Heliyon 10 (2024) e23153

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

How real estate bubbles affect the systemic risk of financial institutions in the United Arab Emirates

Aktham Maghyereh

Department of Economics and Finance, United Arab Emirates University, United Arab Emirates

ARTICLE INFO

JEL classification:
G01
G21
R31

Keywords:
Real estate bubbles
Systemic risk
UAE'S banking sector
Generalized sup ADF approach
Delta CoVaR
MES
Panel data regression

ABSTRACT

The paper addresses a crucial gap in the literature by examining the interplay between real estate price bubbles and systemic risk in the United Arab Emirates (UAE) from 2006 to 2022. The paper employs a three-step testing procedure: bubble detection using the bootstrapped GSADF test, measuring systemic risk using Delta-CoVaR and MES measures, and assessing the impact of real estate bubbles on bank risk through panel data regression. Utilizing a sample of 17 conventional banks operating in the UAE, the study demonstrates that the interplay between real estate price bubbles and systemic risk is influenced by the specific characteristics of banks. Higher levels of loan growth, leverage, and bank size heighten the systemic risk faced by banks during asset price bubbles. Interestingly, the results also indicate that banks with a greater degree of income diversification contribute less to systemic risk during periods characterized by real estate bubbles. The results from this study are useful for policymakers in designing and implementing regulations to stabilize and prevent the UAE's banking sector from being affected by real estate price bubbles.

1. Introduction

Real estate bubbles pose substantial systemic risks to financial institutions [1]. These bubbles occur when real estate asset prices soar to unsustainable levels, primarily driven by speculation and investor demand, rather than underlying economic fundamentals [2]. During these periods of rapid real estate price increases, banks tend to be more inclined to provide loans to property buyers and developers, leading to a surge in overall credit volume circulating within the economy [3]. This situation can result in borrowers taking on excessive debt, while banks become exposed to heightened risk should the real estate bubble burst, causing property values to plummet [2]. Furthermore, banks may encounter a wave of defaults from borrowers who can no longer afford their mortgages or loan repayments, leading to a sharp increase in non-performing loans. This, in turn, can erode bank profitability and result in capital losses. In extreme cases, it can even culminate in bank failures and a systemic crisis that could profoundly impact the broader economy [4–6].

Allen and Gale [7] contend that uncertainty regarding agency risk transfer and credit growth contributes to the formation of asset price bubbles. These bubbles, as per their analysis, tend to burst, subsequently causing financial crises and economic downturns. Neglecting to address the real estate bubble, as emphasized by Crowe, Dell'Ariccia, Igan, and Rabanal [8] and Allen and Gale [7,9], can result in severe and devastating consequences. Numerous studies (e.g. Refs. [10,11]) underscore the potential of fluctuations in real estate prices to generate systemic risks within the financial system.

The real estate sector plays a pivotal role in the UAE's economy, contributing a substantial 5.5 % to the GDP, with Dubai emerging as a prominent global real estate investment epicenter. Notably, other UAE cities like Abu Dhabi and Sharjah have also witnessed

E-mail address: a.almaghaireh@uaeu.ac.ae.

https://doi.org/10.1016/j.heliyon.2023.e23153
Received 16 June 2023; Received in revised form 27 November 2023; Accepted 28 November 2023
Available online 2 December 2023

substantial real estate expansion. However, this pronounced dependence on real estate engenders significant financial vulnerabilities, particularly for the banking sector, owing to their extensive involvement in the industry. Real estate loans represent a significant 20–30 % of the total loans disbursed by UAE banks, and these financial institutions also maintain substantial stakes in the property market, either through direct investments or real estate assets. This heightened exposure renders banks exceptionally susceptible to potential contractions in the real estate market, including the peril of declining property values or diminished property demand [12–14].

While extensive research has explored the impact of asset price bubbles on the broader macroeconomy, as exemplified by studies condtheucted by Jordà, Schularick and Taylor [2], Narayan, Sunila Sharma and Phan [15], Fausch and Sigonius [16], and Hashimoto, Im and Kunieda [17], there remains a limited comprehension of how these bubbles intersect with the accumulation of systemic risk within financial institutions. Notable exceptions to this gap in knowledge are the works of Brunnermeier, Rother and Schnabel [1] and Zhang, Wei, Lee and Tian [6]. Brunnermeier, Rother and Schnabel [1], for instance, conducted an in-depth analysis encompassing 17 advanced countries, delving into the repercussions of real estate bubbles on the systemic risk borne by financial institutions. Their empirical findings distinctly underscore the substantial contribution of these bubbles to the elevation of systemic risk. Likewise, Zhang, Wei, Lee and Tian [6] conducted research on China and identified that both stock market bubbles and real estate bubbles exerted a positive influence on the widespread disruption of the financial system.

Against this backdrop, our paper delves into the experimental examination of how real estate bubbles affect the systemic risk of banks in the UAE. Notably, this specific investigation has not been previously explored in the existing literature, emphasizing the significance of addressing this research gap in the current study. Our study employs a three-step approach. First, it identifies real estate price bubbles using the BSADF method by Phillips and Shi [18]. Then, it assesses systemic risk at the individual bank level using two established measures: Delta-CoVaR by Adrian and Brunnermeier [19] and MES by Brownlees and Engle [20]. Finally, a panel data regression model is used to explore the correlation between systemic risk and binary variables indicating real estate market bubbles. The model also incorporates lagged bank-specific and macroeconomic control variables to consider their potential impact on the relationship.

Our paper contributes the literature in two key ways. Firstly, we bridge a research gap by conducting the first empirical study on how real estate bubbles affect systemic risk in the UAE. Secondly, we consider bank characteristics, revealing fresh insights into the connection between real estate bubbles and systemic risk. This approach also uncovers variations in systemic risk among banks, offering a nuanced perspective.

The study confirms a significant positive relationship between real estate bubbles and the systemic risk of UAE banks. Furthermore, it underscores that this link is influenced by the specific traits of each bank. Particularly, when real estate bubbles occur, higher loan growth, leverage, and larger bank size intensify overall risk for both individual banks and the sector. Conversely, banks with more income diversification contribute less to systemic risk during real estate bubble periods. These results underscore the crucial role of individual bank characteristics in shaping the impact of real estate price bubbles on systemic risk.

These findings hold substantial implications for policymakers as they grapple with the task of designing and implementing regulations aimed at safeguarding the UAE's banking sector from the adverse effects of real estate price bubbles. By shedding light on the complex relationship between these variables, this research provides a valuable foundation for informed decision-making, contributing to the stability and resilience of the UAE's financial system.

Although our study primarily focuses on a single country, its findings can be generalized to other Gulf Cooperation Council (GCC) member countries.[1] The GCC nations share economic reliance on oil revenue, strong sociopolitical ties, and similar systemic risk policies. Their financial systems primarily rely on banks due to underdeveloped capital markets [12–14,21]. Additionally, unlike developed economies, the GCC banking sector is distinct, with a few dominant banks [22–25].

The paper's structure is as follows: Section 2 outlines the methodology, Section 3 describes the data, Section 4 presents results, and Section 5 summarizes findings and policy implications.

2. Methodology

This paper focuses on examining the factors that contribute to systemic risk in UAE banks, with a specific focus on real estate price bubbles. To achieve this, we employ a three-step testing procedure. In the first step, we utilize the bootstrapped GSADF test developed by Phillips and Shi [18] to identify times of explosive UAE real estate market bubbles. In the subsequent stage, we estimate the micro-level of systemic risk using Delta-CoVaR and MES measures. Finally, we use panel data regression analysis to examine how real estate bubbles affect bank systemic risk.

2.1. Bubble identification - GSADF test

This study utilizes the asset pricing model as a theoretical framework to analyze the periodic bubble behaviors arising from market fundamentals, as proposed by Lucas [26]. The model assumes that investors are rational and seek to maximize their utility by accurately valuing assets based on their expected future income. Within this framework, bubbles occur when asset prices become detached from their intrinsic values, often driven by factors such as investor sentiment, herd behavior, or speculative trading. These

[1] The GCC countries comprising Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE).

deviations can lead to temporary periods of overvaluation or undervaluation in asset prices, creating opportunities for profit or potential risks for investors.

To identify asset price bubbles, many tests have been proposed in the area of econometrics, such as variance bounds test, West's two-steps test, and integration test. Gürkaynak [27], on the other hand, found that these tests are susceptible to misspecification and are unable to distinguish between misspecified fundamentals and bubbles, making them inappropriate for reliable bubble identification. In order to address the limitations of the aforementioned bubble tests, Phillips and Shi [18] proposed and developed a novel methodology that involves a wild bootstrap-based implementation of the GSADF test. This modified test allows for the detection of multiple bubble episodes within a single series. This paper uses the bootstrapped GSADF procedure to find explosive real estate price bubbles. A brief overview of this approach is presented below.

