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Exploring the non-linear dynamics between Commercial Real Estate and systemic risk

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ABSTRACT

The commercial real estate (CRE) market significantly influences financial stability, given its size, use as collateral, and cyclicality. This study explores macro-financial vulnerabilities arising from the CRE market, revealing that adverse developments in CRE capital values amplify systemic risk across financial sub-sectors, namely, banks, insurance companies and investment trusts, consistent with the *collateral channel hypothesis*. The CRE and financial markets relationship, however, displays nonlinearities. We introduce a UK CRE Misalignment index which integrates various market indicators to assess deviations from fundamental values in the CRE sector. We find that during market misalignments, the link between systemic risk and CRE growth weakens, suggesting that further property price increases in an overheated market could lead to a bubble and heightened systemic risk, in line with the *deviation hypothesis*. Finally, we employ a quantile regression model that captures another aspect of this non-linear relationship. We find that positive (negative) developments in the CRE market decrease (increase) the right tail of the historical systemic risk distribution, but CRE variation has a weak impact on the left tail and cannot effectively reduce systemic risk in periods of growth.

Introduction

The Commercial Real Estate (CRE) market holds a pivotal position within the economy and can evidently pose a threat to macro-financial stability (Ellis and Naughtin, 2010). The Property Industry Alliance (PIA) (2023) Data Report estimates that the total value of the UK CRE market stands at £887 billion. In addition, CRE makes a substantial contribution of approximately £74 billion to the UK economy, supporting over 1.1 million jobs within the commercial property industry.[2] The upheavals in the CRE sector during the 2007-2009 timeframe, marked by escalating debt levels and pronounced market fluctuations, played a substantial role in precipitating

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[2] It is important to note that this figure may be a conservative estimate. It is derived from a sample of the largest lenders and it does not include all the developers participating in the market. Furthermore, this estimate exclusively considers direct lending and does not factor in bonds, suggesting that the overall exposure to the commercial property sector may be even more significant.

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the broader financial crisis (Benford and Burrows, 2013).[3] Multiple factors contribute to the inherent high-risk nature of this sector, including the presence of leveraged investors, maturity mismatches, and the manifestation of irrational exuberance among both investors and lenders. Extensive attention is paid to the 2008 housing crisis by researchers and policymakers, but the macro-financial importance of CRE has been largely ignored in the empirical literature, despite the fact that the boom and bust in the CRE market were at least equally severe (Duca and Ling, 2020).

The aim of this paper is to shed light on the dynamics between the CRE market and financial institutions and to empirically examine the macro-financial vulnerabilities stemming from CRE. This study addresses a significant gap in the literature by empirically examining the macro-financial implications of the UK CRE market on systemic risk, emphasizing its underexplored role compared to the residential sector despite CRE market's critical impact on financial stability. We focus on the UK market due to its size[4] and data availability. For our empirical analysis, we draw upon a large sample comprising more than 140 FTSE350 UK financial institutions and we estimate the firm-level systemic risk with respect to the UK financial market. Our findings indicate that distress in the CRE market is associated with an increase in the tail risk of the examined institutions. However, the relationship exhibits significant non-linearities. Firstly, misalignments in the CRE market[5] alter the dynamics between CRE and systemic risk over time. More specifically, when the market exhibits signs of a bubble, further increases in CRE capital values have the opposite effect and they result in greater systemic risk. Secondly, declines in CRE capital values shift the upper quantiles of systemic risk distribution further to the right, whereas increases in CRE capital values have a weak effect on the lower tail of the distribution. In other words, a decline in CRE capital values adds to the accumulation of systemic risk, while positive advancements in the CRE market fail to alleviate systemic risk.

The COVID-19 pandemic period served as a catalyst, prompting a significant price correction in the CRE market and unveiling vulnerabilities that pose a credible threat to financial stability (ESRB, 2019). However, the CRE sector's risk assessment is challenging due to persistent data gaps (Ryan et al., 2022). To motivate this study, we take advantage of access to confidential UK CRE lending data. The data presents evidence on how the pandemic affected the UK CRE market, but also the changes in financial institutions' exposure to CRE assets. Since the initiation of lockdown measures in March 2020, the UK CRE market has undergone significant distress, with the aggregate capital growth index witnessing an average decline of 6.1%, as illustrated in Fig. 1. Beyond the short-term impact, the pandemic has further exacerbated pre-existing adverse structural trends in CRE sub-sectors (Deghi et al., 2021). Notably, social distancing measures and the widespread adoption of remote work have led to a substantial 16.9% average year-on-year contraction in the retail sector, primarily driven by challenges in the hospitality industry. Office properties experienced a decline of 2.7%, while industrial CRE properties, particularly in logistics, benefited from the surge in e-commerce, resulting in a modest growth of 0.7% in prices. The combined effects of the pandemic and recent monetary policy tightening in 2022-2023 are anticipated to create a substantial funding gap in the UK CRE lending market, which underscores the pressing need for a nuanced understanding of the evolving landscape, providing valuable insights for stakeholders navigating the complexities of the UK CRE market.

The data depicted in Fig. 2 underscores the aftermath of the disruptions induced by COVID-19, revealing an 8.8% reduction in

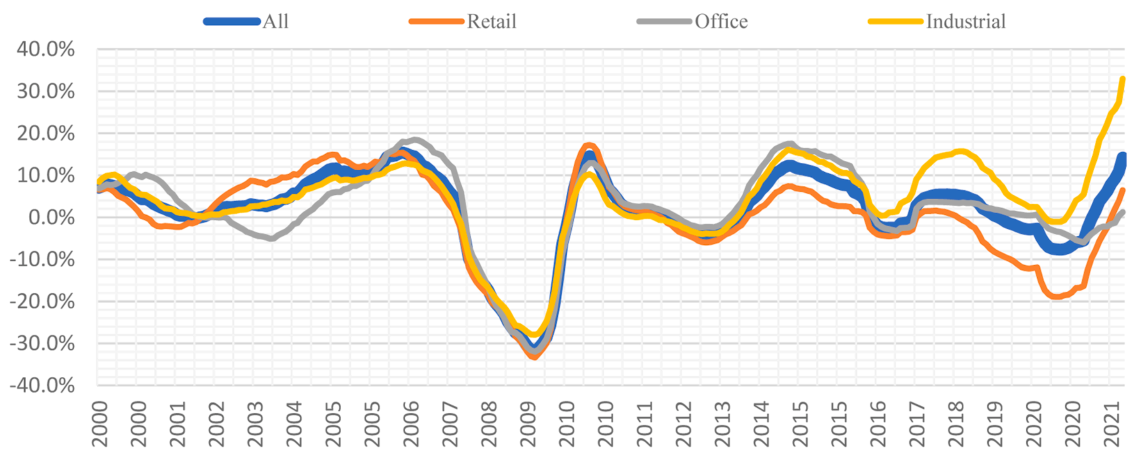


Fig. 1. UK CRE market capital growth index
Note: The Figure displays the year-on-year CRE capital growth for the UK market. The dark blue line refers to the aggregate index, whereas the other three lines represent the three main CRE sub-sectors, namely Retail, Offices and Industrial.
Source: MSCI UK Property data

[3] Reinhart and Rogoff (2009) examine data for past real estate-related crises and find that they have a lasting adverse effect on the macroeconomy.
[4] In June 2022, total lending in the UK CRE market was estimated at more than £180bn.
[5] As measured using the ECB's and the European Systemic Risk Board's methodological approach.

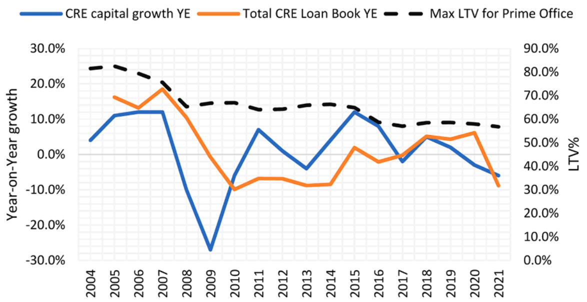


Fig. 2. CRE Capital growth index and lending Volumes
Note: The Figure displays the relationship between total CRE lending volumes (total book held by domestic and international institutions) and year-end CRE capital growth. The dotted line stands for the max LTV for Prime office (benchmark sector) offered by UK CRE market lenders. The data covers the period 2004-2021.
Source: Bayes CRE Lending Report YE (2021)

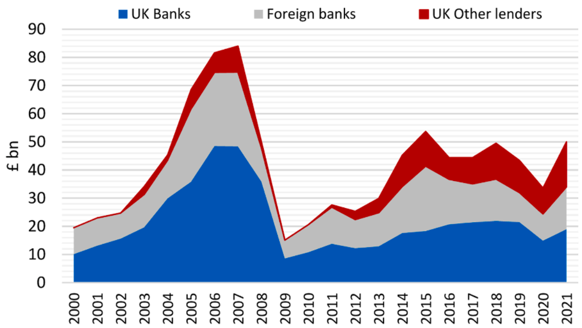


Fig. 3. UK CRE New Loans by lender group
Note: The Figure displays the total UK CRE loan origination for the period 2000-2021. The data are provided by the Bayes CRE Lending Report which uses a dataset of more than 70 of the largest UK lenders including domestic banks, insurers and international banks.
Source: Bayes CRE Lending Report YE (2021)

lending by financial institutions to the UK CRE sector in 2021 compared to 2020. Notably, the maximum Loan-to-Value (LTV) ratio for the benchmark office sector also experienced a decrease, sliding from 58% to 56.8% (Bayes CRE Lending Report, 2021). Fig. 3 explores the landscape of new CRE loans from both UK and foreign financial institutions. The uncertainties brought about by the COVID-19 pandemic prompted a strategic shift among lenders, resulting in a substantial 22% decline in total loan origination. UK banks led the reduction, scaling back their originations by almost a third, while other UK lenders, including insurers, debt funds, and alternative lenders, collectively provided 19% fewer loans in total value. Intriguingly, foreign banks exhibited a comparatively modest reduction, with new loans decreasing by 9%. It's worth noting that despite this decline, their overall exposure to the UK CRE market has been gradually diminishing since the 2016 Brexit referendum.[6]

The rest of the paper is structured as follows. In Section 2, we review the related literature and we explain the contribution of our analysis. In Section 3, we present our data and the estimation of systemic risk. Section 4 presents our empirical findings and all the robustness tests. In Section 5, we use quantile regressions to explore the tail dynamics between CRE and financial markets. Section 6 discusses the main policy implications and Section 7 concludes.

Literature review

Commercial real estate and financial stability

This paper makes unique contributions to several related strands of the literature. Firstly, we contribute the CRE literature by addressing a significant gap in research concerning the relationship between CRE and firm-level stability. The recent developments in the market underscore the pressing need for a comprehensive understanding and examination of the CRE market's macro-financial implications to inform future policy decisions and safeguard against potential crises. Despite CRE's recognition as a crucial market by policymakers, there is a scarcity of studies in this domain. Existing literature tends to focus predominantly on the residential market, which garners more attention due to its political implications directly affecting households (Olszweski, 2013). According to the 2008

[6] In 2017, 35% of the CRE total book was held by foreign lenders, whereas the same figure dropped to 28% in 2021.

Commercial Property Markets report by the European Central Bank (ECB), the dynamics of the CRE market significantly impact financial stability through multiple channels. Primarily, a correction in property prices can reverberate through financial stability, given that real estate lending constitutes a substantial portion of banks' balance sheets in both Europe (ESRB 2019 report)[7] and the US (Antoniades, 2015).[8] This effect, known as the *collateral channel* mechanism, suggests a negative correlation between real estate markets and risk. Specifically, it suggests that increases in the CRE market reduce the probability of default among individual borrowers (Goodhart and Hofmann, 2008; Daglish, 2009; Niinimäki, 2009; Davis and Zhu, 2009).

