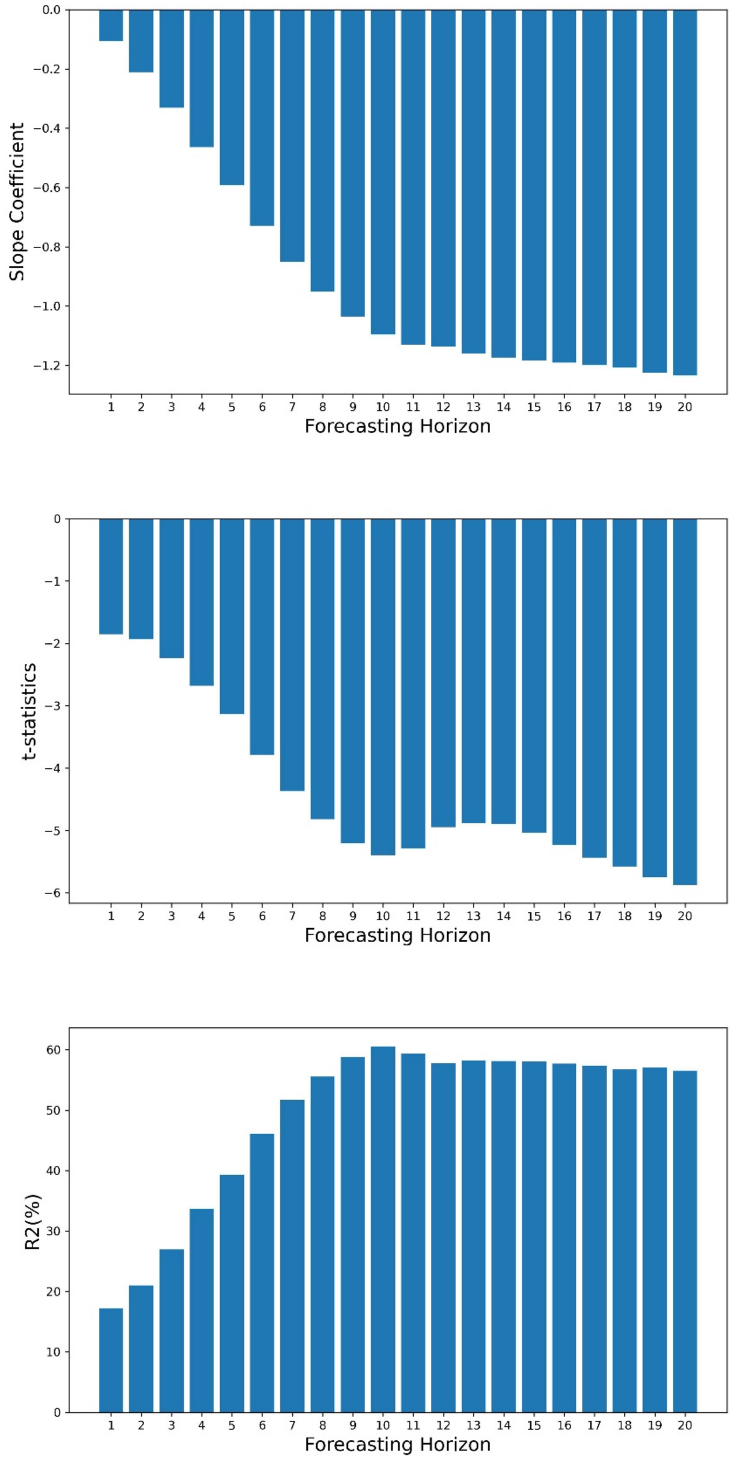


Notes: The figure plots VSI. The grey shaded areas indicate the GFC period.

5.2. In-Sample Regressions

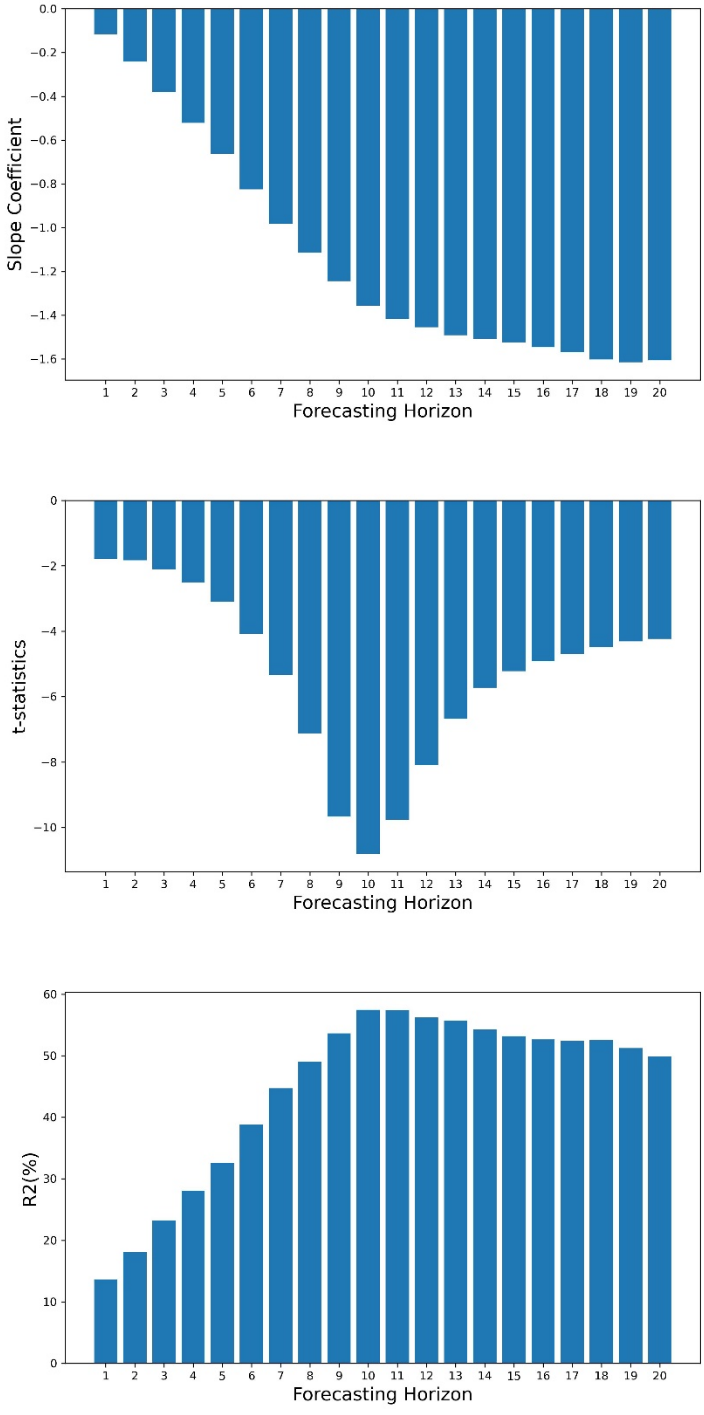
We start by running in-sample forecasting regressions with forecasting horizons from 1 to 20 quarters. Figures 2, 3, and 4 show the estimation results for office, retail, and industrial property, respectively. Slope coefficients, Newey and West (1987) t-statistics, and R^2 are reported. The results show that VSI has significant predictive power for the subsequent capital value growth. The R^2 values show that VSI tracks a substantial amount of the variation in future price movements, especially over a medium to longer horizon. In the subsequent analysis, we use a 12-quarter (three-year) forecasting horizon. The reasons to choose a three-year horizon are the following. First, given the illiquid nature of CRE, from investors' and policymakers' perspectives, they need sufficient time to react. Second, inspired by literature on forecasting business cycles and financial crises (López-Salido et al., 2017; Greenwood et al., 2017), we follow them to forecast at a three-year horizon. Lastly, the UK CRE capital values provided by MSCI are an appraisal-based index. Appraisal smoothing can significantly affect the analysis of lag/lead relationships. However, return smoothing has more limited impact when measuring average return performance over extended periods (Ling, 2005).