The Augmented Dickey-Fuller regression, given in equation (1), forms the foundation of the GSADF test

$$\Delta P_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} P_{t-1} + \sum_{i=1}^{k} \vartheta_i \Delta P_t + \epsilon_t,\ \epsilon_t \sim N\left(0, \sigma^2_{r_1,r_2}\right) \tag{1}$$

where P_t is the real estate price index being examined, r_1 and r_2 are the beginning and ending times of each subsample period, and $r_w = r_2 - r_1$ is the window size. OLS is used to estimate the coefficients α_{r_1,r_2}, β_{r_1,r_2} and ϑ_i, where $\beta_{r_1,r_2} = 1$ represents the null hypothesis and $\beta_{r_1,r_2} > 1$ represents the alternative hypothesis of autocorrelation. Given that the ADF regression is varying within the range $[0, r_2 - r_0]$ with a minimum window size requirement r_0 equal to $0.01 + 1.8/\sqrt{T}$ and a lag order set at $k = 0$, the GSADF statistic, denoted by $GSADF_{r_0}$, can be given as follows in equation (2)

$$GSADF_{r_0} = \underbrace{sup}_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ ADF_{r_1}^{r_2} \right\} \tag{2}$$

where $ADF_{r_1}^{r_2}$ is the supremum value sequence for $r_2 \in [r_0, 1]$.

To detect the existence of bubbles in the series, we can assess the $GSADF_{r_0}$ statistic by comparing it with the appropriate right-tail critical values derived from the wild bootstrap method developed by Phillips and Shi [18]. Confirmation of the presence of at least one bubble during the analyzed period occurs when the computed $GSADF_{r_0}$ statistic at r_0 surpasses the corresponding critical value from the right-tail distribution.

2.2. Systemic risk measures

To quantify how much each individual bank contributes to systemic risk in the financial sector, we first utilize the Delta-CoVaR measure. The Delta-CoVaR captures the additional capital shortfall of a specific bank when there is a systemic stress event, indicating its potential impact on the overall systemic risk. Below is a brief overview of this method.

Given that value-at-risk $(VaR_q^i) = Pr(X^i \leq VAR_q^i) = q\%$ gives the highest loss of a return series at the $q\%$ quantile, the Delta CoVaR can be formulated as follows in equation (3):

$$\begin{aligned} Delta - CoVAR_q^i &= CoVAR_q^{system/X^i = VAR_q^i} - CoVAR_q^{system/X^i = VAR_{50}^i} \\ &= \widehat{\beta}_q^i \left(VAR_q^i - VAR_{50}^i \right) \end{aligned} \tag{3}$$

where $CoVAR_q^{system/X^i = VAR_q^i} = Pr(X^{system}/X^i = VAR_q^i \leq CoVAR_q^{system/X^i = VAR_q^i}) = q\%$ is the banking system's risk j dependent on a certain bank's i distress in the system. Thus, the contribution of bank i to the systemic risk can be achieved by calculating the disparity between the CoVaR when the bank is in a distressed state and the standard CoVaR.

In accordance with the methodology introduced by Adrian and Brunnermeier [19], the VaR and CoVaR are computed based on the daily losses in the value of assets (X) for a specific bank i and the overall banking system of the country as follows in equations (4) and (5):

$$X_t^i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i} = \frac{MA_t^i - MA_{t-1}^i}{MA_{t-1}^i} \tag{4}$$

$$X_t^{system} = \sum_i \frac{MA_t^i}{\sum_i MA_t^i} X_t^i \tag{5}$$

where ME_t^i, LEV_t^i and MA_t^i represent the market value of total equity, leverage, and market value of asset for i at time t, respectively. The daily values of market equity are derived from the daily price of common equity multiplied by the number of outstanding shares. The market-valued total assets are calculated using quarterly balance sheet data. Finally, we employ a modeling approach to estimate the returns of bank i and the overall banking system, taking into account state variables. This enables us to dynamically calculate each bank's contribution to systematic risk over time.

The MES, which was introduced by Acharya, Pedersen, Philippon, and Richardson [28], is our second indicator of systemic risk. This measure quantifies the average expected losses of a particular bank based on the entire system experiencing distress or a severe event. It offers valuable insights into the individual banks' contributions to the overall risk of the entire financial system. By considering the interconnectedness and spillover effects within the system, MES helps identify banks that have a notable influence on systemic risk.

Let $r_{i,t}$ is the bank $i's$ daily return on date t and $r_{system,t}$ is the banking sector's daily index return, following Acharya, Pedersen, Philippon, and Richardson [28], the MES can be calculated using the formula presented in equation (6):

$$MES_{i,t} = -E\left[r_{i,t} \middle| r_{system,t} < c = q5\%\right] \tag{6}$$

where the parameter c represents a threshold that corresponds to the lowest 5 % daily return of the banking sector over the course of a year. To compute the dynamic MES, we employ the methodology developed by Brownlees and Engle [29]. This approach relies on the multivariate GARCH-DCC model originally introduced by Engle [30]. Finally, the quarterly frequency data for both the Delta-CoVaR and MES for each bank are computed by taking the averages daily values over each quarter.

2.3. Determinants of systemic risk

In examining the impact of real estate bubbles on systemic risk, we utilize a panel data model as outlined in equation (7):

$$Sys.\ Risk_{i,t} = \alpha_i + \beta_1 Bub_t + \beta_2 Bank_{i,t-1} + \beta_3 Bub_t \times Bank_{i,t-1} + \beta_4 Mac_{t-1} + \beta_5 Crises_{t-1} + u_{i,t} \tag{7}$$

where $Sys.\ Risk_{i,t}$ refers to the systemic risk of bank i at time t, which is measured using either the Delta-CoVaR or MES. Bub_t refers to two binary variables that serve as indicators of bubble episodes at time t. $Bank_{i,t-1}$ refers to lagged bank characteristics. $Bub_t \times Bank_{i,t-1}$ is the interaction term between the bubble binary variable and bank-specific variables (i.e., loan growth, size, leverage, diversification, profitability). Mac_{t-1} is the lagged macroeconomic control variables. Crises is a binary variable that takes the value 1 during periods that correspond to a crisis (for example, 1 if the period is the COVID-19 pandemic between January 1, 2020 and the end of the sample, and 0 otherwise).

In the above model, it is acknowledged that the explanatory variables may be influenced by factors that create endogeneity issues. Endogeneity occurs when there is a two-way correlation between the explanatory variables and the error term, resulting in biased and inconsistent parameter estimates. This means that the variables are not strictly exogenous and can be influenced by other factors in the model. To mitigate these concerns and control for potential endogeneity, we follow the approach suggested by Renders, Gaeremynck, and Sercu [31] and introduce a lag of one quarter for all explanatory variables. However, including lagged independent variables does not completely eliminate the problem of reverse causality. Instead, it modifies the pathway through which endogeneity introduces bias into the analysis. To provide a robustness check, we further estimate the panel data model using the System Generalized Method of Moments (SYS GMM) estimator. To reduce the impact of extreme values on the analysis, we apply a winsorization technique to the bank-level variables. Winsorization involves adjusting the values at the 1st and 99th percentiles by replacing them with the corresponding percentile values.

In the above specification, the coefficient β_1 measures the influence of real estate bubbles on the bank systemic risk. A positive sign for the coefficients suggests that the occurrence of real estate price bubbles may raise systemic risk. The coefficients of the interaction terms β_3 describe how the link between bubbles and systemic risk differs depending on the balance sheet characteristics of the bank. For example, during a bubble, there is often increased optimism and speculation in the market. As a result, banks may experience higher demand for loans as borrowers seek to take advantage of the rising asset prices or investment opportunities associated with the bubble. This increased demand leads to higher loan growth, as banks extend more credit to borrowers. If the bubble bursts and asset prices decline, borrowers may face difficulties in repaying their loans, leading to a higher number of loan defaults. This can strain the financial health of banks. If multiple banks have significant exposure to the same bubble, a downturn in the bubble can create a domino effect where the failures or financial stress of one bank can impact other banks through interconnectedness in the financial system. This interconnectedness can arise from various channels, such as interbank lending, derivatives contracts, or common exposures to other sectors affected by the bubble.

3. Data set and variables

We estimate real estate bubbles utilizing quarterly UAE real residential property price index data. The sample period is January 2006–October 2022 (a start date determined by data availability) from the Bank for International Settlements database.[2] To estimate systemic risk, we gather daily data from Thomson Reuters' Datastream, including a bank's equity returns, number of outstanding shares, market capitalization, stock market returns, and value-weighted banking returns. We retrieve quarterly financial statement data, specifically the values of total assets, equity, and leverage, from Bureau van Dijk's Bankscope database. Our sample comprises of 17 publicly traded UAE commercial.[3]

[2] The data set can be downloaded through the following link: https://www.bis.org/statistics/pp_selected.htm.

[3] There are 21 listed commercial banks in the UAE. However, Nonetheless, banks that lacked complete data are excluded from the sample.