However, empirical research on the relationship between credit and CRE cycles is limited, hampered by historical data shortages in the CRE market (Davis and Zhu, 2011). To overcome this challenge, we focus on the UK CRE market to take advantage of the available data. The UK is one of the few countries for which data is available in monthly frequency by MSCI. In addition, in the previous section, we use the Bayes CRE Lending report confidential data to present a detailed analysis of the recent developments in the UK CRE market and the impact of the pandemic. All the UK lenders participating in the report are included in our sample that allows us to shed light into the sectors' developments and how they affect lenders' behaviour and financial stability.

In alignment with the *collateral channel*, Fig. 2 illustrates that UK financial institutions responded to the distress during the COVID-19 period by reducing their exposure to the market. In other words, CRE capital growth and the annual change in CRE lending are positively correlated, with lenders reacting with a time lag to the underlying CRE investment market. Consequently, a robust relationship exists between commercial property, bank lending, and profitability, necessitating banks to augment provisions to hedge against credit risk during a CRE market downturn (ECB, 2022). The interplay between banks' lending behaviour and CRE property investments is bidirectional, as suggested by Davis and Zhu (2009, 2011). Their research indicates that bankers' lending decisions significantly impact CRE property transactions, while developments in the CRE market exert an influential effect on the banking sector. Additionally, studies by Elysiani et al. (2010) and Kohlscheen and Takats (2021) underscore the high sensitivity of banks and insurance companies to Real Estate Investment Trusts (REITs) returns, which serve as proxies for the real estate sector performance.

Another factor that makes the CRE market considerably important for financial stability is that it exhibits strong pro-cyclical volatility (ECB, 2011). Financial institutions are inherently exposed to both the residential and commercial real estate sector, through collateralized real estate assets and by providing development finance to construction companies. Consequently, CRE exhibits a high correlation with industrial production, closely tracking the construction and economic cycles.[9] A correction in the CRE market can lead to a direct impact on financial institutions' portfolios, credit losses and a decline in income and profitability, especially in the case that borrowers prove to be unable to meet their debt-servicing obligations (ECB, 2008). At least in the short-term, the real estate market is characterised by fixed supply and therefore it is exposed to fluctuations in the construction industry (Herring and Wachter, 1999; Davis and Zhu, 2009; Ellis and Naughtin, 2010). Moreover, the indirect impact on banks' portfolios stems from potential market distress negatively affecting the real economy, creating a ripple effect throughout the financial system.

Simultaneously, the pronounced dependence of the real estate sector on economic activity and the construction sector renders CRE loans more volatile compared to many other lending types (Davis and Zhu, 2009; Crowe et al., 2013; Hagen and Hansen, 2018). Hiebert and Wredenborg (2012) argue that the volatility of prime CRE values surpasses that of the housing market, with the CRE market experiencing more pronounced peaks. Additionally, CRE market borrowers may not face as strong disincentives to default as households with mortgages (Ellis and Naughtin, 2010), contributing to increased volatility and higher default rates[10], resulting in substantial credit losses.[11] Financial institutions' exposure to the CRE market extends beyond direct lending, with the majority investing in commercial mortgage-backed securities (CMBS). CMBSs are fixed-income securities backed by diverse portfolios of CRE mortgages which present advantages for lenders in terms of not being held on the bank's balance sheet after origination, reducing risk-weighted capital costs. However, this detachment also introduces downsides in terms of financial stability. While this paper does not explicitly focus on the securities market, it explores another channel between financial stability and the CRE market, emphasizing that the CRE market influences CMBS returns.[12]

Determinants of systemic risk

The paper also contributes to the literature investigating systemic risk and its drivers. The extant literature documents that the systemic importance of a financial institution is positively correlated with its size (Pais and Stork, 2013; Laeven et al., 2016; Varotto and Zhao, 2018; Dungey et al., 2022), its leverage (Acharya and Thakor, 2016) and lending as a fraction of total assets (Buch, et al., 2019). Conversely, bank capitalization (Laeven et al., 2016) and liquidity creation (Davydov et al., 2021) are negatively related with systemic risk metrics. The decomposition of financial institutions' loan books also plays a crucial role in their systemic importance. Factors such as unstable funding (Lopez-Espinosa et al., 2013), credit rating downgrades (Kladakis and Skouralis, 2024), significant

[7] The report indicates that EU CRE markets' transactions dropped by 50% in the last three quarters of 2020 compared to 2019. At the same period, the net investments in UK CRE properties were on average -£146.8m (MSCI).

[8] Zhang et al. (2018) find that real estate market variation impacts the regional commercial banks' stability in China.

[9] CRE development finance is sizeable since it accounts for around £22bn. (Bayes CRE Lending report YE2021).

[10] During the crisis, delinquency rates in the US were higher for CRE loans than home mortgages (Antoniades, 2015).

[11] The Bayes CRE Lending Report (2021) documents breaches in CRE portfolios for 48 out of 76 large UK lenders.

[12] The cumulative US CMBS market losses during the 2007-09 financial crisis was around 14%, which together with 8% losses in the CRE mortgages led to a significant increase of bank failures (IMF, 2021). Due to its size and its role in CRE debt financing, the efficient functioning of CMBS markets is of great importance (Pozsar et al., 2010).

dependence on securitization income and foreign capital (Sedunov, 2016), and heightened complexity during crisis periods (Bakkar and Nyola, 2021) can result in increased systemic risk.

Other factors, including market competition (Anginer et al., 2014) and a stricter regulatory framework (Bostandzic and Weiss, 2018), have been identified as mitigating systemic risk. Brunnermeier et al. (2020a) highlight the increased volatility of noninterest income and its association with higher tail risk. Mayordomo et al. (2014) argue that credit derivatives contribute to systemic risk, whereas interest rate derivatives have the opposite effect. Chu et al. (2020) show that geographic diversification affects systemic risk via its impact on asset similarity. This is relevant to our work since real estate investments provide a simple route for lenders to diversify their portfolio into multiple markets. However, at the same time, both commercial and residential real estate markets, are highly correlated and exhibit strong co-movements, which will result to the opposite effect. More recently, Hasan et al. (2023) find evidence of a significant relationship between herding and systemic risk, indicating that herding behaviour might be an ex-ante aspect of systemic risk.

Furthermore, our study aligns with the literature examining how the macroeconomic environment influences systemic risk. Giglio et al. (2016) find that systemic risk metrics are correlated with macroeconomic tail risks. Similarly, Abdymomunov et al. (2020) argue that adverse macroeconomic conditions could increase systemic risk, resulting in heightened destabilization risk for the financial system. Our paper uniquely contributes to this literature by shedding light on how variations in the CRE sector impact systemic risk in the UK financial system. In a study closely related to ours, Deghi et al. (2021) find that excess developments (misalignments) in the CRE market have a significant impact on the projected conditional distribution of GDP growth. Although CRE has drawn considerable amount of attention over the last years, there is no research focused on individual financial institutions, due to the lack of data. This is, to the best of our knowledge, one of the first papers to examine the direct impact of CRE on financial stability and systemic risk.

Non-linearities between real estate markets and macro-financial environment

Lastly, our paper contributes to the expanding literature on non-linearities and tail risks. Pavlidis et al. (2021) find that a decline in house prices is associated with greater systemic risk in UK Real Estate Investment Trusts (REITs). However, based on their findings during periods of exuberance in the residential market, systemic risk is, on average, higher. To capture this non-linear relationship, we construct a UK CRE Misalignment index following the ECB and ESRB's methodological approach.[13] The index, comprising five ratios comparing CRE market developments with macroeconomic fundamentals, reveals evidence of overvaluation in the CRE market before the 2007/2009 global financial crisis, followed by its collapse in 2008. Our empirical results suggest that during the boom phase of the CRE cycle, systemic risk gradually increases and peaks during the subsequent bust phase. These results align with the so-called *financial accelerator* mechanism posited by Kiyotaki and Moore (1997) which comprises two opposing effects on financial stability. The first refers to the *collateral channel* mechanism and the second to the *deviation hypothesis.* This hypothesis posits that prolonged periods of heightened CRE growth may lead to persistent deviations from the fundamental value, creating conditions conducive to a market bubble (Allen and Carletti, 2013; Allen and Gale, 2000; Bernanke and Gertler, 1995). Our empirical evidence indicates support for both hypotheses, underscoring the strength of the relationship between the real estate market and financial stability, albeit with an asymmetric nature (Koetter and Poghosyan, 2010; Pan and Wang, 2013).

Moreover, we employ a quantile regression model to explore an additional dimension of the non-linear dynamics inherent in the relationship between CRE and financial markets. Musso et al. (2011) and Duca and Muellbauer (2013) suggest that a linear model does not capture the relationship between residential real estate and financial markets and yields non-robust findings. The adoption of a quantile regression model, as advocated by Giglio et al. (2016), enables us to grasp the asymmetries and non-linearities between systemic risk and macroeconomic variables. Our empirical findings indicate that a downturn in the CRE market exerts a more pronounced impact on the right tail of the systemic risk's distribution than on the median or the left tail. In other words, fluctuations in CRE values have a limited effect on the left tail and are less effective in mitigating systemic risk during periods of growth. Conversely, the influence on the upper tail, particularly at elevated levels of systemic risk, is substantially more significant. Our analysis aims to provide valuable insights into non-linear relationships and tail risks, enhancing our understanding of systemic risk dynamics in the context of the CRE market.

Data

Measuring systemic risk

According to the joint report of Financial Stability Board (FSB), International Monetary Fund (IMF) and Bank for International Settlements (BIS) (2009) for the G20, systemic risk is defined as "*the risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy*". To measure firm-level systemic risk we employ one of the most prominent measures in the literature, ΔCoVaR by Adrian and Brunnermeier (2016).[14] Our sample consists of weekly data from more than 140 listed UK financial institutions included in the FTSE350. The examined period is between January 2000 and December 2021 and all firm-level data is provided by EIKON Datastream. To calculate systemic risk, we

[13] See ECB (2011), ESRB (2019) and Central Bank of Ireland Systemic Risk Pack (2019).

[14] Our results are robust to alternative systemic risk metrics such as the Marginal Expected Shortfall (MES) by Acharya et al. (2017) and SRISK by Brownlees and Engle (2017). The results are presented in Section 4.4 in Table 6.

need to define our financial system variable. For that purpose, we employ the EIKON Datastream UK Financials index that consists of large financial institutions including banks, insurers, financial services and real estate companies. For the dynamic estimation of systemic risk, we employ a set of state variables as described below which are provided by EIKON Datastream, OECD Database.[15] ΔCoVaR captures the change in the Value-at-Risk (henceforth VaR) of the financial system index when the examined financial institution is under distress.