Figure 2: Different forecasting horizons for office



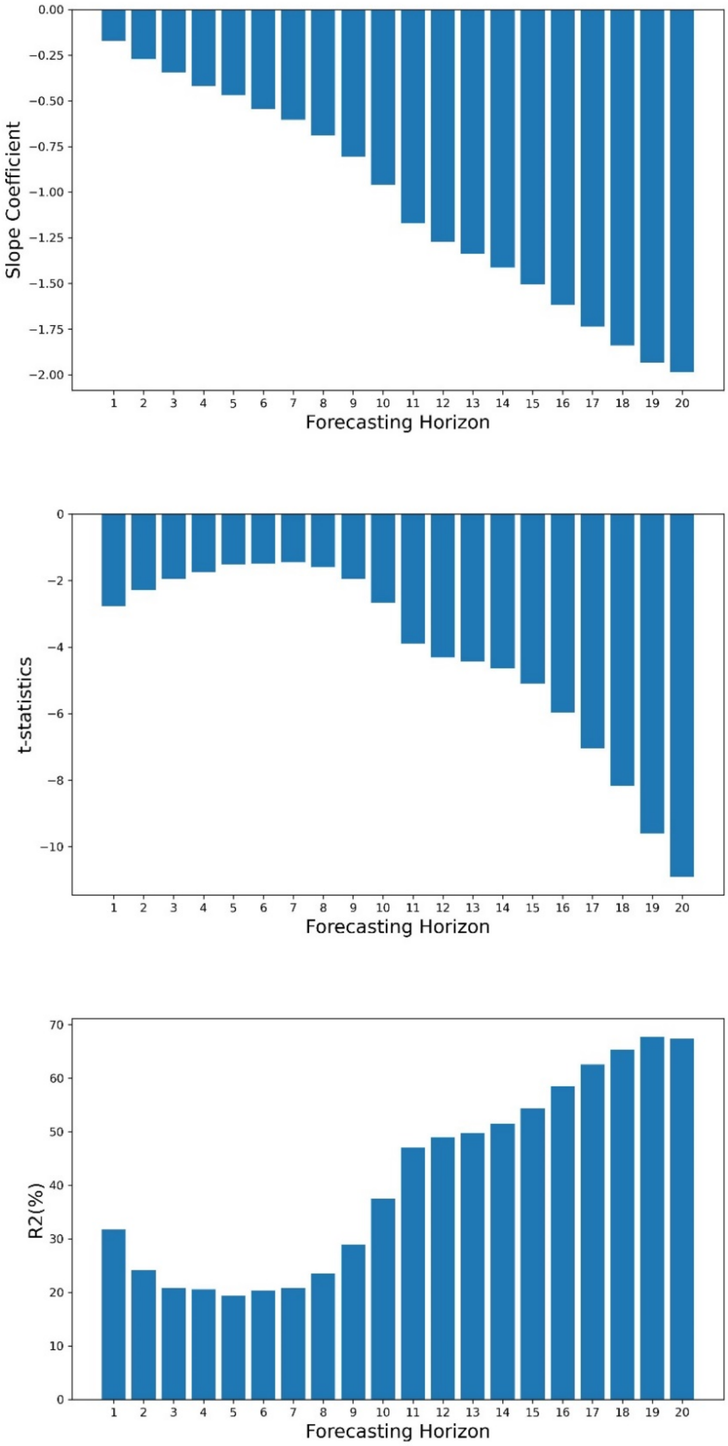
Notes: The figure plots regression slope coefficient, t-statistics, and R^2-values from regression quarterly capital value changes on VSI_{t+h} for $h \in [1, 20]$ for office property. t-statistics are calculated using the Newey and West (1987) procedure with h+4 lags. The forecasting horizon is in quarters.

Figure 3: Different forecasting horizons for retail



Notes: The figure plots regression slope coefficient, t-statistics, and R^2-values from regression quarterly capital value changes on VSI_{t+h} for $h \in [1, 20]$ for retail property. t-statistics are calculated using the Newey and West (1987) procedure with h+4 lags. The forecasting horizon is in quarters.

Figure 4: Different forecasting horizons for industrial



Notes: The figure plots regression slope coefficient, t-statistics, and R^2-values from regression quarterly capital value changes on VSI_{t+h} for $h \in [1, 20]$ for industrial property. t-statistics are calculated using the Newey and West (1987) procedure with h+4 lags. The forecasting horizon is in quarters.

Next, we run the following in-sample forecasting regression at a 12-quarter horizon:

$$CV_{t+12} = \alpha + \beta x_t + \varepsilon_{t+12} \tag{7}$$

where x_t is one of the predictive variables observed at time t. The purpose of this analysis is comparing the in-sample predictive power of VSI with other predictors.

An important question would be whether VSI contains useful information beyond that contained in other predictors. To compare the information contained in VSI with the other predictors, we also estimate the following bivariate regression:

$$CV_{t+12} = \alpha + \beta VSI_t + \phi x_t + \varepsilon_{t+12} \tag{8}$$

From Table 2 Panel A, univariate regression results of office property show that the coefficient of VSI is -1.14, significant at a 1% significance level. This indicates that a one-unit increase in VSI (one percentage point increase in overvaluation) implies a 1.14% decrease in capital value in the subsequent three years. Regarding macroeconomic variables, term spread, unemployment rate, stock return, and new construction order show significant predictive power. Comparing R^2 across all the predictive variables, VSI has a R^2 of 57.7%, which is much higher than R^2 of other variables. This indicates that VSI captures a substantial amount of variation in future capital value movements. Panel B of Table 2 shows the results of bivariate regressions. The coefficients of term spread, unemployment rate, stock return, and new construction order become insignificant. This suggests that VSI provides significant predictive information beyond that captured by these variables. In terms of the cap rate, it shows significant forecasting power with t-value of 1.73 and R^2 of 22.7% in the univariate regression. However, once VSI is added, the coefficient of cap rate becomes insignificant. In addition, the coefficient for CRE sentiment is also not significant once VSI is included.

From Table 3 Panel A, univariate regression results of retail property show that the coefficient of VSI is -1.45 and it is significant at a 1% significance level. This indicates that a one-unit increase in VSI (one percentage point increase in overvaluation) implies a 1.45% decrease in capital value in the subsequent three years. Regarding macroeconomic variables, the yield of three-month government bond, retail sales volumes, and new construction order show significant predictive power. Comparing R^2 across all the predictive variables, VSI has a R^2 of 56.2%, which is much higher than R^2 of macroeconomic variables. This indicates that VSI captures a substantial amount of variation in future capital value movements. Panel B of Table 3 shows the results of bivariate regressions. The coefficients of the yield of three-month government bond, retail sales volumes, and new construction order become insignificant. This suggests that VSI provides significant predictive information beyond that is captured by these variables. In terms of the cap rate, it shows good forecasting power with t-value of 4.59 and R^2 of 53.9% in the univariate regression and it remains significant when VSI is added. CRE sentiment is not significant in either regression.

From Table 4 Panel A, univariate regression results of industrial property show that the coefficient of VSI is -1.27 and significant at a 1% significance level. This indicates that a one-unit increase in VSI (one percentage point increase in overvaluation) implies a 1.27% decrease in capital value in the subsequent three years. Regarding macroeconomic variables, real GDP, real consumption, unemployment rate, saving ratio, and retail sales volumes show significant predictive power. Panel B shows the results of bivariate regressions. Comparing

R^2 across all the predictive variables, VSI has a R^2 of 49%, which is much higher than R^2 of other variables. As with the other sectors this indicates that VSI captures a substantial amount of variation in future capital value movements. Panel B of Table 4 shows the results of bivariate regressions. The coefficients of real GDP, real consumption, and retail sales volumes become insignificant, suggesting that VSI provides significant predictive information beyond that captured by these variables. The cap rate is not significant in either the univariate or bivariate regression. CRE sentiment appears to show significant forecasting power with t-value of 3.97 and R^2 of 14.8% in the univariate regression and the coefficient remains significant when VSI is added.

Past literature and theory suggest that cap rate and sentiment should be able to forecast future returns. However, those two variables did not show consistent predictive power across all three property types. Cap rates seem to help forecast future capital value returns for office and retail properties, but not industrial property.[12] CRE sentiment only helps forecast future capital value returns for industrial property.

[12] Although theory suggests that cap rate should be able to forecast total return and we are using capital return, capital return is a major component of the total return.