To estimate the time-varying systemic risk, we adopt the state variables that have been identified in existing literature [19,28]. In light of the fact that neither the UAE corporate bond market nor the UAE sovereign debt market is very fragmented, we use three US-specific state factors and two UAE-specific variables. The following state variables are utilized in our analysis: a) the daily change in the yield curve; b) the daily change in the three-month yield; c) the daily change in the TED spread; d) the daily change in the market index of the UAE) and the volatility of the UAE equity market. The first three state variables are sourced from the Federal Reserve Bank of St. Louis, while the rest are obtained from Thomson Reuters' Datastream.

Four key bank-specific characteristics are used to identify the key drivers of systemic risk. Following Adrian and Brunnermeier [19], Brunnermeier, Rother and Schnabel [1], Maghyereh and Yamani [32], and Zhang, Wei, Lee and Tian [6], we include loan growth (represented by the first difference of natural logarithms of loans), size (captured by the logarithm of total assets), leverage (computed as the ratio of total assets to equity), diversification (calculated by one minus the adjusted Herfindahl Hirschman Index (1-AHHI)), and profitability (measured by the ratio of net profit after tax to average total equity). Quarterly data on bank-specific characteristics is obtained from Bureau von Dijk' Bankscope.

As discussed earlier, the excessive loan growth associated with a real estate bubble increases the vulnerability of both borrowers and lenders. Borrowers may become overleveraged, relying heavily on loans and facing potential repayment difficulties if property prices decline. Lenders, particularly banks with significant exposure to real estate loans, face higher credit risk if borrowers' default or property values collapse, ultimately posing systemic risks [1,33,34].

The size of a bank is the other major source of systemic risk, and it has been the subject of a great deal of research. Larger banks have the potential to pose a greater systemic risk due to their interconnectedness (see, e.g. Refs. [35–37]), "too big to fail" status (see, e.g. Refs. [38–40]), and risk management complexity (see, e.g. Ref. [41]). However, according to Boyd and Runkle [42], larger banks tend to demonstrate higher profitability and maintain larger capital buffers in comparison to smaller banks. As a result, they are less vulnerable to macroeconomic fluctuations or liquidity disruptions, and, ultimately, have a lower potential contribution to systemic risk. Thus, we expect that the size of a bank significantly influences the level of systemic risk.

Aside from a bank's size and loan growth, the manner in which it acquires financing is another potential element determining its systemic risk. Higher bank leverage can amplify the impact of shocks on a bank's balance sheet. When a bank has high leverage, even a small decline in asset values can lead to a significant erosion of its capital and financial stability. This can trigger a chain reaction, as the bank's distress or failure can transmit shocks to other interconnected financial institutions, potentially causing systemic disruptions [43]. In addition, a high leverage ratio indicates that a larger proportion of a bank's assets are financed by debt rather than equity. This leaves the bank with a thinner capital buffer to absorb losses or unexpected shocks. In times of financial crisis, if a bank's assets experience significant declines in value, it may struggle to meet its obligations and face the risk of default. The default of highly leveraged banks can have cascading effects, leading to contagion and systemic risk [35]. Brunnermeier, Dong, and Palia [44] and Bostandzic and Weiβ [41] provided empirical evidence supporting the proposition that banks with high levels of leverage have a greater impact on systemic risk compared to banks with lower. Thus, we expect a positive impact of leverage on the level of systemic risk.

Diversification of income has the potential to mitigate systemic risk. By generating income from various sources, banks can create a more balanced and diversified portfolio of assets and activities. This diversification can help mitigate the effect of idiosyncratic shocks and moderate the likelihood of systemic events [45]. Income diversification can also enhance a bank's risk-management capabilities and resilience. By engaging in a range of activities, banks can potentially offset losses in one area with gains in others, thereby reducing their vulnerability to shocks [42]. As a result, we that greater income diversification is associated with lower systemic risk.

Higher bank profitability can contribute to reducing systemic risk. Profitable banks tend to have stronger financial positions, higher capital buffers, and better risk management practices. This enables them to absorb losses during times of financial strain, thereby reducing the likelihood of systemic disruptions and contagion effects (see, e.g. Refs. [35,46,47]).

Finally, we consider GDP growth and inflation rate as control variables, obtained from the IMF statistics data, to account for the influence of macroeconomic conditions. The data sources and definitions of variables are presented in Table 1.

4. Empirical results

4.1. Real estate bubbles detection

The dashed green line in Fig. 1 depicts the real residential property price index for the UAE. The blue sold line represents the periods of a bubble, which are identified by surpassing the 95 % bootstrapped critical value of the BSADF test statistic, which are represented by the gray areas. The first time that the BSADF test statistics surpasses its critical value marks the start of a bubble episode. Conversely, the termination of a bubble episode is marked by the point at which the BSADF test statistic falls below its critical value and does not exceed it again for a minimum break length. The 95 % bootstrapped critical values employed in this analysis are derived from 999 bootstrap iterations conducted through Monte Carlo simulations.

The figure shows that residential property prices in the UAE experienced a period of considerable growth until the middle of 2006. This notable upward trend was fueled by the upsurge in oil prices and the implementation of structural reforms in the real estate sector by implementing the foreign property ownership law. These were reversed around the runup to the global financial crisis until the end of 2007. Then markets tumbled significantly until the beginning of 2009. As the economy returned to growth and halted construction projects were resumed, the real estate sector recovered, and the property price index rose strongly to reach its highest level by the end of 2013. However, in the wake of the drop in crude oil prices at the beginning of the fourth quarter of 2014, as well as the Arab Spring and political revolutions in the Middle East, the residential property market experienced a significant collapse. This downward spiral

Table 1
Variables description and sources.

Variable	Description	Frequency	Source
Panel A: Bubble			
Boom	A binary variable has a value of one during a real estate bubble's boom period and zero otherwise; found using the BSADF technique.	Quarterly	Authors' calculations based on data from Bank for International Settlements database
Bust	A binary variable has a value of one during a real estate bubble's bust period and zero otherwise; found using the BSADF technique.	Quarterly	Authors' calculations based on data from Bank for International Settlements database
Panel B.1: Systemic risk			
Delta Conditional Value-at-Risk (DCoVaR)	A metric used to assess systemic risk at the individual bank level introduced by Adrian and Brunnermeier (2016). It quantifies the incremental impact of a specific bank on the overall systemic risk.	Daily	Authors' calculations based on data from Thomson Reuters Datastream, Bankscope, and the Federal Reserve Bank of St. Louis
Marginal Expected Shortfall (MES)	A metric used to assess systemic risk at the individual bank level introduced by Acharya et al. (2017). It calculates the magnitude of a bank's losses within the extreme tail of the loss distribution for the entire banking sector.	Daily	Authors' calculations based on data from Thomson Reuters Datastream
Panel B.2. Systemic risk estimation variables			
Equity returns	The logarithmic first difference of the closing stock price	Daily	DataStream
Market capitalization	The product of the stock price and the number of common shares outstanding	Daily	DataStream
Banking sector returns	The logarithmic first difference of the banking sector index	Daily	DataStream
Stock market returns	The logarithmic first difference of the stock market index	Daily	DataStream
Bank size	The natural logarithm of the total assets.	Quarterly	Bureau von Dijk' Bankscope
Book-to-Market Ratio	The equity's market value divided by its book value	Quarterly	Bureau von Dijk' Bankscope
Change in the yield curve	The difference in yields between the ten-year treasury rate and the three-month T-Bill rate	Daily	Federal Reserve Economic Data (FRED)
TED spread	The difference between the three-month Libor rate and the three-month secondary market bill rate	Daily	Federal Reserve Economic Data (FRED)
Change in the three-month yield	The change in three-month T-Bill rate	Daily	Federal Reserve Economic Data (FRED)
Market Volatility	The standard deviation of the daily equity market return calculated using a rolling window of 22 days.	Daily	DataStream
Panel C: Control variables			
Panel C.1: Bank-specific characteristics			
Loan growth	Growth rate of total loans	Quarterly	Bankscope
Bank size	The natural logarithm of the total assets	Quarterly	Bankscope
Leverage	The ratio of total assets to equity	Quarterly	Bankscope
Diversification	One minus the Herfindahl Hirschman Index (1-AHHI))	Quarterly	Bankscope
Profitability	The ratio of net profit after tax to average total equity	Quarterly	Bankscope
Panel C.2: Macroeconomics			
GDP growth	Percentage growth in real gross domestic product	Quarterly	IMF Statistics Data
Inflation	Percentage growth CPI Consumer Price Index	Quarterly	IMF Statistics Data
COVID-19	A binary variable has a value of one during the COVID-19 pandemic (2020Q1 to the end of the sample), and 0 otherwise	Quarterly	
GFC	A binary variable has a value of one during the Great Financial Crisis (2007Q4-2009Q4), and 0 otherwise	Quarterly	

persisted until reaching the lowest point, or trough level, around the first quarter of 2015. Afterwards, the residential property market witnessed a slight recovery, albeit at a slower pace.