More specifically, the VaR of the institution i is defined as:

$$P\left(\boldsymbol{R}_t^i < \boldsymbol{VaR}^i\right) = \boldsymbol{q} \tag{1}$$

where R_t^i is the weekly returns of firm i and q the examined quantile. The CoVaR of the system (s) when a firm (i) is under distress is calculated as:

$$\boldsymbol{P}\left(\boldsymbol{R}_t^s < \boldsymbol{CoVaR}^{s|i} \middle| \boldsymbol{R}_t^i = \boldsymbol{VaR}^i\right) = \boldsymbol{q} \tag{2}$$

To capture the systemic importance of the examined institution, we estimate the difference between the CoVaR of the system (s) when a firm (i) is under distress and when it is equal to its median ("*normal times*"). As shown in Equation (3), the difference between the two is defined as ΔCoVaR and higher values indicate that the examined institution is more systemically important.

$$\Delta \mathrm{CoVaR}^{s|i} = \mathrm{CoVaR}^{s|i}_{q=0.05} - \mathrm{CoVaR}^{s|i}_{q=0.5} \tag{3}$$

If the examined firm experiences distress, this would have a considerable effect on the VaR of the financial system or the other institution. According to Adrian and Brunnermeier (2016), ΔCoVaR is positively correlated with the financial institution's size and VaR, although the relationship with VaR is relatively weak.[16] Equation (3) estimates the average systemic risk of the examined institution, but it does not allow for changes across different time periods. To add time variation, we use a quantile regression model with a set of state variables that are highly liquid and tractable assets, capturing the change of systemic risk over time. In the first step, we apply a quantile regression model, where the dependent variable is the weekly return $\left(R_t^i\right)$ of the examined firm, with t representing a specific week and the independent variables are the lagged state variables ($StateVar_{t-1}$). This model is used to estimate the Value-at-Risk ($VaR^i_{q,t}$) of the institution i at time t.

$$\boldsymbol{R}^i_{q,t} = \boldsymbol{a}_q + \boldsymbol{\beta}_q\ \boldsymbol{StateVar}_{t-1} + \boldsymbol{u}_q \tag{4}$$

$$\boldsymbol{VaR}^i_{q,t} = \widehat{\boldsymbol{R}^i_{q,t}} \tag{5}$$

In Equation (4), a_q is the intercept term, β_q the vector of coefficients and u_q the residuals for the q-th quantile. Using the predicted value of $\widehat{R^i_{q,t}}$ at $q\ = 0.05$, we obtain the dynamic VaR for each firm. With regards to state variables, we follow Adrian and Brunnermeier (2016) and we use the FTSE100 stock market index weekly average returns and volatility, the change in the three-month government bond, the term and credit spread.[17] All data is provided by EIKON Datastream and the choice of these state variables is consistent across all the firms in our sample.

In the next step, we run the quantile regression model with the returns of the EIKON Datastream UK Financials index as the dependent variable and examined firm (R_t^i) and the state variables ($Statevar_{t-1}$) as explanatory variables. In Equation (7), we replace back the estimates for the quantile regression model and the estimated VaR that has been previously calculated in equation (5) and we obtain the conditional VaR (CoVaR) of the system when the examined firm is under distress. Finally, in Equation (8) we estimate ΔCoVaR as the difference between the CoVaR of the system (s) when a firm (i) is under distress and when it is equal to its median.

$$\boldsymbol{R}^s_{q,t} = \boldsymbol{a}_q^{s|i} + \boldsymbol{\beta}_q^{s|i}\ \boldsymbol{Statevar}_{t-1} + \boldsymbol{\gamma}_q^{s|i}\ \boldsymbol{R}_t^i + \boldsymbol{v}_q \tag{6}$$

$$\boldsymbol{CoVaR}^{s|i}_{q,t} = \widehat{\boldsymbol{a}}_q^{s|i} + \ \widehat{\boldsymbol{\beta}}_q^{s|i} \boldsymbol{StateVar}_{t-1} + \widehat{\boldsymbol{\gamma}}_q^{s|i}\ \boldsymbol{VaR}^i_{q,t} \tag{7}$$

$$\boldsymbol{\Delta CoVaR}^{s|i}_{q,t} = \widehat{\boldsymbol{\gamma}}_q^{s|i}\left(\ \boldsymbol{VaR}^i_{q,t} - \boldsymbol{VaR}^i_{0.5,t}\right) \tag{8}$$

Fig. 4 illustrates the average weekly systemic risk among the four largest and systemically important banking institutions in the UK.[18] ΔCoVaR is based on VaR, and therefore it is not additive and the aggregate index does not have particular information of the level of systemic risk in the UK economy. However, it is presented to highlight the development in the UK financial market and the time variation of systemic risk. The systemic risk aggregate index follows the business cycle with peak values around the Great Recession

[15] See Table A1 for the state variables summary.

[16] The correlation coefficient between VaR and ΔCoVaR is estimated at 28.9%. In the Appendix, Fig. A1 displays the cross-correlation figures.

[17] The selection of state variables is solely constrained by the availability of UK data series. In the Appendix, Table A1 presents the summary statistics of the selected state variables.

[18] We use the data series for Lloyds Banking Group, NatWest, Barclays and HSBC that based on 2022 data account for 40% of the Market Capitalization of our sample. Due to the fact that our sample is unbalanced, we do not present the entire sample's average.

Fig. 4. UK Large Banks Systemic Risk
Note: The Figure displays the average weekly systemic risk value (ΔCoVaR) for the UK largest banking institutions. The estimation period is based on the state variables approach and the period 2000-2021. The set of state variables include the FTSE100 stock market index weekly average returns and volatility, the change in the three-month government bond, the term and credit spread.
Source: Authors' calculations.

(2008/09), the European sovereign debt crisis (2011/12), the Brexit referendum period (2016/17) and the COVID-19 pandemic period.

Table 1 provides an overview of the weekly summary statistics detailing systemic risk across five distinct financial sectors. The average ΔCoVaR is equal to 1.576% which indicates that when a financial institution is under distress the weekly returns-based VaR of the UK financial system increases accordingly.[19] Notably, UK banks emerge as the most significant sector in terms of systemic importance within our sample. Despite comprising only 6.4% of the total number of examined firms, their market capitalization exceeds 50% of the entire sample. Although the high systemic importance of the banking sector was expected, it still highlights its pivotal role in shaping the overall risk profile of the financial sector and underscores the need for close monitoring.

Measuring CRE capital growth

To incorporate the developments in the CRE market we use data on CRE capital values provided by MSCI. Measurement of investment performance in many financial asset categories relies on transaction prices, but direct real estate stands out as an illiquid and diverse investment class. This characteristic poses challenges in creating purely price-based indexes and for that reason MSCI Property Indexes primarily rely on market valuations sourced from professionals, typically conducted by independent valuers.[20] These valuations consider market assumptions and incorporate relevant recent transaction evidence to address the unique nature of direct real estate investments. MSCI CRE indexes and data are widely used by various market participants, including institutional investors, asset managers, real estate professionals, and central banks. We use data for the period 1999m1-2021m12 and we estimate the capital growth as the year-on-year change of capital values. More specifically, capital growth stands for the annual change in asset capital value, net of any capital expenditure and receipts over the period, relative to the capital employed.

Empirical analysis

Benchmark model

In this section, we present the benchmark model specification and empirical results. We estimate a fixed-effects regression model that allows us to control for unobservable differences among financial institutions and eliminate bias from unobservables that are constant across banks but change over time. The empirical model takes the following form:

$$\boldsymbol{\Delta CoVaR}_{i,T} = \boldsymbol{\alpha}_0 + \boldsymbol{\beta}_1 \boldsymbol{CREgro}_{T-1} + \boldsymbol{\beta}_2 \boldsymbol{FC}_{i,T-1} + \boldsymbol{\beta}_3 \boldsymbol{MC}_{T-1} + \boldsymbol{\alpha}_i + \boldsymbol{m}_T + \boldsymbol{\varepsilon}_{i,T} \tag{9}$$

where $\boldsymbol{i}$ and $\boldsymbol{T}$ stand for the examined financial institution and month, respectively, $\boldsymbol{\alpha}_i$ is the firm fixed-effect and $\boldsymbol{m}_T$ is the month fixed-effect. $\boldsymbol{\varepsilon}_{i,T}$ is the error term, assumed to be normally distributed with mean 0 and variance $\boldsymbol{\sigma}^2$. ΔCoVaR, expressed in basis points and estimated at the 5th percentile, serves as the dependent variable and our main variable of interest. To align its frequency with the other variables in our analysis, we transform ΔCoVaR into a monthly series by calculating the monthly average of its weekly values.[21]

[19] VaR is expressed in absolute values. Therefore an increase in VaR should be interpreted as greater idiosyncratic risk.
[20] MSCI provides data on sub-sectors such as Offices, Retail and Industrials among other and the country aggregate index that we are using in our analysis.
[21] To avoid any confusion throughout the paper, we use the notation t and T for weekly and monthly data, respectively.

Table 1
ΔCoVaR summary statistics

Sectors	No. of firms	% as Market MV	Mean ΔCoVaR	Median ΔCoVaR	Lower quartile ΔCoVaR	Upper quartile ΔCoVaR
Banks	9	51%	2.165	1.898	1.455	2.534
Insurance companies	11	15%	1.422	1.041	0.727	1.887
Financial services	28	13%	1.243	1.081	0.738	1.562
Real Estate	13	6%	1.102	0.952	0.671	1.356
Investment Trusts	80	15%	1.711	1.645	1.097	2.181
All	141	100%	1.576	1.460	0.869	2.029

Source: Authors' calculations
Note: The Table displays the weekly systemic risk (ΔCoVaR) summary statistics per sector. The estimation is based on the state variables approach and the sample covers the period 2000-2021.

CREgro is defined as the monthly year-on-year CRE capital growth. In addition, we include controls for firm characteristics ($\boldsymbol{FC}_{i,T-1}$) such as size, idiosyncratic risk (VaR) and profitability (Price/Earnings ratio).[22] Moreover, we control for changes in the UK macroeconomic environment ($\boldsymbol{MC}_{i,T-1}$) We employ data on industrial production growth and inflation.[23] Finally, we use the shadow rate by Wu and Xia (2016) to control for changes in both conventional and unconventional monetary policy.[24]

We present the results both with and without the inclusion of control variables. Consistent with our expectations, we observe that a decline in the CRE market is associated with an increase in systemic risk. The empirical findings confirm the collateral channel hypothesis; a reduction in property values leads to a decline in the value of the portfolios held by financial institutions and consequently to greater risk. The relationship is statistically and economically significant across different model specifications. More specifically, a decline of one standard deviation in CREgro corresponds to a ΔCoVaR increase of up to 28 basis points. Given that the median and standard deviation of ΔCoVaR in our sample stand at 1.460% and 1.003%,[25] respectively, our results underscore a notably economically significant relationship. With regards to the control variables, we find that systemic risk is positively correlated with idiosyncratic risk and size in line with the literature (Adrian and Brunnermeier, 2016). To further address serial correlation concerns, we run the benchmark model using firm × month fixed effects. Models (7)-(8) in Table 2 present the empirical results with firm and month fixed effects. Once more, the outcomes reaffirm our previously established empirical findings. In the following sub-sections, we perform a series of tests to validate the robustness of our findings.

Identifying misalignments in the UK CRE market

The empirical evidence suggests a statistically significant negative relationship between CRE capital value growth and systemic risk, however, this does not necessarily imply that the relationship is homogeneous across time. Real estate bubbles constitute one of the main drivers behind financial crises. Allen and Carletti (2013) support that during the boom phase of the cycle, speculators enter the market and lenders are not fully capable of quantifying the undertaken risk in their portfolios. Real estate lenders are subject to disastrous myopia since overreliance on inflated real estate collateral in boom phases of the business cycle can create a false sense of security (Herring and Wachter, 1999). Hilbers et al. (2001) find that unbalanced developments in the real estate sector contribute to distress in the financial markets and argue in favour of close monitoring of the real estate sector and possible bubbles that might emerge.

In this section, we address the dynamic relationship between real estate and financial stability, acknowledging that this connection is not straightforward and linear, but it can be influenced by market bubbles. To mitigate these complexities, we introduce the UK CRE Misalignment index, a tool designed to capture deviations from fundamental values in the CRE market. There are three main valuation approaches for individual CRE properties, namely, cost, income and sales comparison. However, at the macroeconomic level, there are not many valuation measures commonly acceptable. We follow the ECB (2011) and ESRB research guidelines and construct the UK CRE Misalignment index as a combination of five market indicators. The first two include the year-on-year growth of the CRE capital index and the rent-to-CRE growth index, which provide crucial insights into market dynamics. Additionally, to gauge discrepancies relative to broader economic conditions, we incorporate ratios comparing GDP, employment, and consumption trends with movements in the CRE capital index.[26]

The index is based on the assumption that CRE markets closely reflect economic fluctuations, highlighting the importance of

[22] VaR is estimated using the state variables approach by Adrian and Brunnermeier (2016) and similarly to ΔCoVaR is expressed in basis points. Both size (Market Value of Capital) and PRICE/EARNINGS are transformed using natural logarithms. This transformation helps to normalize the distribution and interpret the coefficient estimates more effectively. All the other explanatory variables are expressed as percentages.
[23] Data on UK industrial production is provided by ONS, inflation, unemployment, GDP and consumption by the OECD database.
[24] The results do not change when we use the Bank of England's base rate.
[25] See Table A3 in the Appendix for summary statistics.
[26] According to ECB (2011) the index captures potential misalignments in the CRE markets, however it presents some caveats since it does not take into account the fact that prime CRE properties adjust quicker than macroeconomic aggregate indices. Similar approach to identify periods of misalignments in the Irish CRE market has been adopted by Kennedy et al. (2021). In addition, the CRE misalignment indicator is included in Central Bank of Ireland's Systemic Risk Pack (2019).