Table 2: In-Sample 12 quarters forecasting performance for office

	Panel A: Univariate			Panel B: Bivariate				
	β	t	$R^2(\%)$	β	t	ϕ	t	$R^2(\%)$
VSI	-1.14	-4.95	57.7					
Yield of three-month bond	1.14	0.27	0.1	-1.14	-5.01	-1.48	-0.47	57.8
Term spread	9.02	2.99	26.9	-0.98	-4.26	4.52	1.55	63.4
Real GDP	1.88	0.80	0.3	-1.16	-5.55	-3.15	-1.45	58.5
Real consumption	3.09	1.52	1.2	-1.13	-5.03	0.43	0.18	57.8
Unemployment rate	-19.17	-1.68	4.0	-1.13	-4.97	-3.05	-0.48	57.8
Saving ratio	0.76	0.69	0.5	-1.14	-5.00	0.75	0.75	58.2
Retail sales volumes	1.27	0.61	0.3	-1.14	-5.10	-1.04	-0.52	57.9
FTSE all share index	0.37	3.26	1.6	-1.13	-4.80	0.11	0.57	57.9
New construction order	0.19	2.03	0.7	-1.13	-4.93	0.09	0.85	57.9
Cap rate	8.84	1.73	22.7	-1.08	-5.12	1.33	0.44	58.1
CRE Sentiment	-0.83	-0.40	0.4	-1.14	-5.46	-1.35	-0.98	58.7

Notes: This table shows in-sample regression results of office property. The forecasting horizon is 12 quarters. Panel A reports results from running univariate forecasting regressions, $CV_{t+12} = \alpha + \beta x_t + \varepsilon_{t+12}$, where CV_{t+12} is the realised 12-quarter-ahead log capital value growth rate and x_t is a predictive variable observed at time t. Panel B reports results from running bivariate forecasting regressions, $CV_{t+12} = \alpha + \beta VSI_t + \phi x_t + \varepsilon_{t+12}$, where VSI_t is VSI and x_t is another preditive variable. For each regression, we report the coefficient, the Newey-West t-statistics (16 lags), and the R^2. The sample period is 1999 Q3 – 2022:Q4.

Table 3: In-Sample 12 quarters forecasting performance for retail

	Panel A: Univariate			Panel B: Bivariate				
	β	t	$R^2(\%)$	β	t	ϕ	t	$R^2(\%)$
VSI	-1.45	-8.09	56.2					
Yield of three-month bond	-6.54	-1.68	1.3	-1.45	-8.06	-3.52	-1.12	56.6
Term spread	4.63	1.19	5.3	-1.57	-7.73	-2.73	-1.58	57.7
Real GDP	1.62	0.34	0.1	-1.46	-8.47	-1.06	-0.41	56.3
Real consumption	4.69	1.13	2.1	-1.44	-9.02	1.20	0.42	56.4
Unemployment rate	-5.18	-0.48	0.2	-1.47	-7.99	6.02	1.02	56.5
Saving ratio	1.81	0.84	2.0	-1.45	-7.25	0.23	0.11	56.3
Retail sales volumes	6.30	1.81	4.8	-1.42	-9.05	2.41	1.34	56.9
FTSE all share index	-0.19	-0.67	0.3	-1.46	-8.77	-0.21	-1.31	56.6
New construction order	0.19	2.26	0.5	-1.46	-8.13	-0.05	-0.41	56.3
Cap rate	21.53	4.59	53.9	-0.88	-4.51	11.42	2.03	62.7
CRE Sentiment	3.98	1.78	5.9	-1.42	-9.29	1.13	0.70	56.7

Notes: This table shows in-sample regression results of office property. The forecasting horizon is 12 quarters. Panel A reports results from running univariate forecasting regressions, $CV_{t+12} = \alpha + \beta x_t + \varepsilon_{t+12}$, where CV_{t+12} is the realised 12-quarter-ahead log capital value growth rate and x_t is a predictive variable observed at time t. Panel B reports results from running bivariate forecasting regressions, $CV_{t+12} = \alpha + \beta VSI_t + \phi x_t + \varepsilon_{t+12}$, where VSI_t is VSI and x_t is another preditive variable. For each regression, we report the coefficient, the Newey-West t-statistics (16 lags), and the R^2. The sample period is 1999 Q3 – 2022:Q4.

Table 4: In-Sample 12 quarters forecasting performance for industrial

	Panel A: Univariate			Panel B: Bivariate				
	β	t	$R^2(\%)$	β	t	ϕ	t	$R^2(\%)$
VSI	-1.27	-4.31	49.0					
Yield of three-month bond	2.04	0.59	0.2	-1.27	-4.26	0.70	0.21	49.0
Term spread	5.71	1.24	10.3	-1.24	-3.93	0.65	0.22	49.1
Real GDP	3.45	1.80	0.8	-1.29	-4.35	-2.21	-0.99	49.3
Real consumption	4.26	2.34	2.1	-1.26	-4.19	0.65	0.31	49.0
Unemployment rate	-31.48	-2.88	10.2	-1.20	-3.87	-15.85	-1.82	51.4
Saving ratio	-2.80	-2.53	6.1	-1.28	-4.29	-2.91	-3.48	55.5
Retail sales volumes	5.13	3.04	4.0	-1.24	-4.15	2.52	1.19	49.9
FTSE all share index	0.12	0.66	0.1	-1.28	-4.19	-0.09	-0.46	49.1
New construction order	0.16	1.24	0.4	-1.28	-4.24	-0.09	-0.76	49.1
Cap rate	1.18	0.23	0.5	-1.41	-5.81	-3.44	-1.51	52.8
CRE Sentiment	5.23	3.97	14.8	-1.17	-3.57	2.66	2.05	52.5

Notes: This table shows in-sample regression results of office property. The forecasting horizon is 12 quarters. Panel A reports results from running univariate forecasting regressions, $CV_{t+12} = \alpha + \beta x_t + \varepsilon_{t+12}$, where CV_{t+12} is the realised 12-quarter-ahead log capital value growth rate and x_t is a predictive variable observed at time t. Panel B reports results from running bivariate forecasting regressions, $CV_{t+12} = \alpha + \beta VSI_t + \phi x_t + \varepsilon_{t+12}$, where VSI_t is VSI and x_t is another preditive variable. For each regression, we report the coefficient, the Newey-West t-statistics (16 lags), and the R^2. The sample period is 1999 Q3 – 2022:Q4.

5.3. In-Sample Robustness

In this section, we perform several robustness checks of our in-sample forecasting. For ease of comparison, Panel A of Table 5 shows our benchmark results. In Panel B of Table 5, we control for the AR (1) term in capital value growth. Given that MSCI index is an appraisal-based index, the growth in capital values exhibits positive serial dependence, the AR (1) term could convey useful information about future capital value growth. The results show that the coefficient of VSI remains strongly statistically significant even when controlling for the AR (1) term.

Our sentiment measures are based on three survey questions. The answers to the survey may be based on the current economic conditions and business cycle factors. To ensure our CRE sentiment measure is not an index of common business cycle factors, we regress our CRE sentiment on a set of macroeconomic variables (including the three-month Treasury Bill yield, the term, real GDP growth, real consumption growth, change in the unemployment rate, saving ratio, stock returns, and new construction orders), then use the residual as our new measure of CRE sentiment. We use the new measure of CRE sentiment in the cap rate model in equation (3) and the results are reported in Panel B of Table 5. VSI remains strongly statistically significant.

Because we are forecasting for 12 quarters, there are overlaps in the dependent variable. The ordinary least square (OLS) estimates are inefficient, and the hypothesis tests are biased. We have used the Newey and West (1987) procedure to address the issue in the benchmark estimation. In Panel D of Table 5, we compute bootstrap standard errors from a circular block bootstrap that resamples the data in blocks of consecutive observations, reproducing serial correlation and other dependencies in the data. We use the Politis and White (2004) automatic selection procedure to choose the optimal block length. We resample the dependent variable and the regressor jointly in blocks with an average size of 10 for office and retail properties, and an average size of 12 for industrial property. The results show that the coefficient of VSI remains strongly statistically significant.

Table 5: Robustness checks

	Office		Retail		Industrial	
Panel A: VSI alone						
	β	t	β	t	β	t
VSI	-1.14	-4.95	-1.45	-8.21	-1.27	-4.31
Panel B: controlling for AR(1) component						
	β	t	β	t	β	t
VSI	-1.17	-5.35	-1.44	-8.80	-1.27	-3.76
Panel C: Macroeconomic orthogonalised CRE sentiment						
	β	t	β	t	β	t
VSI	-1.10	-4.26	-1.49	-8.03	-1.20	-4.03
Panel D: VSI alone with bootstrap standard error						
	β	t	β	t	β	t
VSI	-1.14	-3.49	-1.45	-6.81	-1.27	-2.60

Notes: This table reports the results from predictive regressions, $CV_{t+12} = \alpha + \beta VSI_t + \phi Z_t + \varepsilon_{t+12}$, where CV_{t+12} is the realised 12-quarter-ahead log capital value growth rate and Z_t is a predictive is a vector of control variables.. For regressions in Panel A, B, and C, the Newey-West t-statistics (16 lags) are used. The sample period is 1999:Q3 – 2022:Q4.