The property market's performance has been negatively affected by the COVID-19 pandemic, as evident in its weak performance after 2020. The restrictions, economic uncertainty, and changes in consumer behavior resulting from the pandemic have led to a decrease in demand for properties. Additionally, supply-side disruptions, such as construction delays and reduced inventory, have further contributed to the weakened performance of the property market. At the beginning of 2021, the property market began to show signs of recovery; although the pace of recovery was relatively slow. It's worth noting here that the market was unable to fully recover the losses incurred during the previous period. The recent losses, as well as those from earlier, were never completely recovered. The economic uncertainties and ongoing pandemic-related challenges have hindered a faster rebound.

In Fig. 1, the gray areas represent the periods in which real property price bubbles occurred throughout the sample period. Additionally, Table 2 provides a comprehensive record of the start and end dates for each episode of the price bubble, along with the identification of the boom and bust phases within each bubble episode. Based on the figure, it can be inferred that the UAE real estate market experienced three significant bubble cycles: 2011 Q3 to 2012 Q1, 2013 Q4 to 2014 Q2, and 2021 Q1 to 2021 Q4. All bubble episodes identified in terms of their duration are of a short-lived nature, lasting for a period of fewer than one year. The longest bubble episode in the UAE real estate market occurred from 2021 Q1 to 2021 Q4, lasting for four quarters. In contrast, the bubble episodes that took place during the other two periods spanned three quarters.

When considering the magnitude of the bubble, the period from 2013 Q4 to 2014 Q2 is marked by the highest peak value, indicating a significant degree of bubble during this phase. Furthermore, during this bubble episode, real property prices experienced a

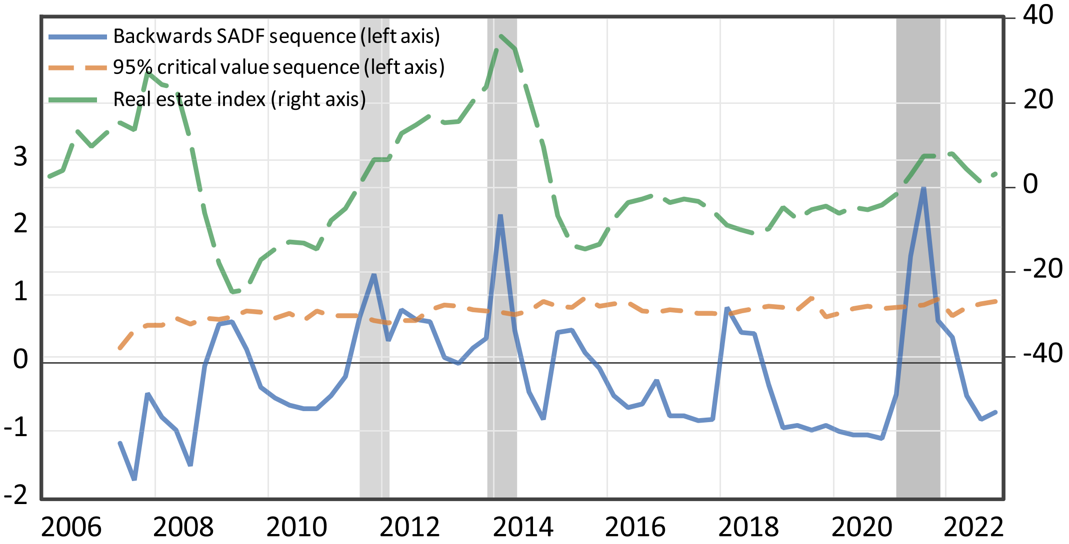

Fig. 1. Bubble periods in the UAE real residential property price index
Notes: The quarterly real residential property price index is represented by the dashed green line, while the sequence of BSADF test statistics is depicted by the solid blue line. The orange dotted line indicates the corresponding 95 % bootstrapped critical value. The shaded areas in gray represent the identified bubble periods, which occur when the BSADF statistic surpasses the 95 % bootstrapped critical value. The critical values used in this analysis were derived from 999 bootstrap replications. The sample size for the analysis is 68, and the smallest window considered in the analysis contains 6 observations. The dataset covers a time period from January 2006 to October 2023. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Results of GSADF test.

	Bubble episodes		
	start	end	length (quarters)
1	2011Q3	2012Q1	3
2	2013Q4	2014Q2	3
3	2021Q1	2021Q4	4
BSADF t-Statistic: 2.89826***			
90 %	2.629144		
95 %	2.031540		
99 %	1.752419		

Notes: The table reports the bubbles origination and termination dates identified with 95 % critical values obtained by the Wald bootstrap procedure of Phillips and Shi (2020). The 95 % bootstrapped critical values obtained from 999 bootstrap replications. The sample size for the analysis is 68, and the smallest window considered in the analysis contains 6 observations. The dataset covers a time period from January 2004 to October 2023. "***" denotes significant at 1 % level.

substantial increase of 36.7 % from the start of the bubble to its peak. Following the peak, there was a decline of 34.60 % in the price from its highest point to the end of the bubble. These empirical findings provide evidence that boom-bust cycles tend to occur when the UAE real estate market undergoes dramatic price variations.

4.2. Systemic risk results

Table 3 provides a statistical summary of the Delta-CoVaR and MES over the sample period. The Delta-CoVaR represents the

Table 3
Summary ***Delta CoVaR*** and MES statistics.

Method	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
Delta CoVaR	0.010	0.047	0.005	0.004	2.752	13.185	24312.3***
MES	0.023	0.122	0.009	0.010	3.071	16.383	36785.7***

Notes: The table presents descriptive the summary statistics of Delta CoVaR and MES at the 95 % confidence level. J-B is the Jarque–Bera test statistics for normality. "***" denotes significant at 1 % level.

estimated asset losses that occur when a specific bank experiences distress. On the other hand, the MES offers a different perspective on systemic banking risk by presenting the estimated losses for a specific bank when the entire financial system encounters distress. Consequently, the higher value observed for MES is not surprising, as it captures the systemic risk originating from the financial system and affecting individual banks, rather than the risk posed by a single bank to the entire system. The results of the descriptive statistics test, including skewness, kurtosis, and the Jarque-Bera test, indicate that our risk estimates do not follow a normal distribution.

Panels A and B of Fig. 2 show the time-series progression of Delta-CoVaR and MES, respectively. The analysis reveals a notable surge in systemic risk in the UAE banks during the Global Financial Crises (GFCs). During the GFC, the interconnectedness of global financial markets led to a contagion effect, causing a surge in systemic risk for banks in the UAE. The turmoil in the global financial system, combined with the decline in real estate prices and a slowdown in economic activity, heightened the vulnerability of UAE banks. The 2014–2016 oil crises also had a notable impact on the systemic risk of UAE banks. The sharp drop in oil prices during that period had wide-ranging repercussions for the financial stability of the banking sector in the UAE. The interconnectedness between the oil industry and the banking system led to increased vulnerability and exposure to risks, resulting in heightened systemic risk for UAE banks during this challenging period.[4]

Similarly, the COVID-19 pandemic had a profound impact on the systemic risk of UAE banks. The systemic risk elevated and reached its peak in March 2020 but began to decline thereafter. The widespread economic disruption, business closures, and market volatility resulting from the pandemic created an environment of heightened uncertainty and financial stress. The containment measures and travel restrictions imposed to control the spread of the virus further strained the economy, leading to increased default risk and credit losses for banks. As a result, the systemic risk of UAE banks increased significantly during this period. The findings of Rizwan, Ahmad, and Ashraf [48] for China, as well as the studies conducted by Maghyereh and Abdoh [25], Maghyereh, Abdoh, and Al-Shboul [23], and Maghyereh and Yamani [32] focusing on the GCC countries, including the UAE, are in line with these results.

4.3. Bubbles and systemic risk

Table 4 presents descriptive statistics for the variables incorporated in our analysis and Table 5 displays the correlation matrix for these variables. The correlation matrix illustrates a strong correlation between the two indicators of market-based systemic risk. Furthermore, the relationship between bank quality and systemic risk is constant across both indicators. Table 5 provides confirmation of a positive correlation between loan growth and systemic risk. The findings also indicate that there is a positive relationship between bank size and leverage and systemic risk. This implies that larger banks and those with higher leverage tend to have a higher level of systemic risk. On the other hand, the correlation matrix reveals a negative relationship between diversification and profitability and systemic risk. This suggests that banks with greater diversification across their activities and higher profitability tend to have a lower level of systemic risk. The profitability and loan activity of banks are influenced by the macroeconomic wellbeing represented by GDP growth. Additionally, there exists a noteworthy inverse relationship between macroeconomic conditions and systemic risk. To obtain a more precise comprehension of how bank attributes influence risk, it is therefore crucial to control for the macroeconomic environment.