Table 2
Regression results

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
CREgro (%)	**-2.916*** **	**-2.915*** **	**-0.453*** **	**-0.444*** **	**-0.593*** **	**-0.587*** **	**-2.911*** **	**-0.578*** **
	(0.175)	(0.175)	(0.070)	(0.095)	(0.077)	(0.077)	(0.181)	(0.079)
VaR (bps)			0.222***	0.223***	0.220***	0.220***		0.221***
			(0.011)	(0.011)	(0.011)	(0.011)		(0.012)
Log SIZE			1.446*	1.501*	7.691***	7.721***		7.751
			(-0.833)	(0.837)	(1.167)	(1.170)		(1.215)
Log PRICE/EARNINGS			1.989**	2.031***	1.002	1.038*		1.005
			(0.915)	(0.918)	(0.909)	(0.911)		(0.940)
SHADOW RATE (%)					1.755***	1.752***		1.751***
					(0.194)	(0.193)		(0.200)
PRODUCTION GROWTH (%)					0.099	0.119		0.129
					(0.075)	(0.075)		(0.078)
INFLATION (%)					3.309***	3.362***		3.308***
					(0.407)	(0.403)		(0.410)
CONSTANT	162.033***	165.388***	37.338***	39.896***	-9.796	-6.505	266.895***	-0.076
	(0.265)	(0.464)	(7.711)	(8.572)	(11.042)	(11.001)	(0.230)	(17.832)
FIRM FE	YES	YES	YES	YES	YES	YES	NO	NO
MONTH FE	NO	YES	NO	YES	NO	YES	NO	NO
FIRM * MONTH FE	NO	NO	NO	NO	NO	NO	YES	YES
OBS.	24,369	24,369	24,146	24,146	24,146	24,146	24,369	24,146
N. OF FIRMS	136	136	133	133	133	133	136	133
R^2 (WITHIN)	0.149	0.153	0.635	0.640	0.645	0.650	0.586	0.830

Note: The Table presents the results of fixed-effects regressions. The dependent variable is ΔCoVaR, expressed in basis points. CREgro is defined as the year-on-year change in CRE capital values and it is expressed as a percentage. VaR is based on the dynamic CoVaR methodology and it is expressed in basis points. Log SIZE and Log PRICE/EARNIGNS are the natural logarithms of Market Value of Capital, and PRICE/EARNINGS ratio, respectively, as provided by EIKON Datastream. PRODUCTION GROWTH and INFLATION are the year-on-year changes in Industrial Production and CPI, respectively. Both of these variables, along with the shadow rate are expressed as percentages. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

macroeconomic and property-specific data in assessing demand and supply dynamics. Through the development of the UK CRE Misalignment index, we aim to deepen insights into market distortions and their impact on financial stability. This index not only provides a nuanced perspective on CRE market dynamics but also serves as a practical tool for policymakers and market participants navigating risks associated with real estate misalignments.

Fig. 5 presents the UK CRE Misalignment index. When the index is positive, this indicates that the growth in the CRE market cannot be explained by the macroeconomic indicators and that there are signs of misalignments in the market. For illustration purposes, these periods are in the shaded area. The results indicate that there were three main periods that developments in the CRE market cannot be explained by the fundamentals; the tech bust (2000-2002), the period just before the GFC (2004-2007) and finally the post-Brexit period (2017-2018). All these periods were followed by a significant increase in systemic risk. According to our estimates in Table 3, periods of misalignment in the CRE market are characterized by strong CRE capital value growth and systemic risk slightly below the average (-2.66%). However, systemic risk reaches its peak soon after the bust phase following a prolonged period of misalignment in the CRE market (2002–2008), defined as the downturn phase by the ESRB (2019). To illustrate this, Table 3 shows the average values for the subsequent quarter, where systemic risk surges by 24% and CRE growth turns negative at -3%. Similar findings are reported by Claessens et al. (2009) and Ferrari et al. (2015), who argue that economic busts preceded by excessive real estate booms tend to be longer, more severe, and impose a greater cost on financial stability.

We then empirically examine if CRE market misalignments alter the relationship between CRE and systemic risk. More specifically, we introduce an interaction term between CREgro and the UK CRE Misalignment index. MISALIGNMENT equals one when the index is positive and zero otherwise. This interaction term allows us to control for the counter effect of the deviation hypothesis and the results confirm our expectations. The results presented in Table 4 indicate that the coefficient of the interaction term is positive and statistically significant across all model specifications. In other words, when the market shows signs of overvaluations, the impact of CRE growth on systemic risk is weaker. As we discussed in the previous section, this opposite effect, that lessens the impact of the collateral channel, is expected and arises from the deviation of the CRE market from the macroeconomic fundamentals that cannot explain its rapid growth rates. These boom periods coincide with strong economic growth and gradual build-up of systemic risk. The risk stemming from the CRE market depends on how excessive lending during this period is funded. Highly leveraged markets are more likely to display signs of overvaluations and are more exposed to CRE market corrections (Crowe et al., 2013).[27] In addition, another driver that can explain the non-linearities between real estate markets and financial stability is the slow response of supply to demand changes and the low degree of liquidity in real estate assets (especially CRE) due to high transaction costs.

[27] As presented in Fig. 2, the maximum LTV offered for Prime office properties is around 57%, dropped significantly since the GFC. LTVs indicate market’s expectations on CRE sub-sectors and vary from less 55% for prime retail properties and up to 59% for residential.

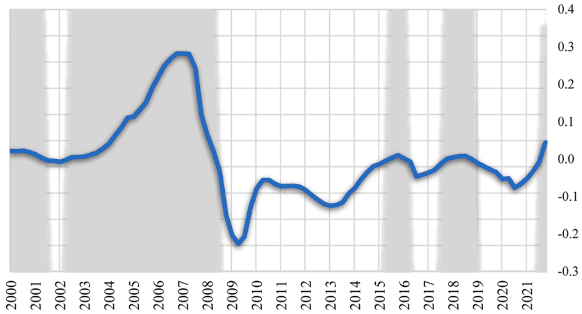


Fig. 5. UK CRE Misalignment Index
Note: The Figure displays the UK CRE Misalignment Index. In line with ECB (2011), the estimation is based on the average between CRE year-on-year growth (CREgro) and of four ratios: GDP/CREgro, Employment/CREgro, Consumption/CREgro, CRE Rent/CREgro. The shaded area represents periods of heightened degree of misalignment in the UK CRE market.
Source: Authors' calculations and MSCI data

Table 3
CRE Misalignment periods summary statistics

	Sample Period Average	CRE Misalignment Period	3mo Post-CRE Misalignment Period
ΔCoVaR (%)	1.576%	1.534%	1.957%
Percentage change:		*-2.66%*	*+24.18%*
CREgro (%)	1.554%	5.869%	-3.046%
Percentage change:		*+277.67%*	*-296.01%*

Note: The Table presents the average values of systemic risk (ΔCoVaR) and year-on-year CRE capital growth. The sample period spans 2000 to 2021, with systemic risk values representing the monthly averages of weekly-estimated ΔCoVaR. The percentage change is calculated as the percentage difference between each value and the sample average.

For this part of the analysis, we do not include time fixed effects, following Brunnermeier et al. (2020b). Their study on the impact of asset bubbles on bank systemic risk argues against using time fixed effects, as these would absorb part of the variation they aim to capture. Since bubbles tend to affect all firms within the impacted country simultaneously, and there are instances of overlapping bubble periods across countries, including time fixed effects would absorb the variation of interest. In addition, to provide robust results, we augment our estimation of CRE market misalignment by introducing the forward-looking Composite Leading Indicator (CLI) from the OECD database. This addition serves to incorporate market expectations, given that CLI captures early signals of an impending recession. The inclusion of CLI results in an adjustment of the misalignment index, revealing 165 months of detected misalignments in the CRE market and rendering the index more sensitive. However, our benchmark model findings remain largely unaffected. Moreover, we utilize the CRE Capital Value-to-Rent ratio as an indicator of market misalignments. This ratio parallels the commonly employed house prices-to-rent ratio, commonly used to gauge affordability in the residential market. In both cases, a high value-to-rent ratio indicates a disparity between capital values and rental income, serving as a potential warning sign of overvaluation and susceptibility to a market correction. Finally, in Models (13)-(14), we introduce the Misalignment indicator based on the Capital Value-to-Rent ratio into the model, and our empirical results persist without substantial alteration. The results strengthen the reliability of our analysis by reaffirming the stability of our findings in the face of various indicators and further underscores the robustness of our methodology.

Endogeneity issues

We conduct a set of tests to ensure the robustness of our results on the negative relationship between CRE returns and firm-level systemic risk. In the first test, we attempt to address possible endogeneity concerns that arise from reverse causality between CRE and ΔCoVaR. We control for endogeneity by employing the two-stage least squares (2SLS) estimator and select two variables as instruments for CRE that are unlikely to affect firm-level systemic risk. In the first stage, the endogenous variable (CREgro) in the benchmark model is replaced with the predicted values obtained from a set of instrumental variables. Instrumental variables are variables that are correlated with CREgro, but are not directly related to the error term.

Our first instrument is BUILDING COST. We use data from the ABI/BCIS House Rebuilding Cost Index by the Building Cost Information Service of the Royal Institution of Chartered Surveyors (RICS) for the Association of British Insurers (ABI). The introduction of the index aimed to assist surveyors with annual revisions. Insurance companies also use this index on policies tied to inflation, allowing them to adjust insured amounts annually. The results are summarized in Table 5. In Model (15), the coefficient of BUILDING COST shows a statistically significant negative relationship with CRE capital growth. This finding suggests that higher building costs are associated with lower CRE capital growth. The second-stage results, presented in Model (16), use the predicted values of CRE capital growth and confirm the negative relationship between CREgro and systemic risk.