5.4. Out-of-Sample Regressions

To be practically useful for investors and policymakers, it is crucial that VSI can provide warning of major capital value changes in real time. The GFC is the best example of a major correction in the study period and we would like to investigate whether our approach could have signalled the potential for a major downturn before the GFC. It is important to have enough initial data to get a reliable regression estimate in order to perform out-of-sample forecasts (Welch and Goyal, 2008). Given that we are interested in testing the early warning signal before the GFC, we only have 32 data points at most for the initial estimation period (1999:Q3- 2007:Q2). The MSCI data and macroeconomic data are all available from 1987. However, the RICS UK Property Monitor data is only available from 1993. In order to expand the estimation dataset, inspired by Bro and Eriksen (2022), we create synthetic real estate sentiment data for the missing history back to 1987. CBI surveys regarding UK economic conditions have a longer history. As mentioned in Section 3.2.2, CBI surveys conditions regarding business sentiment and confidence, sector specific data (e.g. manufacturing, retail), investment plans, employment trends, sales and orders, and pricing trends. We have 156 variables from the CBI survey. In addition, we also use GfK's consumer confidence index. Thus, we have 157 variables to capture economic and confidence conditions in the UK. We are trying to map real estate sentiment variables using economic and confidence variables. Instead of manually choosing which economic and confidence variables are relevant to real estate sentiment, we use the elastic net (ENet) to choose the most informative variables to map CRE sentiment. There are several advantages of using ENet. First, OLS estimation provides the best fit over the estimation period, which can lead to overfitting and poor out-of-sample performance. We aim to extend CRE sentiment backwards in time and therefore prefer a method that guards against overfitting. Second, OLS cannot estimate with a large number of regressors against a limited number of observations of the dependent variable. If we would like to utilise all our economic survey information, OLS would not be feasible. Third, the ENet is a penalised regression that allows for variable selection by shrinking certain parameters to zero through the L_1 component (as would a Lasso regression) but is better equipped to deal with highly correlated regressors by also including an L_2 ridge component in the penalty term. Thus, ENet is a hybrid of ridge regression and Lasso regression. Fourth, given that ENet automatically selects the most relevant determinants and we have three different property types, ENet allows us to choose different economic and confidence variables to create synthetic CRE sentiment for each property type. After creating the synthetic CRE sentiment variable, our dataset begins in 1987 Q1. The CRE sentiment data between 1987 Q1 and 1999 Q2 utilises synthetic values. The remaining series consists of actual values.

Similar to Greenwood et al. (2022), we forecast a three-year horizon. In the training dataset, the predictive variable stops three years prior to the start of the forecasting date. For example, if we are forecasting the next three years' capital growth starting from 2003 Q4, our predictive variables in the training dataset stops at 2000 Q4.[13] At the beginning, we utilise the information of predictive variables over the period 1987 Q1 – 2000 Q4 to estimate the parameters. Then we use the value of the predictive variable in 2003 Q4 to predict 12-quarter-ahead log capital value

[13] The dependent variable of regression is the accumulative return for the future 12 quarters. In case the predictive variable is at 2000:Q4, the dependent variable is accumulative capital value growth between 2000:Q4 to 2003:Q4. This process ensures that no information beyond 2000:Q4 is used in our forecast.

growth rate. We use recursive estimation with an expanding window. For every run, we add an extra quarter of information for estimation and the forecast date moves one quarter later. In addition, for every run, we re-estimate our sentiment index, expected rental growth, equilibrium rent, sentiment-adjusted equilibrium cap rate and VSI, we do not use information beyond the point of forecasting date.

To evaluate the performance of out-of-sample, we use the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OoS}). This is computed as:

$$R^2_{OoS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2)}{\sum_{t=1}^{T}(r_t - \overline{r}_t)^2)} \tag{9}$$

where r_t is the 12-quarter-ahead log capital value growth rate, $\hat{r}_t$ is the predicted 12-quarter-ahead log capital value growth rate using our model, and $\overline{r}_t$ is the historical average 12-quarter log capital value growth rate. Essentially, R^2_{OoS} compare the out-of-sample forecast accuracy with a naïve forecast using the historical average value. A positive value of R^2_{OoS} indicates the outperformance of our model compared to the naïve forecast.

We also use a forecast encompassing test (Chong and Hendry, 1986) to evaluate the performance of VSI compared with other predictive variables:

$$CV_{t+12} = \alpha + \lambda_{diff}\widehat{CV}^{VSI}_{t+12} + \lambda_j\widehat{CV}^{j}_{t+12} + \varepsilon_{t+12} \tag{10}$$

where $\widehat{CV}^{VSI}_{t+12}$ is the predicted 12-quarter-ahead log capital value growth rate using VSI, $\widehat{CV}^{j}_{t+12}$ is the predicted 12-quarter-ahead log capital value growth rate using other predictive variables. Following Møller et al. (2023), we implement the test by estimating.

$$e^{j}_{t+12} = \lambda_{VSI}\left(e^{j}_{t+12} - e^{VSI}_{t+12}\right) + u_{t+12} \tag{11}$$

where $e_{t+12} = CV_{t+12} - \widehat{CV}_{t+12}$ is the forecast error. We test the null hypothesis that $\lambda_{VSI} = 0$, which implies that the variable j's forecast encompasses the forecast of VSI. We also estimate the reverse regression and test whether $\lambda_j = 0$

Table 6 reports the out-of-sample results for office property. R^2_{OoS} of VSI is 44.9%, which is much higher than the other variables. The term spread by itself has a R^2_{OoS} of 20.8% in the out-of-sample forecast. Although cap rate shows significant in-sample forecasting power, the performance is poor in out-of-sample forecasting (R^2_{OoS} is -22.3%). Regarding the encompassing test, λ_{VSI} are strongly statistically significant across all the bivariate regressions. This implies that VSI contains relevant information beyond that contained in the other variables, but not vice versa (λ_j are insignificant across all the bivariate regressions).

Table 6: Out-of-sample forecasting performance for office

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	44.9				
Yield of three-month bond	-0.9	1.09	0.00	-0.09	0.70
Term spread	20.8	0.75	0.01	0.25	0.36
Real GDP	-20.5	1.32	0.00	-0.32	0.20
Real consumption	-13.8	1.19	0.00	-0.19	0.44
Unemployment rate	2.8	1.14	0.00	-0.14	0.64
Saving ratio	-6.0	1.08	0.00	-0.08	0.67
Retail sales volumes	-2.4	1.19	0.00	-0.19	0.52
FTSE all share index	1.3	1.11	0.00	-0.11	0.65
New construction order	0.1	1.07	0.00	-0.07	0.77
Cap rate	-22.3	1.21	0.00	-0.21	0.42
CRE Sentiment	-4.5	1.16	0.00	-0.16	0.53

Notes: This table reports the out-of-sample results of office property. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987:Q1 – 2022:Q4.

Table 7: Out-of-sample forecasting performance for retail

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	15.6				
Yield of three-month bond	2.5	0.81	0.23	0.19	0.78
Term spread	-8.2	1.10	0.07	-0.10	0.86
Real GDP	2.9	0.80	0.22	0.20	0.75
Real consumption	4.3	0.75	0.23	0.25	0.69
Unemployment rate	-1.2	0.89	0.17	0.11	0.86
Saving ratio	1.2	0.82	0.25	0.18	0.80
Retail sales volumes	4.7	0.74	0.22	0.26	0.67
FTSE all share index	1.3	0.84	0.21	0.16	0.80
New construction order	1.8	0.82	0.21	0.18	0.78
Cap rate	25.1	0.35	0.49	0.65	0.20
CRE Sentiment	3.7	0.75	0.25	0.25	0.70

Notes: This table reports the out-of-sample results of retail property. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987:Q1 – 2022:Q4.

Table 7 reports the out-of-sample results for retail property. R^2_{OoS} of VSI is 15.59%, which is much higher than the other variables except cap rate. The cap rate shows out-of-sample forecasting power with R^2_{OoS} of 25.1% The R^2_{OoS} of all other variables (excluding cap rate) are all below 5%. VSI appears to be less effective for the retail sector than for other sectors. In the encompassing test, λ_{VSI} is only significant when VSI is used alongside term spread (when the term spread variable becomes insignificant). Using the other variables (except term spread) the VSI is not significant which implies it does not contain relevant information that can improve on the prediction obtained using other variables. In addition, λ_j are insignificant across all the bivariate regressions. This implies that other variables do not contain relevant information that can improve the predictions obtained by VSI. We notice that the relatively poor performance of VSI for retail is mainly due to the post-Covid period. This is discussed in Section 5.5.1.