To initially assess the impact of real estate bubbles and bank characteristics on systemic risk, we conduct a panel linear regression analysis without including interaction terms. In this regression, we incorporate bank-fixed and time-fixed effects to address heterogeneity and temporal variability. Bank-fixed effects are instrumental in accounting for disparities among individual banks that may impact the dependent variable. These fixed effects enable us to control for latent characteristics specific to each bank that could influence the outcomes. Time-fixed effects, on the other hand, handle changes that happen at different times and affect the dependent variable across all banks. This makes it easier to see how trends, shocks, or changes in time affect the outcomes. Incorporating both types of fixed effects enhances the model's stability by reducing any potential bias arising from bank-specific or time-specific factors that remain hidden.

Table 6 presents the results of the analysis, where the findings without (with) crisis variables are presented in Columns 1 (2) and 3 (4), respectively. The results of our analysis provide compelling evidence supporting a strong association between real estate price bubbles and an impactful rise in systemic risk. Specifically, we observe that the coefficients of the bubble indicator are positive, indicating a positive relationship with systemic risk. The impact of the bubble on bank systemic risk, measured by Delta-CoVaR and MES, is estimated to be 0.0237 and 0.0386, respectively. This suggests that the real estate price bubbles increased the 95 % tail of the loss distribution by 2.37 % (for Delta-CoVaR) and 3.86 % (for MES). It is noteworthy that the losses arising from MES are greater than those from Delta-CoVaR. This discrepancy arises because MES takes into account the effect of the overall financial system on an average bank, providing a more comprehensive assessment of systemic risk. On the other hand, Delta-CoVaR focuses on the reverse relationship, evaluating the impact of individual banks on the overall system.

Furthermore, these coefficients are highly significant, underscoring the robustness and reliability of our findings. These results imply that the presence of real estate price bubbles is accompanied by a notable and meaningful increase in systemic risk within the UAE banking system. As real estate price bubbles expand, the vulnerability and interconnectedness of financial institutions intensify, magnifying the potential impact of distress or failure within the system. Thus, our results support the previously identified positive correlation between diversification and banking sector stability. Thus, our findings support the previously established positive relationship between real estate price bubbles and bank systemic risk, as highlighted by Brunnermeier, Rother, and Schnabel [1].

[4] The UAE is heavily reliant on oil revenues to support its economies. The decline in oil prices had significant implications for the UAE's economy, including its banking sector, as it impacted government revenues, investment levels, and overall economic growth.

Panel A: Delta CoVaR

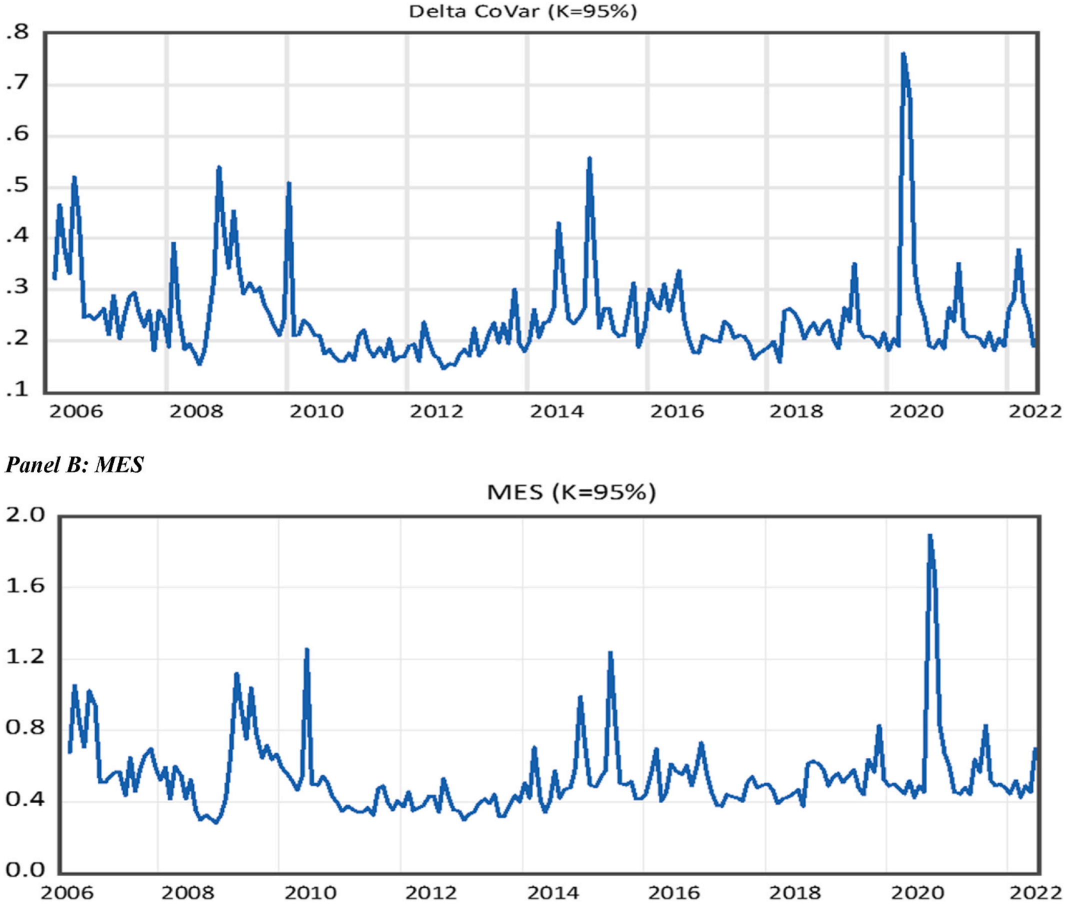

Fig. 2. The results of Delta CoVaR and MES
Panel A: Delta CoVaR, Panel B: MES, Notes: Panel A of the figure illustrates the average systemic risk measures ΔCoVaR, while Panel B represents the MES for the UAE banking system, with the confidence level set at 95 %. The dataset covers a time period from January 2006 to October 2023.

Table 4
Summary statistics.

	Mean	Std. Dev.	Min	Max
A. Dependent Variables (Systemic risk)				
Δ*CoVaR*	0.0103	0.0094	0.0004	0.0701
MES	0.0163	0.0119	0.0004	0.0701
B. Independent variables				
Bank-specific variables				
Loan growth	0.4106	0.2162	0.0382	0.4886
Bank size	7.8555	0.5671	6.7993	8.9823
Leverage	0.3091	0.2933	0.1100	0.9860
Diversification	0.3357	0.0813	0.1486	0.5000
Profitability	0.3459	0.3323	−0.6400	0.9980
Macroeconomic variables				
GDP growth	0.0221	0.0758	−0.1101	0.1506
Inflation	0.0212	0.0353	−0.0247	0.1490

Notes: The table provides a summary of the variables' statistics during the period from Q1-2006 to Q3-2022. Table 1 includes the definitions and sources of the variables.

When looking at bank attributes, our findings indicate a positive correlation between loan growth and leverage and systemic risk. This implies that as banks exhibit higher levels of loan growth and leverage, their exposure to systemic risk increases. When banks expand their lending activities rapidly or rely heavily on debt financing, they become more susceptible to adverse economic conditions or market downturns. In such situations, a higher level of systemic risk arises due to the interconnectedness and potential contagion

Table 5
Correlation matrix.

	ΔCoVaR	MES	Loan growth	Bank size	Leverage	Diversification	Profitability	GDP growth	Inflation
ΔCoVaR	1								
MES	0.7975***	1							
	(0.0000)								
Loan growth	0.2991**	0.1612***	1						
	(0.0141)	(0.0001)							
Bank size	0.5690***	0.5892***	0.1544***	1					
	(0.0000)	(0.0000)	(0.0179)						
Leverage	0.1642***	0.2381***	0.0246	0.3546***	1				
	(0.0010)	(0.0000)	(0.2626)	(0.0000)					
Diversification	−0.4185***	−0.2928***	0.0474	0.3529***	−0.1089**	1			
	(0.0000)	(0.0000)	(0.2419)	(0.0000)	(0.0303)				
Profitability	−0.2517**	−0.1348***	0.1213*	−0.2979***	−0.1044**	0.1459**	1		
	(0.0202)	(0.0008)	(0.0599)	(0.0000)	(0.0380)	(0.0267)			
GDP growth	−0.1126***	−0.1854***	0.2112**	−0.0170	0.0963*	0.0371	0.1643**	1	
	(0.0053)	(0.0000)	(0.0278)	(0.6755)	(0.0555)	(0.4586)	(0.0123)		
Inflation	−0.1644**	−0.1952**	0.2046***	−0.0178	0.0388	0.0473	0.0448	0.4479***	1
	(0.0112)	(0.0185)	(0.0000)	(0.5156)	(0.4410)	(0.2429)	(0.2684)	(0.0000)	

Notes: The table displays the correlation matrix for the variables utilized in our regression analyses. The analysis covers the sample period from Q1-2006 to Q3-2022. Table 1 includes the definitions and sources of the variables. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels. *P*-values are in parentheses.