Table 4
Evidence from periods of CRE market Misalignment

Models:	(9)	(10)	(11)	(12)	(13)	(14)
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Misalignment:	**ECB**	**ECB**	**ECB+CLI**	**ECB+CLI**	**CV/RENT**	**CV/RENT**
CREgro (%)	**-3.233******	**-0.510******	**-3.610******	**-0.507******	**-2.917******	**-0.584******
	(0.193)	(0.079)	(0.228)	(0.097)	(0.177)	(0.084)
MISALIGNMENT*CREgro	**1.056******	**0.116*****	**2.975******	**0.133****	**1.357******	**0.330******
	(0.098)	(0.048)	(0.181)	(0.075)	(0.113)	(0.060)
MISALIGNMENT	0.154	-10.168***	-20.410***	-6.818***	-23.001***	-14.644***
	(1.522)	(0.835)	(1.046)	(0.722)	(1.934)	(1.251)
VaR (bps)		0.218***		0.218***		0.215***
		(0.011)		(0.011)		(0.062)
Log SIZE		8.583***		0.753***		0.215***
		(1.216)		(1.161)		(0.011)
Log PRICE/EARNINGS		0.973		1.073		0.412
		(0.914)		(0.916)		(0.954)
SHADOW RATE (%)		2.493***		1.887***		2.591***
		(0.223)		(0.201)		(0.257)
PRODUCTION GROWTH (%)		0.082		0.161**		0.250***
		(0.075)		(0.073)		(0.072)
INFLATION (%)		2.889***		3.063***		3.280***
		(0.388)		(0.402)		(0.430)
CONSTANT	160.034***	-9.995	165.263***	-3.576	168.242***	-27.756**
	(0.626)	(11.151)	(0.452)	(10.834)	(0.807)	(12.535)
FIRM FE	YES	YES	YES	YES	YES	YES
MONTH FE	NO	NO	NO	NO	NO	NO
OBS.	24,369	24,146	24,369	24,146	24,369	24,146
N. OF FIRMS	136	133	133	133	136	133
R^2 (WITHIN)	0.152	0.647	0.182	0.646	0.167	0.651

Note: The Table presents the results of fixed-effects regressions. The dependent variable is ΔCoVaR, expressed in basis points. CREgro is defined as the year-on-year change in CRE capital values and it is expressed as a percentage. In line with ECB (2011), the estimation of the MISALIGNMENT is based on the average between CRE year-on-year growth (CREgro) and of four ratios: GDP/CREgro, Employment/CREgro, Consumption/CREgro, CRE Rent/CREgro. In Models (11) – (12) we use an augmented misalignment index with the inclusion of CLI. In Models (13)-(14) we use the RENT/Capital Value as a Misalignment Index. Each model also includes firm control variables, namely VaR, Log SIZE and Log PRICE/EARNIGNS. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5
2SLS model results

Models:	(15)	(16)	(17)	(18)	(19)	(20)
	CREgro	ΔCoVaR	CREgro	ΔCoVaR	CREgro	ΔCoVaR
CREgro (%)		**-1.821****		**-.953******		**-1.965******
		(1.027)		(0.158)		(0.336)
AGR LAND (%)			1.423***		0.793***	
			(0.041)		(0.041)	
BUILDING COST	-0.019***		-0.025***		-0.026***	
	(0.002)		(0.004)		(0.003)	
MISALIGNMENT						-9.440***
						(0.837)
MISALIGNMENT*CREgro						**1.342******
						(0.261)
CONSTANT	0.393	-11.508	2.331	-12.224	-1.369	-13.161
	(2.084)	(12.055)	(1.983)	(11.310)	(1.668)	(11.642)
FIRM CONTROLS	YES	YES	YES	YES	YES	YES
MACRO CONTOLS	YES	YES	YES	YES	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
MONTH FE	YES	YES	YES	YES	NO	NO
OBS.	23,395	23,395	23,395	23,395	23,395	23,395
N. OF FIRMS	133	133	133	133	133	133
R^2 (WITHIN)	0.305	0.632	0.339	0.649	0.487	0.628
F-statistic	271.61		336.31		4000.09	
Sargan-Hansen				0.336		0.225
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Stage	First-stage	Second-stage	First-stage	Second-stage	First-stage	Second-stage

Note: The Table presents the results of fixed-effects and two-stage least squares (2SLS) regressions. The dependent variable is systemic risk (ΔCoVaR), expressed in basis points. The two instruments for CREgro are BUILDING COST, calculated using the ABI/BCIS House Rebuilding Cost Index by RICS, and AGR LAND, defined as the change in the percentage of land area covered by agricultural land in the UK. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Our second instrument, AGR LAND, is the change in the percentage of agricultural land area in the UK. Hilber and Vermeulen (2016) argue that the scarcity of developable land can constrain the supply of real estate that successively may affect prices. Scarcity-related constraints may be more binding in highly developed locations such as London. According to the Department for Levelling Up, Housing & Communities (2022), only 8.7%[28] of land was classified as developed, while 91.3% was non-developed or vacant. The non-developed land in England consists of forestry (20.1%), agricultural land (63.1%), and residential gardens (4.9%). In line with the above, we argue that a decline in agricultural land can increase the supply of commercial real estate (CRE) and drive its prices down. At the same time, there is no theoretical link between the selected variables and firm-level systemic risk, which further supports their validity as instruments.

In Models (17)–(20), we incorporate both instruments, as well as the results with the misalignment index. Across all specifications, BUILDING COST consistently exhibits a negative sign, while AGR LAND shows a positive sign, both statistically significant at the 1% level, fully aligning with our expectations. The estimated coefficients suggest that a one standard deviation increase in agriculture land is associated with a 2 basis points increase in CREgro, while a similar increase in BUILDING COST corresponds to a 149 basis points decrease in CREgro. The first-stage F-statistic indicates that our instruments are strong and valid according to the conventional threshold ($F > 10$). In the second stage, instead of using the original endogenous variable (CREgro) in the main regression equation, we substitute it with the predicted values obtained from the first stage. The second-stage results presented in Models (18) and (20) further confirm our initial findings and alleviate endogeneity concerns. To test the validity of our instruments, we also use the Sargan-Hansen test. The null hypothesis is not rejected indicating that the instruments are correctly excluded from the second round of the 2SLS estimation. The results again confirm our empirical findings and mitigate any endogeneity concerns.

Alternative measures of systemic risk

Our analysis is based on ΔCoVaR to measure firm-level systemic risk. However, there are alternative metrics in the literature such as the Marginal Expected Shortfall (MES) by Acharya et al. (2017) and SRISK by Brownlees and Engle (2017). In this section, we briefly describe these two measures of systemic risk and we present the empirical findings where they are used as the dependent variable in our model.

Marginal Expected Shortfall (MES)

The Marginal Expected Shortfall (MES), introduced by Acharya et al. (2017), captures each financial institution's contribution to systemic risk as its propensity to be undercapitalized when the system as a whole is undercapitalized. The estimation is based on the concept of Expected shortfall:

$$ES_{i,q} = E\left[R_i \middle| R_i \le VaR_{i,q}\right] \tag{10}$$

where R_i denotes firm's returns and $VaR_{i,q}$ the Value-at-Risk at the qth percentile. Given a system of N firms, the market index is a value-weighted (w_i) average of each all individual returns (R_i). MES captures the marginal contribution of an institution to the expected shortfall of the financial system. The expected shortfall of the system's index is defined as:

$$ES_{m,q}(C) = E_{t-1}\left(R_{m,t} \middle| R_{m,t} \le C\right) = \sum_{i=1}^{N} w_{i,t} E_{t-1}\left(R_{i,t} \middle| R_{m,t} \le C\right) \tag{11}$$

where $R_{m,t}$ and $R_{i,t}$ are the average weekly returns of the market (m) and the individual firm i, respectively. C is the threshold, set at 10% in line with the literature. Based on Equation (12), MES is defined as the partial derivative of the system ES with respect to the weight of firm i in the economy:

$$MES_{i,t}(C) = \frac{dES_{m,q}(C)}{dw_{i,t}} = E_{t-1}\left(R_{i,t} \middle| R_{m,t} \le C\right) \tag{12}$$

MES measures the additional market risk (ES_m) induced by a marginal increase in the weight of firm i in the system. In the Appendix, section A.1 we present the step-by-step estimation procedure we follow to calculate MES. As Brunnermeier et al. (2020b) point out, ΔCoVaR and MES are likely to be correlated, but they capture a different aspect of risk. ΔCoVaR measures the contribution to the market's systemic risk, whereas MES captures the exposure to the market.[29]

SRISK

SRISK was introduced by Brownlees and Engle (2017) and it is defined as the expected capital shortfall of a financial entity conditional on a prolonged market decline. According to the authors, SRISK can be useful for comparison/ranking purposes and it also provides early warning signals of macroeconomic distress. SRISK depends on the following factors: the size of the firm, its leverage, and its expected equity loss conditional on the market decline. To estimate SRISK, we need to define capital shortfall (CS) of the firm i and

[28] The proportion of developed land is projected to increase to 10.4%.

[29] In the Appendix, Fig. A.2 displays the average UK MES. The two systemic risk metrics present similarities across time with two main peak periods, the GFC and the recent COVID-19 induced recession.

time T:

$$CS_{i,T} = k\, A_{i,T} - \; W_{i,T} \tag{13}$$

where $A_{i,T}$ is the value of quasi-assets, $W_{i,T}$ is the market value of capital and k is the prudential capital fraction, which is set at 8%. The value of quasi assets is calculated as the sum of the market value of capital and the book value of debt $(D_{i,T})$. All the data are provided by EIKON Datastream. Based on the above, SRISK is defined as the expected capital shortfall conditional on a systemic event:

$$SRISK_{i,T} = E_t\left(CS_{i,T} \middle| R_{T+1:t+h} < C\right) \tag{14}$$

$$SRISK_{i,T} = kE_t\left(D_{i,T+h} \middle| R_{T+1:T+h} < C\right) - (1-k)\; E_t\left(W_{i,T+h} \middle| R_{t+1:T+h} < C\right) \tag{15}$$

The horizon h is set at one month and the threshold C at -10% in line with Brownlees and Engle (2017). The SRISK predicts the level of capital shortfall a firm would experience in case of a systemic event. The calculation of SRISK is determined using the formula in Equation (16), and the resulting value is expressed in British pounds (£). For our analysis, we use the logarithmic transformation of SRISK (see Zhao et al., 2024). The estimation of $LRMES_{i,T}$ is based on weekly returns and the Kernel Density Estimation in line with section 4.4.1 and Appendix, section A.1.

$$SRISK_{i,T} = \; k \times \; DEBT_{i,T} - (1-k) \times W_{i,T} \times \; \left(1 - \; LRMES_{i,T}\right) \tag{16}$$

Results for MES and SRISK

In Table 6, we substitute our primary dependent variable and measure of systemic risk, ΔCoVaR, with MES and SRISK. MES, in line with ΔCoVaR in the benchmark model specification is based on the monthly-average of weekly values and is expressed in basis points, while SRISK is represented as its natural logarithm (lnSRISK). Models (21) and (24) show that the results are consistent with the benchmark model, and both models reveal a noteworthy and negative association that is statistically significant. To augment our analysis, Models (22)-(23) and (25)-(26) introduce additional firm and macroeconomic controls and month fixed effects. Despite the fact that the alternative measures capture another aspect of systemic risk, our empirical findings validate and reinforce the initial results and conclusions.

Additional robustness tests

In Table 7, we alter the benchmark model specification by adding a series of additional control variables. We use the house price growth to capture changes in the residential market, however the empirical results persist unchanged from the previous findings. In addition, we include a several forward-looking variables, such as the Composite Leading Indicator (CLI) that is designed to provide early signals of turning points in business cycles and the Business Confidence Index (BCI) that include information on future developments, based on surveys on developments in production, orders and stocks of finished goods in the industry sector.

The empirical results are displayed in Table 7, Models (28) – (29) and once more, the findings underscore the consistency of our previously established empirical conclusions. Moreover, 13 out of the 141 companies in our sample are REITs and we expect them to be more sensitive to real estate markets variation. To ensure the robustness of our findings in Model (30), we run the benchmark model excluding REITs. In both cases, the results hold and validate our empirical conclusions. Finally, we run the model excluding the GFC period to examine if the empirical relationship is driven by the crisis. The results are presented in Model (31), in which we exclude the 2008-2009 period and the results hold.[30]

Do CRE developments contribute to financial tail risk?

Our empirical results show that CRE adverse developments are associated with greater firm-level systemic risk. In this section, we further explore the tail dynamics between CRE and financial stability. Firstly, to provide a more comprehensive understanding, we modify the CoVaR methodology. This adaptation allows us to compute the Value at Risk (VaR) of the financial system index, contingent upon the state of the CRE market. This novel metric precisely quantifies the supplementary tail risk embedded in the UK financial sector when the CRE market undergoes a significant event. Secondly, we employ a quantile regression model to examine whether the impact of CRE distress is homogeneous across the entire distribution of systemic risk.

CRE-Exposure ΔCoVaR

In this section, we introduce a new metric that quantifies the exposure of the financial sector to CRE market tail risks. The method is based on the aforementioned CoVaR measure by Adrian and Brunnermeier (2016), which captures the VaR of the financial system when a specific institution is under distress. However, CoVaR is a directional measure and can be used to study which institutions are more in danger if there is a sharp fall in stock markets. In our approach, we focus on the probability of distress in the CRE market. To

[30] We selected to exclude the period of 2008-2009 since UK returned to positive growth in the first quarter of 2010. We run additional tests by focusing on the period before or after the GFC and the empirical results are in line with our benchmark model.