Table 8 reports the out-of-sample results for industrial property. R^2_{OoS} of VSI is 26.3%, higher than the other variables. CRE sentiment shows a good out-of-sample forecast with R^2_{OoS} of 21.7%. Regarding the encompassing test, λ_{VSI} are strongly statistically significant across all the bivariate regressions except for term spread and CRE sentiment. This implies that VSI contains relevant information beyond that s contained in the other variables (excluding term spread and CRE sentiment), but not vice versa (once again, λ_j are insignificant across all the bivariate regressions).

Table 8: Out-of-sample forecasting performance for industrial

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	26.3				
Yield of three-month bond	-0.4	1.22	0.02	-0.22	0.67
Term spread	5.1	1.18	0.11	-0.18	0.81
Real GDP	-2.4	0.96	0.00	0.04	0.91
Real consumption	-1.7	0.90	0.00	0.10	0.67
Unemployment rate	9.2	0.85	0.05	0.15	0.72
Saving ratio	-3.0	1.10	0.05	-0.10	0.85
Retail sales volumes	2.9	0.96	0.01	0.04	0.92
FTSE all share index	0.4	1.19	0.03	-0.19	0.71
New construction order	0.3	1.15	0.02	-0.15	0.76
Cap rate	-66.0	1.66	0.00	-0.66	0.02
CRE Sentiment	21.7	0.57	0.16	0.43	0.28

Notes: This table reports the out-of-sample results of industrial property. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987 Q1 – 2022 Q4.

Figure 5 compares the out-of-sample forecast and actual subsequent 12-quarter log capital value growth rate. The x-axis is the prediction date (not the actual date of capital value growth rate), the red line shows the forecast 12-quarter-ahead log capital value growth rate, and the blue line shows the actual 12-quarter-ahead log capital value growth rate. The larger the gap between the red and the blue lines, the larger the forecasting errors. The shaded areas indicate that at least one of the quarters in the 12-quarter-ahead belongs to the Covid and post-Covid periods. We designate 2020 Q2 – 2022 Q4 as the COVID period and 2020 Q2 – 2022 Q4 as the post-Covid period in the later context.

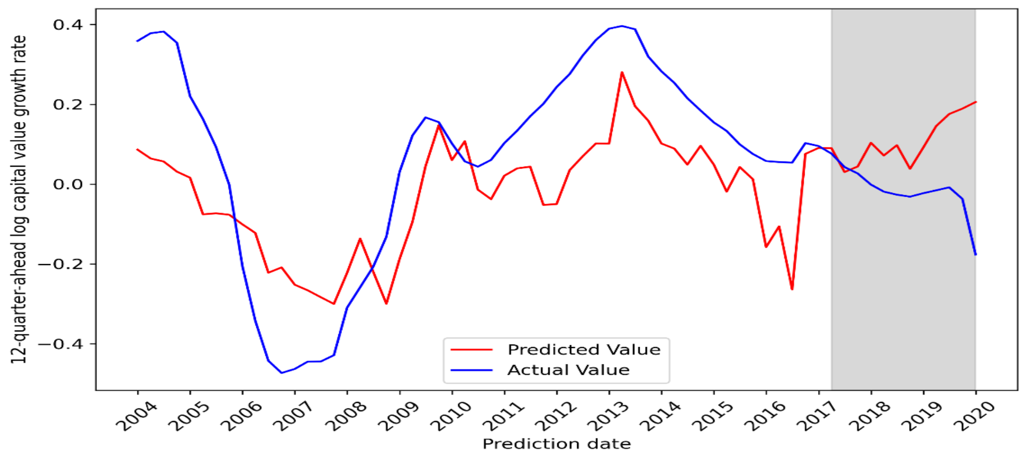
Panel A shows the result for office property. The red line shows large negative values before the GFC period. The red line began to show a negative value of -7.58% in 2005 Q1. Afterwards, the red line showed negative values of -22.2% in 2006 Q2 and -28.3% at 2007 Q2. VSI forecast showed a warning signal of major declines before the GFC. In addition, for the prediction date during the post-GFC period between 2010 and 2012, the out-of-sample forecasts almost perfectly track the actual values. Thus, the prediction successfully predicted the recovery. However, there was a bi mishit in the forecast during 2016, this might be due to Brexit. For the forecasts involving the post-COVID period, the forecast value and the actual value showed divergence. Especially for our last prediction date, 2019 Q4, it showed a large forecasting error. In general, the out-of-sample forecast performed well in real time before the Covid pandemic.

Panel B shows the results for retail property. The red line shows a negative value of -16.2% at 2006 Q2 and followed by -8% for the subsequent four quarters. In general, VSI forecast shows a warning signal of decline before the GFC. For the forecasts involving the post-COVID period, the results show large forecast errors.

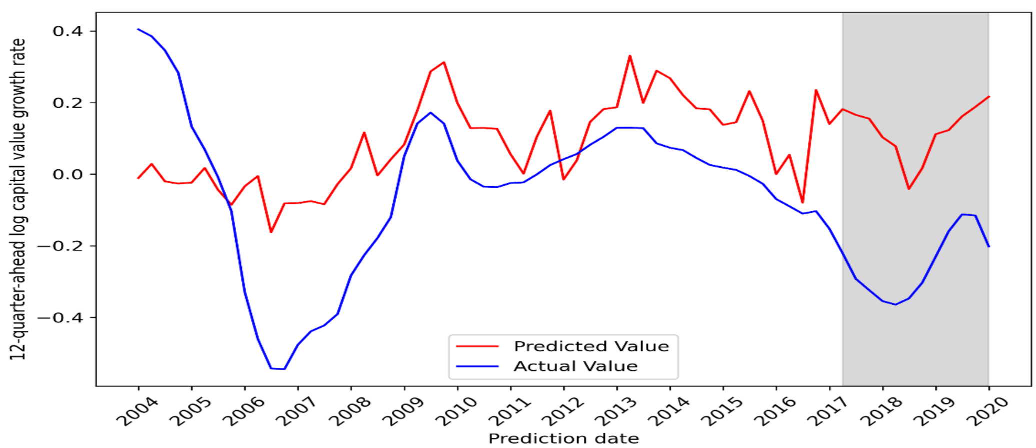
Panel C shows the results for industrial property. The red line began to show a negative value of -6.66% in 2006 Q2 and reached a negative peak at 2007 Q2 with a value of around -14.3%. In general, VSI forecast shows a warning signal of decline before the GFC. For the forecasts involving the post-COVID period, it shows some large forecast errors when the prediction date passes 2018. Interestingly, for our last two prediction dates, 2019 Q3 and 2019 Q4, the predicted value is around 22.0% which is close to the actual value. Thus, our estimates indicate that there is a significant undervaluation of industrial property just before the Covid pandemic.

Figure 5: Out-of-Sample forecast and realised 12-quarter-ahead log capital value growth rate.

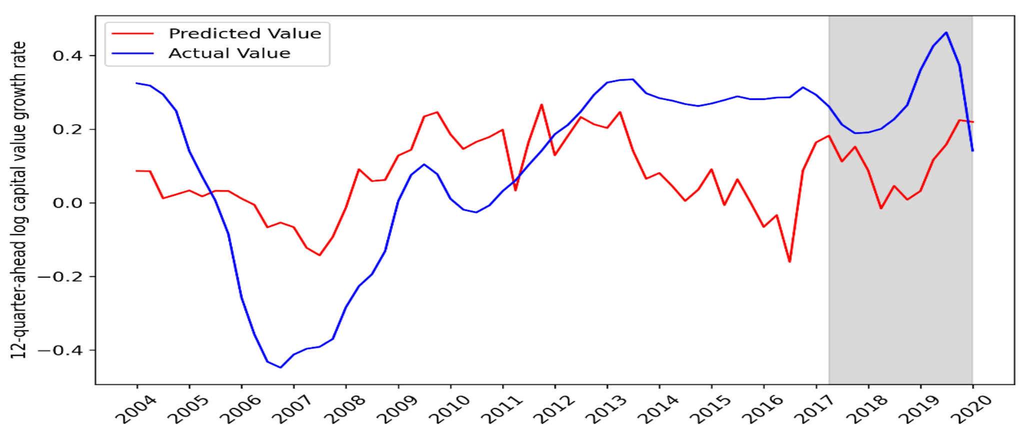
Panel A: Office



Panel B: Retail



Panel C: Industrial



Notes: The figures compare the out-of-sample forecast of subsequent 12-quarter log capital value growth rate with the realised 12-quarter-ahead log capital value growth rate. The x-axis is the prediction date The grey shaded areas indicate that the forecasting period involves post-Covid period.