Table 6
Baseline regressions.

	$\Delta CoVaR$		MES	
	(1)	(2)	(3)	(4)
Bubbles	0.0192**	0.0237***	0.0342***	0.0386***
	(0.0170)	(0.0030)	(0.0010)	(0.0000)
Loan growth	0.0009**	0.0047*	0.0015**	0.0094**
	(0.0405)	(0.0502)	(0.0240)	(0.0284)
Bank size	0.0064***	0.0072***	0.0106***	0.0114***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Leverage	0.0015**	0.0011**	0.0021**	0.0017**
	(0.0218)	(0.0340)	(0.0168)	(0.0247)
Diversification	−0.0340***	−0.0338***	−0.0242***	−0.0239***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Profitability	−0.0011**	0.0024**	−0.0023*	0.0035***
	(0.0289)	(0.0260)	(0.0820)	(0.0080)
GDP growth	−0.0579***	−0.0296**	−0.0616***	−0.0339**
	(0.0000)	(0.0210)	(0.0000)	(0.0330)
Inflation	−0.0387***	−0.0037*	−0.0412***	−0.0070*
	(0.0010)	(0.0660)	(0.0030)	(0.0647)
GFC		0.0786***		0.0761***
		(0.0000)		(0.0000)
COVID-19		0.0853***		0.05191***
		(0.0000)		(0.0000)
Constant	−0.0387***	−0.0605***	−0.0796***	−0.0864***
	(0.0010)	(0.0000)	(0.0000)	(0.0000)
Bank-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
# of observations	611	611	611	611
Adj. R2	0.4426	0.4933	0.4605	0.5348

Notes: The table reports the estimates of panel model regressions of quarterly $\Delta CoVaR$ and MES systemic risk measures on real estate bubbles, bank-specific variables and various control variables over the sample period from Q1-2006–Q3-2022. Regressions are estimated with firm and time-fixed effects with robust standard errors. The regressions report with one lagged explanatory variables. Variable definitions are provided in Table 1. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels. *P*-values are in parentheses.

effects within the financial system.

As anticipated, our analysis reveals a negative relationship between diversification and profitability with systemic risk. This suggests that as banks increase their diversification efforts, they experience a decrease in systemic risk. Diversification allows banks to spread their risks across various activities, reducing their vulnerability to idiosyncratic shocks and enhancing their overall stability. Consequently, banks that have a more diversified income base and a wider range of operations are better equipped to navigate challenging market conditions and withstand potential shocks. It is worth noting that our findings align with prior research that has explored the relationship between bank attributes and systemic risk (e.g. Refs. [1,6,19,32]).

Regarding the macroeconomic control variables, we find a statistically significant negative relationship between both real GDP growth and inflation and systemic risk. A robust and expanding economy provides a favorable environment for banks, leading to increased lending opportunities, improved asset quality, and overall stability in the financial system. Lower levels of inflation are generally indicative of a more stable economic environment. When inflation is low, it signifies that prices are relatively stable, reducing the likelihood of sudden price shocks or disruptions. This stability can have a positive impact on the banking sector by mitigating systemic risks.

Our analysis reveals that the GFC led to a significant increase in the 95 % tail of the loss distribution, with estimated effects of 7.86 % and 7.61 % for Delta-CoVaR and MES, respectively. This implies that the GFC had a substantial impact on elevating the level of risk within the UAE banking sector. Furthermore, we examine the effect of the COVID-19 pandemic on bank risk, measured by Delta-CoVaR and MES. The results indicate that the pandemic led to an increase in bank risk, with estimated effects of 0.0853 for Delta-CoVaR and 0.05191 for MES. These two events have exposed vulnerabilities in the UAE banking sector, increased interconnectedness, and amplified the potential for contagion and spillover effects.

Moving on to the analysis of interactions, we aim to investigate the initial impact of real estate bubbles and bank attributes on systemic risk. By examining these interactions, we can assess how these factors interact and potentially amplify or mitigate the overall systemic risk. Table 7 reports the regression results, including the interactions of the relevant specific-bank characteristics with the bubble indicator. As we can see, the coefficients of the bubble indicator remain qualitatively unchanged with the inclusion of interaction terms. However, we observe a significant increase in the contribution of a bank with bank-specific characteristics to systemic risk during bubble phases. Specifically, we observe a significant increase in the systemic risk contribution when real estate bubbles are present. This finding implies that, during bubble phases, banks with median balance sheet characteristics play a more prominent role in amplifying systemic risk compared to other periods.

The analysis reveals a strong and statistically significant positive relationship between loan growth and systemic risk during bubble

Table 7
Interacting with the real estate bubbles.

	ΔCoVaR	MES
	(1)	(2)
Bubbles	0.0243**	0.0306***
	(0.0310)	(0.0460)
Loan growth	0.0012***	0.0063***
	(0.0387)	(0.0454)
Loan growth × Bubbles	0.0022***	0.0010*
	(0.0163)	(0.0592)
Bank size	0.0065***	0.0106***
	(0.0000)	(0.0000)
Bank size × Bubbles	0.0033**	0.0038**
	(0.0270)	(0.0370)
Leverage	0.0019**	0.0028**
	(0.0179)	(0.0116)
Leverage × Bubbles	0.0043	0.0047
	(0.1330)	(0.1780)
Diversification	−0.0310***	−0.0199***
	(0.0000)	(0.0020)
Diversification × Bubbles	−0.0100**	−0.0101**
	(0.0363)	(0.0459)
Profitability	−0.0019**	−0.0021
	(0.0131)	(0.0171)
Profitability × Bubbles	0.0010	0.0056*
	(0.6780)	(0.0700)
GDP growth	−0.0325**	−0.0352**
	(0.0120)	(0.0270)
Inflation	0.0018	0.0087
	(0.8880)	(0.5720)
GFC	0.0746***	0.0722***
	(0.0000)	(0.0000)
COVID-19	0.0378***	0.0418***
	(0.0067)	(0.0004)
Constant	−0.0546***	−0.0789***
	(0.0000)	(0.0000)
Bank-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
# of observations	611	611
Adj. R2	0.4951	0.5178

Notes: The table reports the estimates of panel model regressions of quarterly ΔCoVaR and MES systemic risk measures on real estate bubbles, bank-specific variables and various control variables over the sample period from Q1-2006–Q3-2022. Regressions are estimated with firm and time-fixed effects with robust standard errors. The regressions report with one lagged explanatory variables. Variable definitions are provided in Table 1. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels. *P*-values are in parentheses.

phases. This finding indicates that as loan growth increases, so does the level of systemic risk. The results also show that the interaction coefficient between bank size and real estate bubbles is positive and statistically significant, indicating that the contributions of big banks to systemic risk are higher than those of small banks during the time of price bubbles. This finding suggests that the size of a bank plays a crucial role in amplifying systemic risks, particularly during episodes of real estate bubbles. The greater ability of large banks to spread risks can be attributed to their extensive networks, larger balance sheets, and interconnectedness within the financial system. These findings highlight the importance of closely monitoring the activities and risk exposures of large banks, especially during periods of real estate bubbles.

The analysis suggests that bank leverage has a positive effect on systemic risk during real estate bubbles, but this effect is not statistically significant. This implies that the relationship between bank leverage and systemic risk during these periods is uncertain. The results also indicate that income diversification has a significantly negative coefficient during real estate bubbles. This suggests that a more diversified income structure is associated with a reduction in systemic risk during periods characterized by real estate bubbles. During real estate bubbles, when there is an excessive increase in property prices and potentially unsustainable lending practices, banks heavily exposed to the real estate sector may face higher risks. However, banks with more diversified income streams can better withstand the impact of a potential real estate market downturn.

The positive coefficient suggests that higher bank profitability during real estate bubbles is also associated with an elevated level of systemic risk. This could be due to several factors. For example, banks that are overly focused on the real estate sector may become highly exposed to potential downturns or shocks in that market. Additionally, increased profitability may incentivize banks to take on higher levels of risk or engage in riskier lending practices, potentially amplifying systemic risk.

The interaction of profitability and real estate bubbles in the table is positive and significant, indicating that higher levels of bank profitability are associated with an increase in systemic risk during periods characterized by real estate bubbles. These unexpected results could be due to several factors. For example, banks that are overly focused on the real estate sector may become highly exposed to potential downturns or shocks in that market. Additionally, increased profitability may incentivize banks to take on higher levels of risk or engage in riskier lending practices, potentially amplifying systemic risk.