Table 6
Alternative measures of systemic risk

Models:	(21)	(22)	(23)	(24)	(25)	(26)
	MES	MES	MES	lnSRISK	lnSRISK	lnSRISK
CREgro (%)	**-6.720*****	**-1.144*****	**-0.719****	**-0.014****	**-0.014****	**-0.012****
	(0.666)	(0.331)	(0.331)	(0.006)	(0.006)	(0.005)
VaR		0.490***	0.491***		0.026*	0.027*
		(0.021)	(0.021)		(0.015)	(0.014)
Log SIZE		5.184	-2.941		0.426**	0.392**
		(4.914)	(5.982)		(0.181)	(0.173)
Log PRICE/EARNINGS		-7.962**	-6.216*		0.009	0.016
		(3.522)	(3.347)		(0.160)	(0.156)
SHADOW RATE (%)			-2.589***			-0.010
			(0.594)			(0.027)
PRODUCTION GROWTH (%)			-1.183***			-0.003
			(0.295)			(0.004)
INFLATION (%)			-1.321			-0.007
			(2.183)			(0.066)
CONSTANT	307.934***	4.908	61.599	7.777***	4.724***	4.958***
	(1.805)	(34.0185)	(40.588)	(0.014)	(1.406)	(1.261)
FIRM FE	YES	YES	YES	YES	YES	YES
MONTH FE	YES	YES	YES	YES	YES	YES
OBS.	24,369	24,146	24,146	23,440	23,217	23,217
N. OF FIRMS	136	133	133	133	130	130
R^2 (WITHIN)	0.122	0.457	0.461	0.004	0.019	0.019

Note: The Table presents the results of fixed-effects regressions. The dependent variables is Marginal Expected Shortfall (MES), expressed in basis points and lnSRISK. CREgro is defined as the year-on-year change in CRE capital values and it is expressed as a percentage. Firm controls include VaR, Log SIZE and Log PRICE/EARNIGNS and the county controls include the year-on-year changes in Industrial Production and CPI, along with the shadow rate expressed as percentages. VaR is expressed in basis points in Models (21)-(23) and in percentages in Models (24)-(26) for illustration purposes. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

estimate CRE-exposure CoVaR, we run the quantile regression with the monthly average weekly returns of the examined systemically important institutions and year-on-year CRE capital growth (CREgro):

$$\mathrm{R}^{\mathrm{i}}_{\mathrm{q,T}} = \mathrm{a}^{\mathrm{i}}_{\mathrm{q}} + \beta^{\mathrm{i}}_{\mathrm{q}}\ \mathrm{CREgro}_T + e_q \tag{17}$$

$$\textit{Exposure}\ \mathrm{CoVaR}^{\mathrm{i|CRE}}_{\mathrm{q}} \equiv \widehat{\mathrm{R}}^{\mathrm{i}}_{\mathrm{q}} = \widehat{\mathrm{a}^{\mathrm{i}}_{\mathrm{q}}} + \widehat{\beta^{\mathrm{i}}_{\mathrm{q}}} \times \mathrm{quantile}(\mathrm{CREgro}_{\mathrm{t}}, q = 5\%) \tag{18}$$

The estimate of the $\beta^{\mathrm{i}}_{\mathrm{q}}$ coefficient captures how the variation in the CRE market affects the tail risk in the financial market. Therefore, by replacing back the coefficient estimates, we obtain the quantile regression estimate for $\mathrm{R}^{\mathrm{i}}_{\mathrm{q,T}}$, which is by definition the $\mathrm{VaR}^{\mathrm{i}}_{\mathrm{q}}$ of the examined firm returns and in this case it is conditional on the developments in CRE market. For the CRE-exposure CoVaR value to be comparable, we estimate the conditional VaR when the CRE capital growth is equal to its median value. The difference between the growth distribution's tail and its median growth rate is defined as its CRE-exposure ΔCoVaR (q = 5%) and it captures the additional tail risk coming from the conditional CRE tail event.[31] Therefore, the mathematical representation of CRE exposure ΔCoVaR is defined as:

$$\mathrm{CRE\ exposure\ \Delta CoVaR}^{\mathrm{q=5\%}} = \mathrm{CRE\ exposure\ \Delta CoVaR}^{\mathrm{median}} - \mathrm{CRE\ exposure\ \Delta CoVaR}^{5\%} \tag{19}$$

$$\mathrm{CRE\ exposure\ \Delta CoVaR}^{\mathrm{q=5\%}} = \widehat{\beta^{\mathrm{i}}_{\mathrm{q}}}\left(\mathrm{CREgro}^{\mathrm{UK}}_{5\%} - \mathrm{CREgro}^{\mathrm{UK}}_{\mathrm{median}}\right) \tag{20}$$

The new metric, CRE − exposure $\Delta\mathrm{CoVaR}^{5\%}_{\mathrm{T}}$, depends on the value of the quantile regression coefficient $(\widehat{\beta_q})$ that captures the tail dependency between the firm's returns and the CRE capital growth and on the difference between the historical 5% tail and median value of CRE capital growth. In Fig. 6.A, we present the scatter-plots of the CRE-Exposure ΔCoVaR for each financial institution in our sample against their systemic risk, as measured by ΔCoVaR[32] and their size. We find that the new metric that captures the exposure to the CRE market is correlated with systemic risk (35.14%), suggesting that important firms tend to be more exposed to the domestic CRE market. On the other hand, the size of the financial institution, as discussed before, appears to be weakly associated with CRE-Exposure

[31] The CRE-exposure ΔCoVaR is estimated for the entire time period and it has not a time dimension, since this would require additional assumptions on the state variables that capture its variation on the conditional moments similarly to ΔCoVaR in the previous subsection.

[32] For comparison purposes, in Fig. 6, we present ΔCoVaR estimates based on the monthly averages of weekly returns, rather than the monthly averages of weekly ΔCoVaR. This approach aligns with the methodology used for CRE-exposure ΔCoVaR, which is constrained by the lower frequency of the CRE capital value series.

Table 7
Robustness tests

Models:	(27)	(28)	(29)	(30)	(31)
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Model:	+HPgro	+CLI	+BCI	Excl. REITS	Excl. GFC (2008-2009)
CREgro (%)	**-0.646*****	**-0.584*****	**-0.526*****	**-0.616*****	**-0.708*****
	(0.078)	(0.064)	(0.064)	(0.083)	(0.074)
VaR	0.221***	0.220***	0.219***	0.233***	0.217***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)
Log SIZE	7.929***	7.717***	8.174***	7.354***	4.510***
	(1.202)	(1.166)	(1.282)	(1.202)	(0.923)
Log PRICE/EARNINGS	0.972	1.040	0.998	1.324	0.204
	(0.924)	(0.915)	(0.905)	(0.954)	(0.903)
SHADOW RATE (%)	1.696***	1.753***	1.714***	1.803***	1.382***
	(0.188)	(0.199)	(0.188)	(0.201)	(0.185)
PRODUCTION GROWTH (%)	0.112	0.121*	0.176***	0.130	0.206
	(0.075)	(0.068)	(0.051)	(0.082)	(0.070)
INFLATION (%)	3.845***	3.264***	3.635***	3.441***	0.562*
	(0.454)	(0.403)	(0.477)	(0.445)	(0.323)
HOUSE PRICES (%)	0.167***				
	(0.055)				
CLI		-0.035			
		(0.292)			
BCI			-0.645		
			(0.404)		
CONSTANT	-10.068	-2.936	54.964	-1.827	21.392**
	(11.527)	(32.161)	(39.867)	(10.783)	(8.200)
FIRM FE	YES	YES	YES	YES	YES
MONTH FE	YES	YES	YES	YES	YES
OBS.	24,146	24,146	24,146	21,431	22,087
N. OF FIRMS	133	133	133	120	133
R^2 (WITHIN)	0.650	0.650	0.650	0.661	0.597

Note: The Table presents the robustness test based on a fixed-effects panel regression model. The dependent variable is ΔCoVaR, expressed in basis points. CREgro is defined as the year-on-year change in CRE capital values and it is expressed as a percentage. Firm controls include VaR, Log SIZE and Log PRICE/EARNIGNS and the county controls include the year-on-year changes in Industrial Production and CPI, along with the shadow rate expressed as percentages. Additional data series included as controls, namely the year-on-year house price growth, the Composite Leading Indicator (CLI) and the Business Confidence Index (BCI). In Models (30) and (31) we exclude real estate companies and the GFC period, respectively to test the robustness of our findings. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

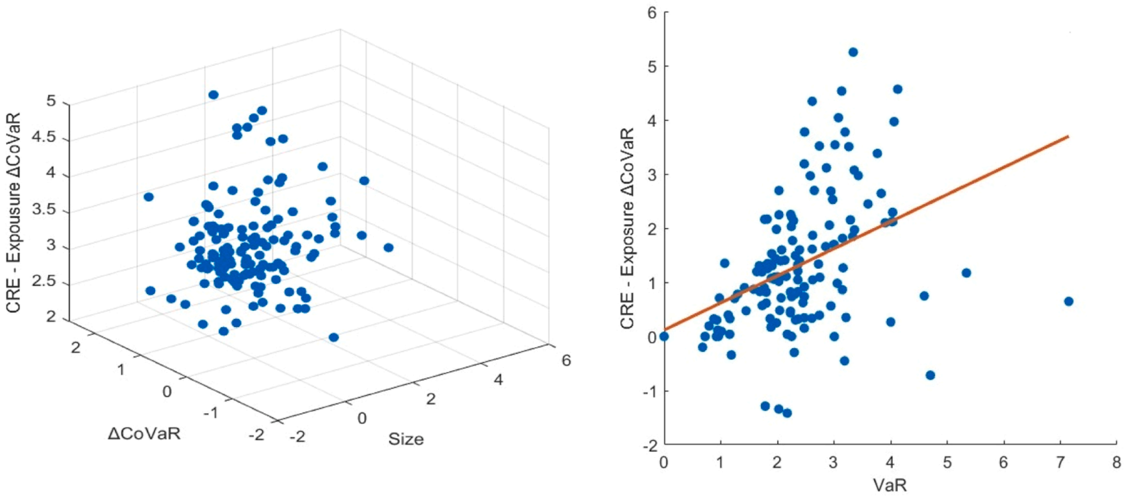
ΔCoVaR (10.13%). In Fig. 6.B, we display the cross-sectional relationship with VaR. As expected, the relationship is positive and stronger (40.74%) compared to the dynamics between systemic risk and VaR. CRE-Exposure ΔCoVaR measures the exposure of a firm to this particular sector, and as so the high degree of vulnerabilities to the pro-cyclical CRE market is associated with higher idiosyncratic risk (VaR).

Table 8 presents the summary statistics for the CRE-exposure ΔCoVaR. The average value for the entire sample and examined period is 1.308%, that indicates that when the CRE market shifts from distress to normal times, the VaR of UK financial institutions will increase, on average, by 1.308% in absolute terms. Real estate companies and REITs are the most exposed sectors to the developments in the CRE market with an average CRE-exposure ΔCoVaR of 2.092%. Banks and Insurance companies also present considerable exposure of 1.510%, whereas investment trusts exhibit a weaker exposure of 1.128%.

We then present the results for CRE sub-sectors, namely, Retail, Industrial and Offices and for the London market and the rest of Great Britain. Banks appear to be more exposed to the non-London market in line with the findings of the Bayes CRE Lending report (2021) that suggests that is the groups of companies with the lowest percentage of total lending invested in the London market. Insurance companies have around a third of the total lending in the Office market and this results in an average exposure ΔCoVaR of 1.343%. Retail and Industrials account for a fraction between 10-15% of the portfolio and their exposure to these markets is not as significant.