5.5. Additional Analysis for Out-of-Sample Forecasting

In this section, we modified our model with different specifications and compare the out-of-sample R-squared with our benchmark model. Table 9 reports the results. For the ease of comparison, the R^2_{OoS} of our benchmark model is reported in Panel A.

Table 9: Out-of-sample R-squared of VSI for different model specifications

	Office	Retail	Industrial
Panel A: Benchmark model			
VSI	44.9	15.59	26.3
Panel B: Excluding Covid period (using sample period 1987:Q1 - 2019:Q4)			
VSI	51.6	30.95	29.0
Panel C: Variable risk premium			
VSI	43.8	11.6	16.7
Panel D: Set zero to wrong sign			
VSI	44.9	13.0	26.4
Panel E: Set zero to negative real risk-free rates			
VSI	40.3	33.9	-12.1
Panel F: Different proxy for long-term expected rental growth			
VSI	59.5	-5.0	12.0
Panel G: Macroeconomic orthogonalised CRE sentiment			
VSI	37.7	9.22	19.3
Panel H: Exclude CRE sentiment			
VSI	28.9	7.4	21.2
Panel I: One-year forecasting horizon with CRE sentiment			
VSI	24.8	0.6	2.7
Panel J: One-year forecasting horizon without CRE sentiment			
VSI	0.6	-3.4	1.2
Panel K: Two-year forecasting horizon with CRE sentiment			
VSI	37.2	5.2	9.3
Panel L: Two-year forecasting horizon without CRE sentiment			
VSI	21.2	-3.5	6.2
Panel M: Four-year forecasting horizon with CRE sentiment			
VSI	46.8	26.3	25.8
Panel N: Four-year forecasting horizon without CRE sentiment			
VSI	29.1	23.5	20.1

Notes: This table reports out-of-sample R^2 (R^2_{OoS}) of VSI with different model specifications.

5.5.1. The Effect of the Covid Pandemic

The Covid pandemic had a major impact on the valuation of commercial real estate; we have shown that out-of-sample forecasts are unlikely to capture the capital value dynamics as a result of Covid and its aftermath. In Table 9 Panel B, we report R^2_{OoS} for the pre-Covid period. The results show that R^2_{OoS} increases for all three property sectors. The increase in R^2_{OoS} is particularly striking for retail property. The R^2_{OoS} doubled after excluding the post-Covid period. In the full sample analysis, we observed the following results for retail property: 1) R^2_{OoS} of VSI is lower than R^2_{OoS} of the cap rate; 2) VSI does not contain relevant information that can improve on the predictions obtained using other variables (except term spread); and 3) large forecasting errors in the post-Covid period (shown in Figure 5 Panel B). In order to investigate further for the effect of the Covid pandemic, we perform forecast encompassing tests using samples excluding the post-Covid period (shown in Appendix B). Table B2 shows the results for retail property. By excluding the post-Covid period, the R^2_{OoS} are similar for VSI and the cap rate. More importantly, the coefficients of λ_{VSI} become strongly statistically significant across all the bivariate regressions (except the cap rate).

Our findings suggest that the COVID-19 pandemic has disrupted CRE valuation models. This raises the possibility that we either need a fundamentally new equilibrium model to reflect the changing market dynamics or that the market itself remains in disequilibrium. Unfortunately, the illiquidity of CRE and limited post-pandemic data make it difficult to determine which of these possibilities is right. Further research is needed, including expanding the dataset, exploring alternative valuation models, and analysing market (and sub-market) trends to better understand Covid's impact on CRE valuation.

5.5.2. A Variable Risk Premium

In the benchmark model, we assumed a constant risk premium. In this section, we adopt variable risk premia. Although we do not have CRE risk premium measures, we use the general market credit risk premium captured by the yield difference between BBB-rated corporate bond and 10-year gilts. We assume the equilibrium cap rate is a function of the market credit risk premium. In particular, when we model the equilibrium cap rate in equation (3), we add the market credit risk premium into the equation as an extra independent variable.

The yield of BBB-rated corporate bonds is collected from Standard & Poor's. Unfortunately, the data only begins in 1998 Q1. We backfill the historical data using estimates. The Bank of England provides monthly corporate bond yield data from 1945. Specifically, we use the yield on debentures, loan stocks and other corporate bonds. The series has a correlation of 0.69 with the S&P BBB-rated corporate bond yield during their overlapping period. We run an OLS regression of S&P BBB-rated corporate bond yield on the Bank of England series and create estimated historical values.

R^2_{OoS} are reported In Table 9 Panel C. For all three property types, R^2_{OoS} is lower than the benchmark case. This indicates that using a variable risk premium did not improve the forecasting power.

5.5.3. Adjusting for deviations from theory

Given that we are using recursive estimation with an expanding window it is possible that the coefficients for equilibrium rent modelling and equilibrium cap rate modelling could have the "wrong" signs (that is, different from the theoretically expected sign). Following Campbell and

Thompson (2008), we set the regression coefficient to zero whenever it has the 'wrong sign'. R^2_{OoS} are reported In Table 9 Panel D. The R^2_{OoS} are very similar to the benchmark case for all three property types.

Appendix C plots all the coefficients in the recursive estimation of equations (1) and (3). Figure C1, C2 and C3 show the estimates for office, retail, and industrial properties, respectively. The x-axis shows the ending date of the estimation window, which begins in 1983:Q1. For office property, all the coefficients show the expected sign across all the estimation windows. For the equilibrium rent model, the coefficients of supply and demand are negative and positive, respectively, as expected. For the equilibrium cap rate model, the coefficients for real risk-free rate are positive. The coefficients for sentiment and expected rental growth are negative. For retail property, the coefficients of supply in the rent model show the opposite sign for estimation windows ending before 2005. The rest of the coefficients show the expected sign. For industrial property, the coefficients of CRE sentiment in the cap rate model show the opposite sign for estimation windows ending between 2006 to 2008. The rest of the coefficients show the expected sign. Overall, the estimated coefficients show the robustness of our models for equilibrium rent and cap rate.

5.5.4. Adjusting for Negative Real Risk-free Rates

Because of quantitative easing, there is a good argument that real risk-free rates did not represent 'fundamental' risk-free rates and we observe negative risk-free rates in certain periods. In this section, we set real risk-free rates to zero whenever the real risk-free rate is less than zero. R^2_{OoS} are reported In Table 9 Panel E. The results are different for three property types. After adjusting for negative real risk-free rates, the R^2_{OoS} improves for retail property, whereas R^2_{OoS} decreases for industrial property. For the office property, the R^2_{OoS} changes little.

5.5.5. Different Proxy for Long-term Expected Rental Growth

Bialkowski et al. (2023) used the average growth rate over the previous three years to measure the expected rental growth rate. In this section, we follow the same approach to the expected rental growth rate. R^2_{OoS} are reported In Table 9 Panel F. The results are different for three property types, the R^2_{OoS} improves for office property, whereas R^2_{OoS} decreases for retail and industrial properties. In general, the expected rental growth rate estimation based on surveys performs better than using the historical rental growth rate.

5.5.6. Orthogonalized CRE Sentiment

Similar to the robustness check for the in-sample analysis, we use orthogonalised CRE sentiment in the cap rate model. R^2_{OoS} are reported In Table 9 Panel G. For all three property types, R^2_{OoS} decrease after using the orthogonalised CRE sentiment. However, all the R^2_{OoS} are positive. This indicates that our model still outperforms the naïve forecast using the historical average value.

5.5.7. The Importance of Adjusting Sentiment in Valuation

As we discussed in Section 3.4, it is important to consider sentiment in price correction as it will potentially help us make more accurate predictions for future values and the range of possible outcomes. In this section, we empirically explore whether sentiment measures help improve forecasting accuracy. Specifically, when we model the equilibrium cap rate in equation (3), we drop the CRE sentiment variable. R^2_{OoS} are reported In Table 9 Panel H. For all three property types, R^2_{OoS} decrease after dropping CRE sentiment in the cap rate model. The results show the importance of considering sentiment when forecasting. Panel I to Panel J shows R^2_{OoS} with various forecasting horizons.