In summary, the findings presented above provide additional evidence from an emerging market to support the notion that certain characteristics of banks play a significant role in determining their contributions to systemic risk during episodes of real estate price bubbles. These findings align with previous studies conducted by Adrian and Brunnermeier [19] and Brunnermeier, Rother, and Schnabel [1], which also observed similar patterns in the relationship between bank characteristics and systemic risk. Specifically, their results indicate that during periods of real estate price bubbles, there is an increase in the systemic risk contributions associated with loan growth, bank size, and leverage.

4.3.1. Robustness check

To address potential endogeneity concerns and ensure the validity of our results, we used the SYS GMM estimator of Arellano and Bover [49] and Blundell and Bond [50]. This method is well-suited for addressing endogeneity issues by utilizing moment conditions

Table 8
Robustness check: SYS GMM estimator.

	Δ*CoVaR*	MES
	(1)	(2)
Bubbles	0.0110**	0.0251**
	(0.0460)	(0.0120)
Loan growth	0.0015***	0.0024***
	(0.0020)	(0.0000)
Loan growth × Bubbles	0.0039***	0.0021*
	(0.0000)	(0.0770)
Bank size	0.0007***	0.0032***
	(0.0000)	(0.0000)
Bank size × Bubbles	0.0009**	0.0027*
	(0.0344)	(0.0620)
Leverage	0.0028***	0.0047***
	(0.0000)	(0.0000)
Leverage × Bubbles	0.0027*	0.0019**
	(0.0850)	(0.0408)
Diversification	−0.0417***	−0.0309***
	(0.0000)	(0.0000)
Diversification × Bubbles	−0.0193***	−0.0202**
	(0.0000)	(0.0110)
Profitability	−0.0030***	−0.0023***
	(0.0000)	(0.0040)
Profitability × Bubbles	0.0016	0.0043**
	(0.1990)	(0.0160)
GDP growth	−0.0456***	−0.0437***
	(0.0000)	(0.0000)
Inflation	−0.0157**	−0.0013**
	(0.0100)	(0.0881)
GFC	0.0020**	0.0013**
	(0.0250)	(0.0167)
COVID-19	0.0005*	0.0037***
	(0.0543)	(0.0040)
Constant	−0.0108*	−0.0240***
	(0.0840)	(0.0000)
Bank-fixed effects	Yes	Yes
Time-fixed effects	Yes	Yes
# of observations	611	611
Sargan test (p-value)	0.7968	0.8847
AR (1) (p-value)	0.3010	0.1892
AR (2) (p-value)	0.4624	0.2879

Notes: The table reports the estimates of panel model regressions of quarterly ΔCoVaR and MES systemic risk measures on real estate bubbles, bank-specific variables and various control variables using two-step system GMM estimations of Blundell and Bond (1998) over the sample period from Q1-2006–Q3-2022. Lagged levels for differences and lagged differences for levels are utilized as instruments in the analysis. A Sargan test is employed to assess the over-identifying restrictions in the GMM estimation, where the null hypothesis assumes no correlation between the instruments and the residuals. Furthermore, the AR(1) and AR(2) Arellano-Bond tests are conducted to examine the presence of first and second-order serial correlations. To account for heteroskedasticity and serial correlation, bank-level clustered standard errors is employed. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels. *P*-values are in parentheses.

and instrumental variables. In addition, the system GMM estimator has a lower bias and higher efficiency compared to other panel data estimators (such as OLS, level GMM, and first-differences GMM), especially when dealing with a limited number of individuals (see e.g. Refs. [51,52]). In our analysis, we have adjusted the standard errors for heteroskedasticity using a Windmeijer correction.

The results of the SYS GMM method are reported in Table 8. Consistent with what is reported in Table 7, we continue to find that when real estate prices are experiencing a bubble, there is a marked escalation in the systemic risk posed by factors such as loan growth, bank size, and leverage. Additionally, we report a negative and statistically significant coefficient for the interaction between income diversification and real estate bubbles. This finding confirms our previous findings that during periods characterized by real estate price bubbles, income diversification plays a notable role in magnifying the systemic risk. Overall, employing the SYS GMM methodology strengthens and supports our previous findings.

5. Conclusion

This article makes a significant contribution to the existing literature by addressing a crucial gap in research. It investigates the intricate relationship between real estate price bubbles and systemic risk, especially within the context of emerging markets. Despite the increasing recognition of the potential implications of real estate bubbles on systemic risk, there has been a scarcity of research in this area, particularly within emerging market contexts.

Our research utilizes a three-step procedure to assess the influence of real estate bubbles on systemic risk exposure for 17 conventional banks operating in the United Arab Emirates (UAE). In the first step, we identify real estate bubbles employing the BSADF approach. The second step involves quantifying systemic risk exposure using the Delta-CoVaR and MES methods for the selected 17 conventional banks in the UAE. In the final phase of our analysis, we employ a panel data regression model to investigate the relationship between systemic risk and binary variables signifying the presence of real estate market bubbles.

Our findings reveal that the connection between real estate price bubbles and the amplification of systemic risk contributions is closely tied to loan growth, bank size, and leverage. This suggests that as real estate markets become overheated and prices surge, the risk associated with these variables intensifies, potentially endangering the financial system's stability. One particularly notable result from our study is the significantly negative coefficient observed for income diversification during periods characterized by real estate bubbles. This implies that when real estate prices enter a bubble phase, banks with a higher degree of income diversification tend to have a reduced impact on systemic risk.

Our findings demonstrate that the relationship between real estate price bubbles and the amplification of systemic risk contributions is linked to loan growth, bank size, and leverage. This implies that as real estate markets become overheated and prices soar, the risk associated with these variables intensifies, potentially jeopardizing the stability of the financial system. One noteworthy result from our study is the significantly negative coefficient observed for income diversification during periods characterized by real estate bubbles. This suggests that when real estate prices are in a bubble phase, banks with a greater degree of income diversification tend to have a lower impact on systemic risk. These results align with previous research by Adrian and Brunnermeier [19], who observed an increase in systemic risk contributions with the size of an institution and its leverage. They are also consistent with the findings of Brunnermeier, Rother, and Schnabel [1], which highlight that systemic risk contributions are influenced by bank characteristics, particularly bank size and loan growth.

In conclusion, this research not only bridges a vital gap in the existing literature but also sheds light on the distinct factors influencing the interplay between real estate bubbles and systemic risk in an emerging market context. Our findings contribute valuable insights for policymakers, regulators, and financial institutions in managing and mitigating risks associated with real estate market fluctuations, thereby safeguarding financial stability and fostering sustainable economic growth. Policymakers should closely monitor the real estate market and proactively implement measures to prevent the formation of price bubbles. This can involve implementing macroprudential policies, such as stricter lending standards, to curb excessive lending and speculative activities in the real estate sector. Secondly, regulators should enhance their supervision of banks during periods of real estate bubbles. This includes monitoring the risk exposures of individual banks, especially those with significant loan portfolios tied to the real estate sector. Regulators should assess the adequacy of the capital buffers and risk management practices of these banks, considering the potential amplification of systemic risk. Implementing stress tests and scenario analyses that specifically consider the impact of real estate market downturns can provide valuable insights and inform regulatory actions. Policymakers and regulators should also encourage banks to adopt robust income diversification strategies that encompass a mix of revenue streams. This can help reduce their vulnerability to real estate market fluctuations and the amplification of systemic risks.

While our study makes substantial contributions, it is imperative to acknowledge its limitations and delineate directions for future research. Firstly, constrained by data availability, our primary focus centered on the UAE. To attain a more comprehensive perspective and facilitate cross-country comparisons within the GCC region, it is advisable for forthcoming research to encompass data from other GCC nations. This expansion will enrich the contextualization of findings. Secondly, our study provides a static depiction of the relationship between real estate bubbles and systemic risk. Subsequent research endeavors can augment our comprehension by delving into the dynamic evolution of this relationship over time. Finally, fortifying the analysis by scrutinizing the impact of government policies on the interplay between real estate bubbles and systemic risk is of paramount significance. This can provide valuable insights into the intricacies of this interaction, thereby empowering policymakers to make better-informed decisions.

Data availability

The data are obtained from Thomson Reuters Datastream database. The models and data analysis are applied through computer software such as MATLAB, R, and Stata. All data and codes will be available from the authors upon request upon request.

Funding

SURE Plus 2023, Grant Number G00004344.

CRediT authorship contribution statement

Aktham Maghyereh: Writing - review & editing, Writing - original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The author thanks Yating Zhang, an editorial section manager, and two anonymous referees for their constructive comments. I acknowledge the financial support from the United Arab Emirates University under the SURE Plus 2023 Grant, Grant Number G00004344. The author thanks the undergraduate students Maitha Al Ameri, Abdullah Alnairabie, Reem Khaled Abdallah, Aysha Almarri, and Maram Shat for their assistance in collecting the data.