As expected, the four largest UK banks are significantly exposed to the UK CRE market since they own almost 20% of the CRE total lending.[33] Lloyds Banking Group and NatWest are among the most vulnerable financial institutions to variation in the CRE sector with the exposure ΔCoVaR to be 2.64% and 2.29% respectively. Barclays follows with 1.81% and HSBC with 1.05%. Pavlidis et al. (2021) estimate the ΔCoVaR of the individual banks when the REITs sector is under distress and their findings indicate that NatWest (RBS) and Lloyds Banking Groups exhibit the stronger tail correlation, whereas in line with our findings, HSBC present the lowest value across these four banks.

[33] The percentage represents the total lending among the participants of the Bayes CRE lending report (2021) and not all the market.



A. Systemic Risk and Size

B. VaR

Fig. 6. CRE-Exposure ΔCoVAR: Cross-section dynamics
Note: Figure A displays the cross-sectional correlation between CRE-Exposure ΔCoVaR, ΔCoVaR and size (log Market Capital Value). The right-hand side Figure shows the cross-sectional relationship between idiosyncratic risk (VaR) and CRE-Exposure ΔCoVaR. The estimation period is based on monthly-average weekly returns and the period 2000m1-2021m12. Each points refer to the average value for each one of the financial institution in our sample.
Source: Authors' calculations.

Table 8
CRE Exposure - ΔCoVaR summary statistics

Sectors	All CRE	Retail	Offices	Industrials	London	Rest of GB
Banks	1.510	1.382	1.242	1.421	1.208	1.468
Insurance companies	1.492	1.017	1.343	1.122	1.433	1.350
Financial services	1.320	0.729	0.683	1.066	0.927	1.088
Real Estate	2.092	1.666	1.552	1.931	1.902	2.055
Investment Trusts	1.128	0.885	0.824	0.960	0.883	1.017
All	1.308	0.968	0.930	1.112	1.049	1.181

Source: Authors' calculations and MSCI data
Note: The Table displays the average value of the exposure ΔCoVaR to the CRE market. The estimation is based on the monthly-average of weekly returns and the year-on-year CRE capital growth. The sectoral indices are provided by MSCI and the Rest of the GB is an equally weighted average of all the UK regions except London. The London index is a combination of City, Inner and Outer London region as provided by MSCI.

Quantile regression model

Our empirical results show that CRE developments matter more for securing financial stability during booms and busts. Similarly, Deghi et al. (2021) find that the CRE market misalignments have an heterogenous effect on macro-financial stability across time. They use a quantile regression model and examine how CRE misalignments impact the conditional distribution of GDP growth. They find that there is a negative relationship between the CRE market and estimated GDP tail risks.[34] In this section, we explore another aspect of the non-linear relationship between CRE market and systemic risk. We employ a panel quantile regression model to examine how changes in the CRE market impact the estimated distribution of systemic risk. Following Machado, et al. (2021), the mathematical form of the model is the following:

$$\mathrm{Q_q}\left(\Delta\mathrm{CoVaR}_T^{\mathrm{s|i}}|\mathrm{X}_T^{\mathrm{i}}\right) = \widehat{\beta_{\mathrm{q}}}\mathrm{X}_T^{\mathrm{i}} \tag{21}$$

$$\widehat{\beta_{\mathrm{q}}} = \mathrm{argmin}\sum_{T=1}^{N}\left(\rho_{q(}\Delta\mathrm{CoVaR}_T^{\mathrm{s|i}} - \widehat{\beta_{\mathrm{q}}}\mathrm{X}_T^{\mathrm{i}}\right) \tag{22}$$

where $\Delta CoVaR_T^{s|i}$ is the systemic risk and X_T^i is a matrix that includes a constant, the CRE capital growth, which is the main explanatory

[34] More specifically, a one standard deviation increase in their CRE misalignment index results in a 1.4% drop in GDP growth distribution left tail.

variable of interest and a set of firm- and market-level control variables. Equation (22) describes the estimation of the coefficient that captures the marginal effect on systemic risk conditional on the parameters of the explanatory variables estimated at the q-th percentile. Quantile regressions differ from the standard OLS approach in two aspects; To obtain $\widehat{\beta_q}$, we minimize the sum of absolute not squared errors and it imposes different weights on the error term depending on whether they are above or below the examined quartile (see Adrian et al., 2019). The estimate of β_q depends on the dependent and independent variables and the quantile loss function (ρ_q) that is defined in equations (23) and (24).

$$\rho_q(u) = (q-1)\ u\ for\ u < 0 \tag{23}$$

$$\rho_q(u) = qu\ for\ u \geq 0 \tag{24}$$

Table 9 displays the quantile regression empirical results. We examine how the variation in the CRE market affects the entire distribution of systemic risk and not just the median as in the benchmark model specification. For illustration purposes, in Fig. 7, we present the estimates of the quantile regression coefficient for CRE growth across different percentiles. The empirical findings, based on the median estimation, suggest that a one standard deviation decline in CRE capital growth will increase systemic risk by 19 basis points. However, the effect is more significant at the right/upper tail of systemic risk's distribution that is greater by more than 30bps. On the other hand, rapid CRE growth should mitigate systemic risk according to our benchmark model specification, but according to our findings in Table 8, the estimated coefficient for the left/lower tail is around 5bps and therefore the effect is largely economically insignificant.

In summary, positive (negative) developments in the CRE market, decrease (increase) the right tail and therefore narrow (broaden) the gap with the relative constant left tail. With respect to the latter, the empirical results suggest that regardless of the excessive growth that the CRE market might experience, this would only reduce the upper tail or in other words will improve the worst-case scenario, but it will not eliminate systemic risk in the market. These results emphasize the importance of allowing for non-linearities when we investigate the relationship between real estate and financial markets.

Policy implications

The CRE sector could threaten financial stability due to its size and the fact that it relies on debt-funding, and thus continued vigilance is required to mitigate such risks. Our empirical findings suggest that there is a negative relationship between CRE capital values growth and firm systemic risk. Therefore, in alignment with the recommendations by the IMF (2021), stress-testing emerges as a crucial tool to ensure the stability and resilience of banks in the face of substantial declines in CRE capital values. Such declines not only impact the quality of banks' loan portfolios, but also pose a threat to the adequacy of their capital buffers. It is essential to note that the relationship exhibits nonlinearities; thus, policymakers should not solely focus on periods of market distress. Our findings suggest that in low volatility and high growth environments, there is a tendency for market participants to underestimate risks and become overly confident in the stability of the market. As a result, these periods of overvaluation in the CRE market might foster an environment where systemic risks are overlooked or downplayed.

Based on our empirical findings, it is recommended that policymakers contemplate several crucial actions. Firstly, the establishment of effective monitoring systems to discern early signs of market overvaluation is essential. Early detection provides policymakers with a valuable opportunity to enact preventive measures before the emergence of a potential bubble. Secondly, the utilization of macroprudential tools is advised to address excessive risk-taking in the CRE market during periods of overvaluation. These countercyclical tools may encompass loan-to-value ratios, stress testing, or other regulatory measures aimed at curbing speculative behaviour. Thirdly, effective communication with market participants regarding the risks associated with overvalued CRE markets is paramount. This communication strategy ensures a comprehensive understanding of potential vulnerabilities. Additionally, fostering coordination among regulatory bodies is encouraged to facilitate the sharing of information and insights. Lastly, it is recommended that policymakers regularly review and update stress-testing scenarios to account for evolving dynamics in the CRE market. This should include scenarios capturing potential feedback loops between the CRE sector and broader financial markets. By incorporating these aforementioned policies, policymakers can develop a comprehensive framework to address the challenges and risks associated with the CRE market, ultimately contributing to the overall stability of the financial system.

Conclusions

The real estate market is characterised by strong pro-cyclicality and has historically been an amplifier of adverse macro-financial shocks. While considerable policy attention and research focus have been directed towards the residential real estate market, the CRE sector has been largely overlooked. Considering CRE sector's macro-financial significance, this paper aims to bridge the existing gap in the literature by empirically investigating how corrections in the CRE market influence systemic risk within the UK economy. The

Table 9
Quantile regressions

Models:	(32)	(33)	(34)	(35)	(36)	(37)	(38)
Quantile	0.05	0.10	0.25	0.50	0.75	0.90	0.95
	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
CREgro (%)	-0.314*	-0.440***	-0.946***	-1.996***	-1.899***	-2.556***	-3.159***
	(0.172)	(0.150)	(0.210)	(0.285)	(0.242)	(0.311)	(0.333)
FIRM CONTROLS	YES	YES	YES	YES	YES	YES	YES
MACRO CONTROLS	YES	YES	YES	YES	YES	YES	YES
MONTH FE	YES	YES	YES	YES	YES	YES	YES
OBS.	24,146	24,146	24,146	24,146	24,146	24,146	24,146
N. OF FIRMS	133	133	133	133	133	133	133
R^2	0.218	0.243	0.265	0.276	0.282	0.271	0.267
Parente-Santos Silva test	886.33***	869.49***	931.11***	942.47***	683.96***	449.58***	324.91***

Note: The table presents the results of the panel quantile regression model. The dependent variable is ΔCoVaR, expressed in basis points. and the explanatory variable is the year-on-year growth of the UK CRE capital value index. The estimation includes firm and country control variables. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

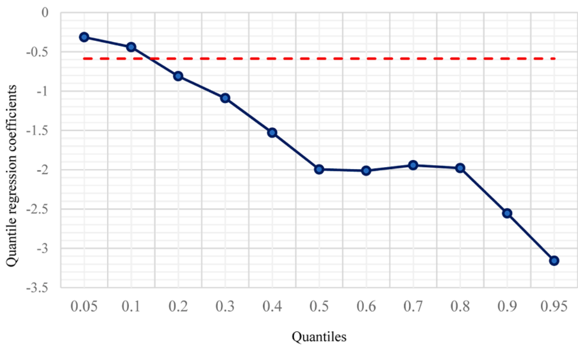


Fig. 7. Quantile regression estimated coefficients
Note: The Figure displays the estimated quantile regression coefficient across different percentiles between 5% to 95%. The dependent variable is systemic risk (measured by ΔCoVaR) and the explanatory variable is the year-on-year growth of the UK CRE capital value index. The estimation includes firm and country control variables. For comparison purposes, the dotted line is the estimated coefficient of CREgro as estimated in the linear benchmark model specification.
Source: Authors' calculation

results of our empirical analysis indicate that a decline in CRE capital growth is associated with an increase in systemic risk, but the relationship is not linear. Periods when the CRE sector expands (boom phase) are followed by a sharp drop and a sizeable increase in systemic risk and weaken the collateral channel effect. This counter-effect is coming from the highly leveraged market that is gradually building the vulnerabilities of the financial system in the scenario of adverse developments in the CRE market. Furthermore, we explore an additional dimension of this non-linear relationship by examining tail correlation. Employing a quantile regression model, we ascertain that CRE capital growth exhibits stronger correlation with the upper tail of the systemic risk distribution and weaker correlation with the median and left tail. Empirical results indicate that turbulence in the CRE market shifts the upper tail of the distribution further to the right, with negligible impact on the left tail.

Our empirical findings yield significant policy implications and underscore the necessity for a comprehensive regulatory framework that accounts for the exposure of non-bank financial institutions to real estate markets, aligning with the IMF (2021) recommendations. From an investor's perspective, our study highlights the nuanced dynamics of CRE as an asset class. Specifically, investors should adopt adaptive asset allocation strategies that incorporate real-time assessments of CRE market conditions since during periods of market misalignment, the traditional role of CRE in diversified portfolios may require careful reconsideration and heightened caution. By integrating risk metrics such as CRE-Exposure ΔCoVaR into portfolio construction, investors can better navigate volatility and enhance long-term resilience against potential systemic shocks originating from the CRE sector.

Data statement

The article makes use of existing (secondary) data which are cited at the references. Some of the data is confidential for business purposes of Bayes Business School, City St George's, University of London and some from paid subscriptions to financial databases.