5.5.8. Different Forecasting Horizon

Our benchmark forecasting model is based on a three-year horizon. In this section, we also check the out-of-sample predictive accuracy using one-, two-, and four-year horizons. In addition, to further verify the importance of sentiment, for each time horizon, we also show R^2_{OoS} for models without sentiment.

Our results show that for all horizons and property types, R^2_{OoS} are positive. This indicates that VSI has a better forecasting power than the naïve model using the historical average value. We notice that the longer the forecasting horizon, the better the forecasting power (higher R^2_{OoS}). This result supports our discussion in Section 3.4. The adjustment of CRE capital values towards true equilibrium value is not instant and may take a few years. For each time horizon, when we drop the sentiment in the cap rate model, R^2_{OoS} are always lower for all property types. The results again show the importance of considering sentiment when forecasting.

6. Conclusion

Based on economic theories, we develop VSI as an indicator of future CRE capital values. Our model is based on the Gordon Growth Model (1962), the price of the property equals the rent divided by the cap rate. We model equilibrium rent and a sentiment-adjusted equilibrium cap rate. Equilibrium capital values are calculated and compared with actual capital values.

Based on data for the three traditional property sectors (office, retail, and industrial) in the UK, we show that VSI is a strong predictor of future CRE prices. This result holds for both in-sample and out-of-sample analysis for a three-year forecasting horizon. We further verify whether VSI can provide useful warning signals before the GFC. VSI predicted large negative returns before the crisis. Overall, the results suggest that our model for sentiment-adjusted equilibrium capital value and VSI has significant predictive power for the future price movement of commercial real estate.

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Appendix A: Persistence of sentiment index.

	CRE sentiment		
Variable	Office	Retail	Industrial
L1.CRE sentiment	0.9042***	0.9314***	0.9187***
	(18.898	(20.931)	(13.357)
Constant	-0.0345	-0.0475	-0.0173
	(-0.983)	(-0.651)	(-0.232)

Notes: This table shows the estimation of AR(1) models of CRE sentiment. Newey and West (1987) t-statistics with 3 lags are reported in parentheses. ***, **, *Denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix B: Out-of-sample forecasting performance excluding post-Covid period.

Table B1: Out-of-sample forecasting performance for office excluding post-Covid period

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	51.6				
Yield of three-month bond	-1.2	1.21	0.00	-0.21	0.31
Term spread	21.5	0.82	0.00	0.18	0.48
Real GDP	-22.0	1.46	0.00	-0.46	0.01
Real consumption	-15.3	1.34	0.00	-0.34	0.04
Unemployment rate	2.5	1.28	0.00	-0.28	0.22
Saving ratio	-4.4	1.14	0.00	-0.14	0.41
Retail sales volumes	-3.2	1.35	0.00	-0.35	0.11
FTSE all share index	1.2	1.23	0.00	-0.23	0.25
New construction order	0.7	1.19	0.00	-0.19	0.33
Cap rate	-23.6	1.46	0.00	-0.46	0.03
CRE Sentiment	-5.0	1.28	0.00	-0.28	0.14

Notes: This table reports the out-of-sample results of office property excluding post-Covid period. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987:Q1 – 2019:Q4.

Table B2: Out-of-sample forecasting performance for retail excluding post-Covid period

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	30.9				
Yield of three-month bond	1.0	1.30	0.02	-0.30	0.59
Term spread	-12.9	1.64	0.00	-0.64	0.08
Real GDP	2.2	1.29	0.02	-0.29	0.60
Real consumption	1.0	1.29	0.02	-0.29	0.60
Unemployment rate	-5.6	1.39	0.01	-0.39	0.44
Saving ratio	-1.0	1.29	0.02	-0.29	0.60
Retail sales volumes	4.2	1.23	0.03	-0.23	0.67
FTSE all share index	-1.4	1.32	0.02	-0.32	0.55
New construction order	0.9	1.32	0.02	-0.32	0.56
Cap rate	33.2	0.75	0.16	0.25	0.63
CRE Sentiment	-11.6	1.46	0.00	-0.46	0.31

Notes: This table reports the out-of-sample results of retail property excluding post-Covid period. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987:Q1 – 2019:Q4.

Table B3: Out-of-sample forecasting performance for industrial excluding post-Covid period

Variable	R^2_{OoS} (%)	λ_{VSI}	p_{VSI}	λ_j	p_j
VSI	29.0				
Yield of three-month bond	0.0	1.87	0.00	-0.87	0.08
Term spread	12.2	1.65	0.08	-0.65	0.48
Real GDP	0.2	1.21	0.00	-0.21	0.53
Real consumption	0.8	1.20	0.00	-0.20	0.42
Unemployment rate	13.1	1.19	0.02	-0.19	0.69
Saving ratio	-13.3	1.85	0.00	-0.85	0.04
Retail sales volumes	3.6	1.37	0.00	-0.37	0.29
FTSE all share index	0.1	1.84	0.00	-0.84	0.09
New construction order	1.6	1.79	0.00	-0.79	0.11
Cap rate	-58.4	1.94	0.00	-0.94	0.00
CRE Sentiment	21.9	0.87	0.11	0.13	0.80

Notes: This table reports the out-of-sample results of industrial property excluding post-Covid period. The first column reports out-of-sample R^2 (R^2_{OoS}). The rest of the columns report the coefficient estimate from forecasting encompassing tests and their associated p-values. The sample period is 1987:Q1 – 2019:Q4.