References

[1] M. Brunnermeier, S. Rother, I. Schnabel, Asset price bubbles and systemic risk, Rev. Financ. Stud. 9 (2020) 4272–4317.
[2] Ò. Jordà, M. Schularick, A.M. Taylor, Betting the house, J. Int. Econ. 96 (S2–S18) (1995).
[3] V.V. Acharya, S. Viswanathan, Leverage, moral hazard, and liquidity, J. Finance 66 (1) (2011) 99–138.
[4] M. Liu, W.C. Choo, C.C. Lee, The response of the stock market to the announcement of global pandemic, Emerg. Mark. Finance Trade 56 (15) (2020) 3562–3577.
[5] X.M. Zhang, T. Zhang, C.C. Lee, The path of financial risk spillover in the stock market based on the R-vine-Copula model, Phys. Stat. Mech. Appl. 600 (2022), 127470.
[6] M. Zhang, C. Wei, C.-C. Lee, Y. Tian, " Systemic risk of Chinese financial institutions and asset price bubbles,", N. Am. J. Econ. Finance 64 (2023), 101880.
[7] F. Allen, D. Gale, Bubbles, crises, and policy, Oxf. Rev. Econ. Pol. 15 (3) (1999) 9–18.
[8] C. Crowe, G. Dell'Ariccia, D. Igan, P. Rabanal, How to deal with real estate booms: lessons from country experiences, J. Financ. Stabil. 9 (3) (2013) 300–319.
[9] F. Allen, D. Gale, Bubbles and crises, Econ. J. 110 (460) (2010) 236–255.
[10] J. Geanakoplos, R. Axtell, D. Farmer, P. Howitt, B. Conlee, J. Goldstein, M. Hendrey, N. Palmer, C.-Y. Yang, Getting at systemic risk via an agent-based model of the housing market, Am. Econ. Rev. 102 (3) (2012) 53–58.
[11] B. Kivedal, Testing for rational bubbles in the US housing market, J. Macroecon. 38 (2013) 369–381.
[12] A. Maghyereh, B. Awartani, Bank distress prediction: empirical evidence from the Gulf cooperation council countries, Res. Int. Bus. Finance 30 (2014) 126–147.
[13] A. Maghyereh, B. Awartani, The effect of market structure, regulation, and risk on banks efficiency: evidence from the Gulf cooperation council countries, J. Econ. Stud. 41 (3) (2014) 405–430.
[14] A. Maghyereh, Bank competition, concentration and risk-taking in the UAE Banking industry, Econ. Int. 71 (2) (2018) 129–148.
[15] P.K. Narayan, S. Sunila Sharma, H.B. D, Phan, Asset price bubbles and economic welfare, Int. Rev. Financ. Anal. 44 (2016) 139–148.
[16] J. Fausch, M. Sigonius, "Are speculative bubbles welfare improving? A note on Wang and Wen 2012,", Econ. Lett. 190 (2020), 109076.
[17] K.I. Hashimoto, R. Im, T. Kunieda, Asset bubbles, unemployment, and a financial crisis, J. Macroecon. 65 (2020), 103212.
[18] P. Phillips, S. Shi, " Real time monitoring of asset markets: bubbles and crises,", Handb. Stat. 42 (2020) 61–80.
[19] T. Adrian, M.K. Brunnermeier, CoVaR. American economic review, 106, 1705–41, Am. Econ. Rev. 106 (2016) 1705–1741.
[20] C. Brownlees, R. Engle, SRISK: a conditional capital shortfall measure of systemic risk, Rev. Financ. Stud. 30 (1) (2017) 48–79.
[21] M. Al-Shboul, A. Maghyereh, A. Hassan, P. Molyneux, " Political risk and bank stability in the Middle East and North Africa region,", Pac. Basin Finance J. 60 (2020), 101291.
[22] M. Belkhir, A. Maghyereh, B. Awartani, " Institutions and corporate capital structure in the MENA region,", Emerg. Mark. Rev. 26 (2016) 99–129.
[23] A. Maghyereh, H. Abdoh, M. Al-Shboul, Oil structural shocks, bank-level characteristics, and systemic risk: evidence from dual banking systems, Econ. Syst. 46 (4) (2022), 101038.
[24] A. Maghyereh, B. Awartani, The influence of competition on the financial stability of banks in the GCC countries, J. Econ. Res. 21 (1) (2016) 135–173.
[25] A. Maghyereh, H. Abdoh, The effect of structural oil shocks on bank systemic risk in the GCC countries, Energy Econ. 103 (2021), 105568.
[26] R.E. Lucas Jr., Asset prices in an exchange economy, Econometrica: J. Econom. Soc. 46 (6) (1978) 1429–1445.
[27] R. Gurkaynak, Econometric tests of asset price bubbles: taking stock, J. Econ. Surv. 22 (2008) 166–186.
[28] V.V. Acharya, L.H. Pedersen, T. Philippon, M. Richardson, " Measuring systemic risk,", Rev. Financ. Stud. 30 (2017) 2–47.
[29] C. Brownlees, R. Engle, SRISK: a conditional capital shortfall measure of systemic risk, Rev. Financ. Stud. 30 (1) (2017) 48–79.
[30] R. Engle, Dynamic conditional correlation: a simple cass of multivariate generalized autoregressive conditional heteroskedasticity models, J. Bus. Econ. Stat. 20 (3) (2002) 339–350.
[31] A. Renders, A. Gaeremynck, P. Sercu, Corporate-governance ratings and company performance: a cross-European study, Corp. Govern. Int. Rev. 18 (2) (2010) 87–106.
[32] A. Maghyereh, E. Yamani, Does bank income diversification affect systemic risk: new evidence from dual banking systems, Finance Res. Lett. 47 (2022), 102814.
[33] A. Senhadji, C. Collyns. Lending booms, real estate bubbles and the Asian crisis, IMF Working Paper No. 2002/020, 2002. Available at SSRN: https://ssrn.com/abstract=879360.
[34] X. Bian, Z. Lin, Y. Liu, House price, loan-to-value ratio and credit risk, J. Bank. Finance 92 (2018) 1–12.
[35] V.V. Acharya, N. Gennaioli, L. Laeven, Understanding systemic risk in the banking sector, CEPR Discussion Paper No. DP7761. (2010).
[36] S. Wu, M. Tongb, Z. Yangc, T. Zhang, Interconnectedness, systemic risk, and the influencing factors: some evidence from China's financial institutions, Phys. Stat. Mech. Appl. 569 (2021), 125765.
[37] Y. Chen, " Bank interconnectedness and financial stability: the role of bank capital,", J. Financ. Stabil. 61 (2022), 101019.
[38] E. Farhi, J. Tirole, Collective moral hazard, maturity mismatch, and systemic bailouts, Am. Econ. Rev. 102 (1) (2012) 60–93.

[39] N. Gennaioli, A. Martin, S. Rossi, Too many to fail—an analysis of time-inconsistency in bank closure policies, J. Financ. Intermediation 22 (4) (2013) 532–555.
[40] P. Gandhi, H. Lustig, " Size anomalies in U.S. bank stock returns,", J. Finance 70 (2015) 733–768.
[41] D. Bostandzic, G.N. Weiß, Why do some banks contribute more to global systemic risk? J. Financ. Intermediation 35 (2018) 17–40.
[42] J.H. Boyd, D.E. Runkle, Size and performance of banking firms: testing the predictions of theory, J. Monetary Econ. 31 (1) (1993) 47–67.
[43] D.W. Diamond, R.G. Rajan, " A theory of bank capital,", J. Finance 55 (6) (2000) 2431–2465.
[44] M.K. Brunnermeier, G. Dong, D. Palia, Banks' non-interest income and systemic sisk, The Review of Corporate Finance Studies 9 (2) (2020) 229–255.
[45] R.S. Demsetz, P.E. Strahan, Diversification, size, and risk at bank holding companies, J. Money Credit Bank. 29 (3) (1997) 300–313.
[46] M.J. Flannery, Financial crises, payment system problems, and discount window lending, J. Money Credit Bank. 30 (3) (1998) 804–824.
[47] A.N. Berger, C.H. Bouwman, " Bank liquidity creation, financial crises, and the role of monetary policy,", J. Finance 64 (3) (2013) 1703–1732.
[48] M.S. Rizwan, G. Ahmad, D. Ashraf, Systemic risk: the impact of COVID-19, Finance Res. Lett. 36 (2020), 101682.
[49] M. Arellano, O. Bover, Another look at the instrumental variable estimation of error-components models, J. Econom. 68 (1995) 29–51.
[50] R. Blundell, S. Bond, " Initial conditions and moment restrictions in dynamic panel data models,", J. Econom. 87 (1998) 115–143.
[51] K. Hayakawa, Small sample bias properties of the system GMM estimator in dynamic panel data models, Econ. Lett. 95 (2007) 32–38.
[52] M. Soto, System GMM estimation with a small sample, Barcelona Economics Working Paper Series, Working Paper no 395, 2009 available at, https://bse.eu/research/working-papers/system-gmm-estimation-small-sample.