CRediT authorship contribution statement

George Kladakis: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Nicole Lux:** Writing – review & editing, Supervision, Resources, Data curation. **Alexandros Skouralis:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix

Table A1, Table A2, Table A3, Table A4, Fig. A1, Fig. A2

A1. Estimation of systemic risk measures: Marginal Expected Shortfall (MES)

The estimation of MES is based on the monthly average of weekly returns of our sample of 141 UK financial institutions and the Kernel Density Estimation.[35] In the first step, we standardise the financial system returns by dividing the DS Financials returns with the index standard deviation.

$$r_{m,t} = \frac{R_{m,t}}{s_m} \tag{A1}$$

The standardisation of the firm returns are based on the following equation:

$$r_{i,t} = \frac{R_{i,t}/s_i \; - (\rho_i {}^* \; r_{m,t})}{z} \tag{A2}$$

Where $r_{m,t}$ and $r_{i,t}$ stand for the standardised returns of the financial system index and firm i. ρ_i is the correlation coefficient between the returns of firm i $(R_{i,t,})$ and the system index returns $(R_{m,t,})$. z is equal to $\sqrt{1-\rho_i^2}$ and s_i, s_m is for the standard deviation of the firm and system's returns. In the next step, we use kernel smoothing for the estimation of the probability density. The Kernel Density Estimation (KDE) helps to smooth out the data points to provide a continuous and smooth estimate of the density of the data. The values of the cumulative distribution function (CDF) of the normal distribution for the standardized quantiles are computed as follows:

$$f = normcdf\left(\frac{\frac{c}{s_m} - \; r_{m,t}}{h}\right) \tag{A3}$$

where c is the qth quantile of the DS Financials index returns $(R_{m,t,})$. The bandwidth h is a parameter that controls the smoothness of the density estimate. Its estimation is computed using the minimum of the standard deviation and the interquartile range (IQR) adjusted by a factor of 1.349. In the next step, the CDF values are then summed up to normalize them:

$$f_{sum} = \sum f \tag{A7}$$

The weighted average of the standardized market and firm returns $r_{i,t}$ is calculated using the CDF values f:

$$k_m = \frac{\sum (r_{m,t} \times f)}{f_{sum}} and k_i = \frac{\sum (r_{i,t} \times f)}{f_{sum}} \tag{A8}$$

Finally, the MES is estimated by combining the weighted averages (k_1 and k_2) with the standard deviation of the firm returns $s_f$the correlation coefficient ρ_i and z:

$$MES_i = (s_f \times \rho_i \; \times k_1) + (s_f \times z \; \times k_2) \tag{A9}$$

MES captures the expected shortfall of a firm's returns in the tail of the market return distribution, adjusted for correlation and volatility.

[35] The estimation is based on the Matlab codes by Tommaso Belluzzo and they are available at: https://uk.mathworks.com/matlabcentral/fileexchange/62482-systemic-risk

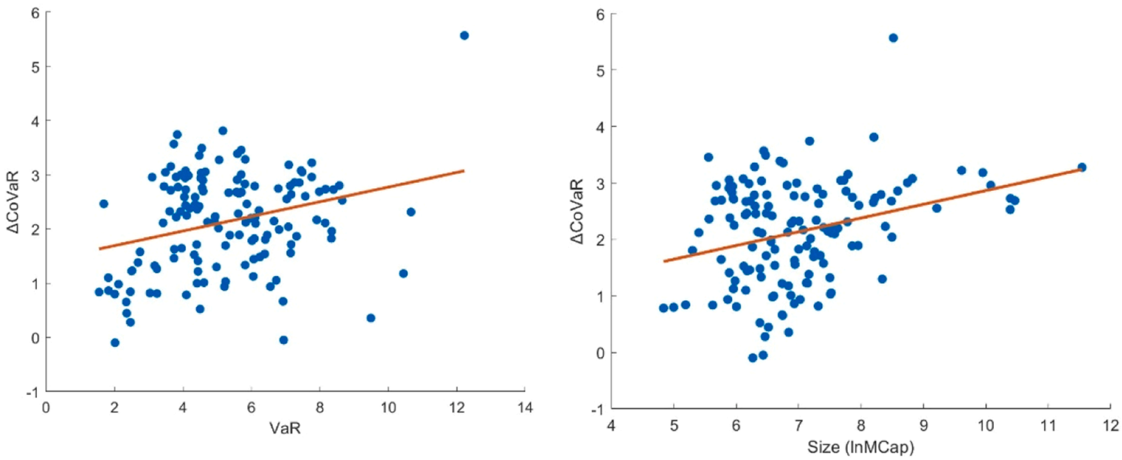


Fig. A1. Cross-Section of ΔCoVaR and VaR

Note: The Figure displays the cross-sectional correlation between ΔCoVaR and idiosyncratic risk (VaR) and size (log Market Capital Value). Both measures are estimated based on weekly returns from 2000 to 2021. Each points refer to the average value for each one of the financial institution in our sample.

Source: Authors' calculation

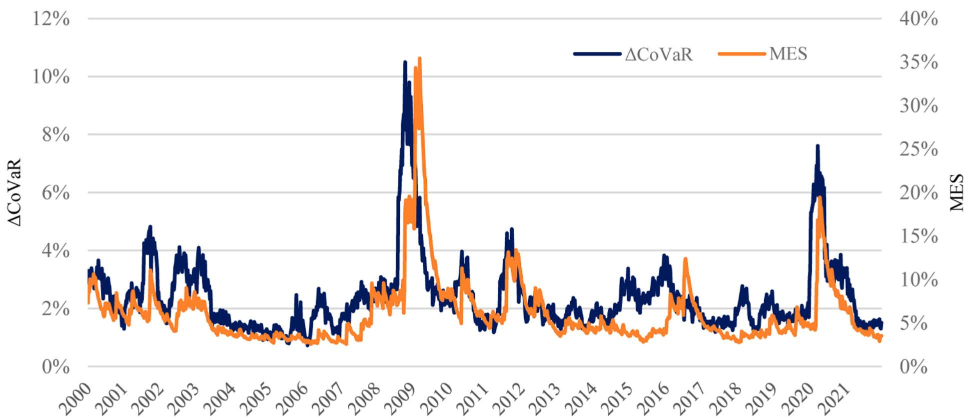


Fig. A2. UK Aggregate Systemic Risk: ΔCoVaR vs. MES

Note: The Figure displays the average weekly systemic risk value, measured by ΔCoVaR and MES for the UK four largest and systemic banking institutions. The estimation of ΔCoVaR is based on the state variables approach and the period 2000-2021.

Source: Authors' calculation

Table A1

State Variables Summary Statistics

Variable	Mean	St. Dev.	Min	Max	Source
Change in 3mo interest rate	-0.005	0.165	2.704	2.569	OECD Database
Term Spread	0.865	1.125	-1.095	3.750	OECD Database
Credit Spread	0.298	0.754	-2.154	2.328	Bloomberg
FTSE 100 Returns	0.037	2.425	-21.047	13.411	EIKON Datastream
FTSE 100 Volatility	0.437	0.228	0.155	1.620	EIKON Datastream

Note: The Table summarizes the state variables used in the dynamic estimation of ΔCoVaR. The data are at a weekly frequency and cover the period from December 1999 to December 2021.

Table A2

Variable definitions

VARIABLE	Definition	Source
ΔCoVaR	Defined as the increase in the Conditional Value-at-Risk of the UK financials index when an institution shifts from its median returns to its Value-at-risk.	EIKON Datastream & Authors calculations
MES	Defined as the Expected Shortfall of the UK financials index when an institution is at its historical distribution left tail (5%).	EIKON Datastream & Authors calculations

(*continued on next page*)

Table A2 (*continued*)

VARIABLE	Definition	Source
SRISK	SRISK measures the capital shortfall (in £bn) of a firm conditional on a severe market decline. In our analysis we use the natural logarithm of SRISK.	EIKON Datastream & Authors calculations
CREgro	CRE capital value year-on-year growth.	MSCI
MISALIGNMENT	Combination of five CRE and macroeconomic indices that detect periods of misalignments in the CRE market.	OECD Database & Authors calculations
VaR	Value-at-Risk. The static version is obtained by the historical distribution of returns based on the examined period 2000-2021. The dynamic version is obtained in line with Adrian and Brunnermeier (2016) and a set of state variables.	EIKON Datastream & Authors calculations
SIZE	Market Value of Capital. The values are transformed using the natural logarithm.	EIKON Datastream
PRICE/EARNINGS	The natural logarithm of the Price – to- Earnings ratio.	EIKON Datastream
SHADOW RATE	Policy rate that captures both conventional and unconventional forms of monetary policy.	Wu and Xia (2016)
PRODUCTION GROWTH	Year-on-year growth of the Index of Production.	ONS
INFLATION	Year-on-year growth of the Consumer Price Index (CPI).	OECD Database
HOUSE PRICES	Year-on-year growth of the UK House Price index.	Halifax
BUILDING COST	ABI/BCIS House Rebuilding Cost Index.	RICS, EIKON Datastream
AGR LAND	The change in the percentage of agricultural land area in the UK.	World Bank Open Data
CLI	Composite Leading Indicator.	OECD
BCI	Business Confidence Index.	OECD

Note: The Table describes the main variables utilized in our empirical analysis, along with their respective sources.

Table A3
Descriptive statistics

VARIABLE	OBS.	MEAN	MEDIAN	ST. DV.	5TH PERC.	95TH PERC.
ΔCoVaR (%)	24,583	1.576	1.460	1.003	0.324	3.234
MES (%)	24,583	3.266	2.812	2.299	0.747	6.935
lnSRISK	23,640	7.765	8.753	1.039	0.000	14.813
CREgro (%)	264	1.699	2.889	9.681	-21.623	13.241
MISALIGNMENT (index)	264	0.284	0.000	0.452	0.000	1.000
VaR (%)	24,583	5.102	4.474	3.004	1.917	10.355
SIZE (log Market Value)	24,580	6.906	6.765	1.439	4.815	9.804
PRICE/EARNINGS (log)	24,357	-1.136	-1.306	1.198	-0.269	0.984
SHADOW RATE (%)	264	-0.472	-1.938	4.476	-6.468	5.778
PRODUCTION GROWTH (%)	264	0.476	0.475	5.300	-6.218	8.324
INFLATION (%)	264	1.968	1.915	0.900	0.553	3.774
HOUSE PRICES (%)	264	6.155	5.976	7.582	-7.729	18.434
BUILDING COST (index)	264	258.953	254.300	56.714	159.720	346.400
AGR LAND (%)	264	0.009	-0.106	1.380	-1.491	1.228
BCI (index)	264	100.221	100.458	2.097	96.526	103.088
CLI (index)	264	99.944	100.280	2.029	96.315	102.358

Note: The table displays the summary statistics of the main variables used in our empirical analysis. The values are based on the period 2000m1-2021m12.

Table A4
2SLS Instruments

Dependent variable:	CREgro	CREgro	CREgro	CREgro	CREgro	CREgro
BUILDING COST (index)	**-0.019*****	**-0.019*****	**-0.019*****			
	(0.001)	(0.004)	(0.004)			
AGR LAND (%)				**2.283*****	**1.380*****	**1.378*****
				(0.038)	(0.040)	(0.040)
FIRM CONTROLS	NO	YES	YES	NO	YES	YES
MACRO CONTOLS	NO	YES	YES	NO	YES	YES
FIRM FE	YES	YES	YES	YES	YES	YES
MONTH FE	NO	NO	YES	NO	NO	YES
OBS.	24,155	23,935	23,935	22,501	24,146	23,395
N. OF FIRMS	136	133	133	133	133	133
R^2 (WITHIN)	0.011	0.303	0.305	0.103	0.332	0.334
F-statistic	195.66	324.64	297.61	3670.21	467.45	383.43

Note: The Table presents the panel regression results from the first stage of the 2sls estimation for each one of the instruments separately.

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