Appendix C: Recursive estimation coefficients

Figure C1: Office

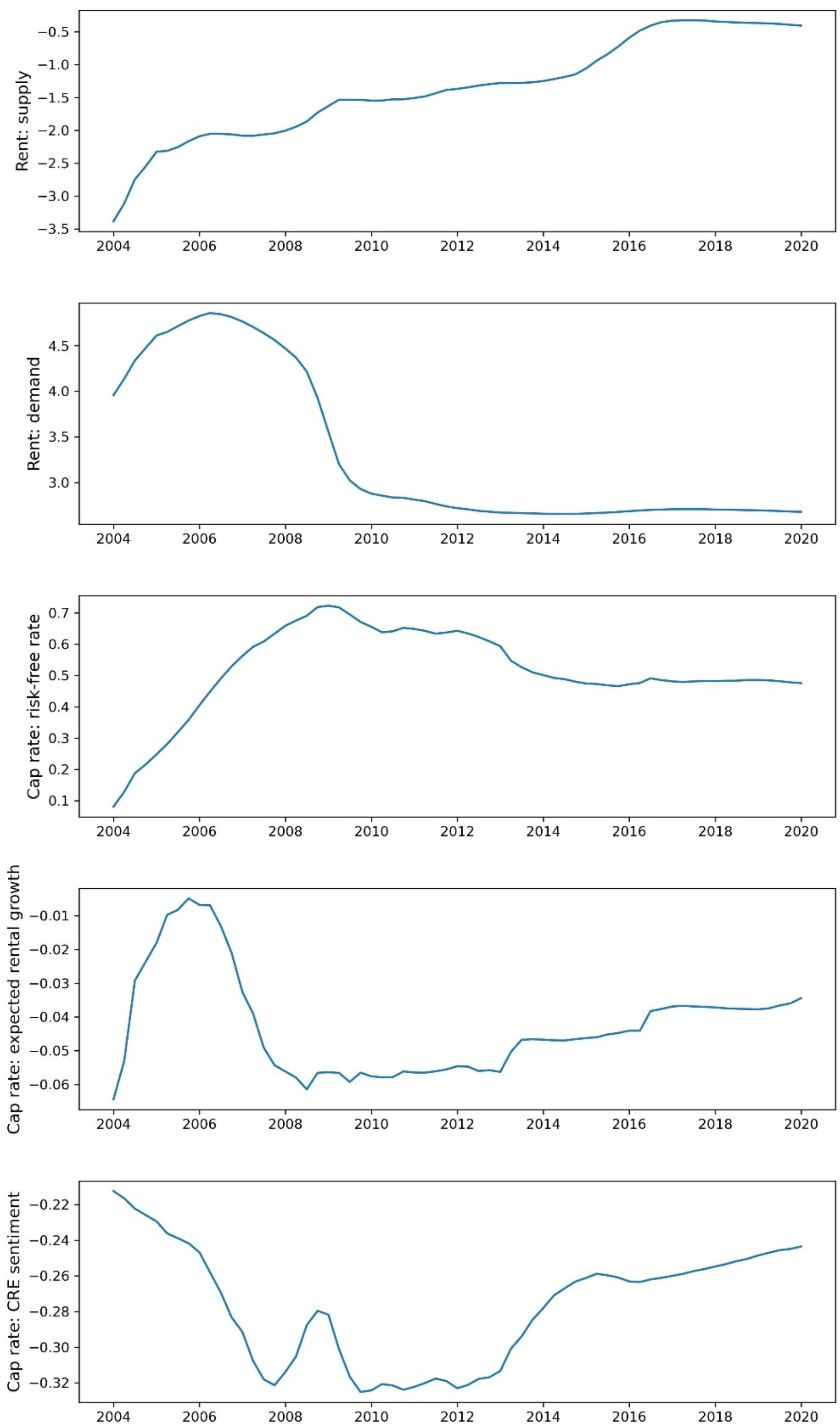


Figure C2: Retail

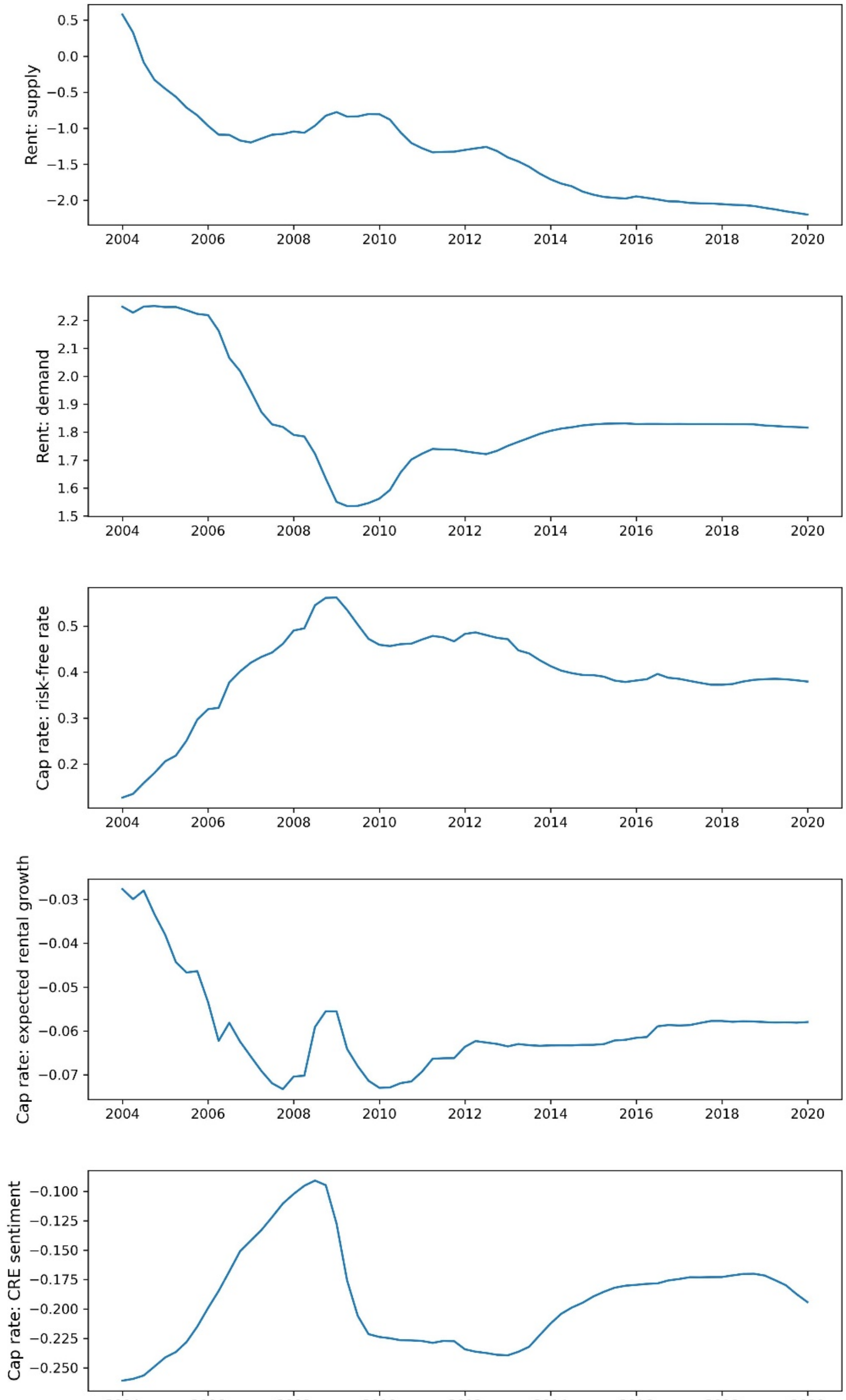
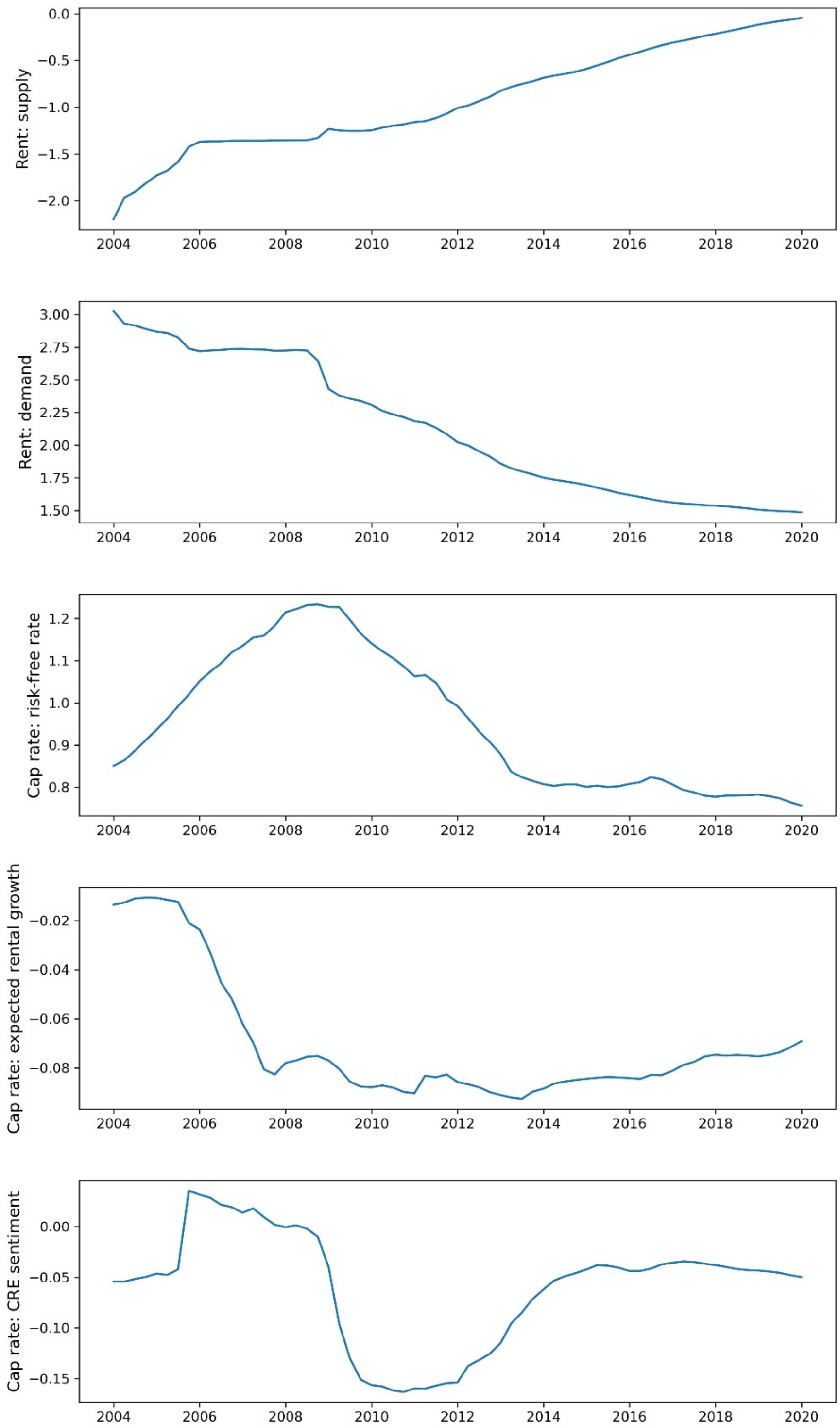


Figure C3: Industrial



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