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Systemic risk under the radar: Evidence from building societies and challenger banks

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ABSTRACT

This paper provides the first comprehensive quantification of the systemic risk posed by non-listed financial institutions in the UK, focusing on building societies, digital-only challenger banks, and foreign-owned retail banks. Using an indirect estimation approach, systemic risk is measured through balance sheet characteristics, calibrated against listed institutions' SRISK values. The findings reveal that Nationwide ranks among the top ten systemically important institutions, while several other building societies contribute significantly to aggregate systemic risk. In contrast, digital-only challenger banks exhibit low systemic risk due to high equity ratios and limited interconnectedness, despite rapid growth and persistent financial losses. Santander, a foreign-owned retail bank, emerges as the ninth most systemically important institution, with risk levels comparable to systemically-important domestic banks. We conduct extensive robustness checks, including alternative predictors and SRISK specifications, out-of-sample forecasting, and Principal Component Analysis, which confirms the strong co-movement between building societies and the largest UK banks. Finally, we compare SRISK with traditional Z-score metrics to highlight their complementary nature. These findings underscore the need to extend systemic risk frameworks beyond listed entities and support calls to expand the stress testing perimeter to include large non-listed and foreign-owned firms.

1. Introduction

The concept of systemic risk became a topic of attention since the 2007–2009 Global Financial Crisis (GFC), during which the failure of a few large financial institutions led to widespread economic disruption (Engle, 2018). Systemic risk refers to the likelihood that an event, whether at the firm or sectoral level, will lead to heightened uncertainty and significant losses in economic value or confidence across a substantial portion of the financial system, potentially spreading distress throughout the broader economy (BIS, 2001). Alternatively, Billio et al. (2012) define systemic risk as the set of circumstances that have the potential to cause financial instability and uncertainty within the financial system. Systemic risk can arise from both exogenous shocks and endogenous factors within the financial system, impacting multiple systemically important intermediaries or market (ECB, 2009). Given the interconnected nature of modern financial systems, understanding and measuring systemic risk is crucial for maintaining financial stability.

Despite its importance and due to its complexity, there is no widely accepted measure of systemic risk. Systemic risk is typically assessed through market-based data for publicly listed financial institutions, as these entities provide equity price data necessary for

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risk measures.[1] However, the exclusion of non-listed firms from systemic risk analyses can lead to incomplete assessments of financial fragility (Armanious, 2024). Non-listed financial institutions, such as state-owned banks, mutuals (including building societies), fintech firms, challenger banks, and foreign-owned subsidiaries, can exhibit substantial systemic importance due to their size and interconnectedness within the financial system. BoE (2023a) notes that distress in smaller or challenger banks can impact the wider system by triggering shifts in mortgage and savings rates, amplifying asset fire sales, and raising funding costs. Their concentrated exposures and reliance on less stable funding make them vulnerable to shocks, while confidence effects can lead to broader contagion.[2]

This paper contributes to both academic and policy debate by providing the first comprehensive quantification of the systemic importance of two increasingly significant (non-listed) sectors of modern financial systems: building societies and digital-only challenger banks. We focus on the UK as a representative case, given its well-developed mutual sector and its role as a global hub for leading digital-only banks. Finally, to complement our analysis, we also examine the systemic importance of foreign-owned retail banks, which are often excluded from standard macroprudential assessments but can act as transmission channels for cross-border financial stress.

Our paper builds on recent studies by Engle et al. (2024) and Engle and Jung (2023), who develop an indirect mapping method based on balance sheet characteristics to approximate systemic risk for non-listed banks in the Euro area and Latin America, respectively. While their approach represents a major advancement in extending systemic risk measurement beyond listed firms, it remains limited in both geographic scope and institutional coverage. In contrast, we apply and adapt this methodology to the UK financial system, which features a distinctive institutional structure characterised by a strong mutual sector and a rapidly expanding digital banking ecosystem. By broadening both the scope of entities analysed and the national context, our paper provides a more inclusive and policy-relevant assessment of systemic vulnerabilities. Following their methodological approach, we implement a three-step estimation procedure. First, we estimate the systemic risk of a large panel of UK listed financial institutions using the SRISK methodology developed by Brownlees and Engle (2017). Next, we utilize a panel fixed-effects model to identify which balance sheet characteristics can predict the systemic risk levels of these institutions. Finally, we construct a dataset of balance sheet characteristics for non-listed financial institutions, derived from annual reports spanning 2008 to 2023, and predict SRISK for these institutions using the estimated coefficients obtained in the previous step.

Our findings show that the largest building society, Nationwide, and the largest non-listed international bank, Santander, contribute 2.5% and 2.8%, respectively, to the UK's total systemic risk. Additionally, our estimates indicate that four other building societies, along with TSB Bank, have systemic risk contributions ranging between just over £1 billion and £2.5 billion. These results underscore the need to broaden the regulatory perimeter and to integrate market-based tail-risk measures, such as SRISK, alongside traditional stress testing tools, in order to better detect emerging vulnerabilities in the financial system.[3] Lastly, we observe that digital-only challenger banks, despite their rapid growth and persistent losses, exhibit low levels of systemic risk. This is largely attributed to their relatively small size and high equity ratios (ECB, 2025). By including non-listed entities such as building societies and challenger banks, our analysis offers a more holistic assessment of the financial system and highlights the importance of extending regulatory frameworks beyond listed entities.

The focus of the paper is motivated by the growing importance of these overlooked segments of the global financial system. First, mutual financial institutions (building societies, credit unions, cooperative banks) are integral to the financial system, particularly in mortgage lending and community-based financial services and the sector has traditionally been viewed as more stable than the banking sector due to its mutual ownership structure (McKillop et al., 2020; FCA, 2024). However, they exhibit increasing exposure to systemic vulnerabilities. Their mutual ownership limits access to external equity, constraining the ability to absorb losses or recapitalise under stress (McKillop et al., 2020; Shepperd, 2024). While Bank of England (BoE) is currently considering the removal of certain regulatory constraints to enhance building societies' competitiveness relative to banks (PRA, 2025), the sector is also facing mounting challenges, including higher interest rates, persistent inflation, and geopolitical uncertainty (FCA, 2024). These developments underscore the need to reassess the systemic importance of mutual institutions.

Second, digital-only challenger banks have expanded rapidly in recent years, reshaping the competitive landscape both in the UK and globally.[4] Yet, academic research on their systemic implications remains limited. As noted by the ECB (2025) and BSA (2024), their business model introduces distinct vulnerabilities, including a heavy reliance on small retail deposits and limited funding diversification. Structural profitability challenges, such as high IT and marketing costs, compressed interest margins, and intense competition for deposits, further affect their resilience. As their market presence increases, digital banks may indirectly elevate systemic risk by weakening the stable funding base of traditional banks and prompting riskier behaviours in the broader sector. Our findings suggest that digital-only banks do not currently pose a major systemic risk to the UK financial system. However, this does not mean that they are not vulnerable to systemic shocks. Our results align with Saklain (2024), who finds that FinTech firms are more exposed to macro-financial shocks than traditional financial institutions, but are not as systemically important.

[1] Bisias et al. (2012) summarize systemic risk measures, noting that firm-level and network-based metrics rely on market data such as returns and volatility, making them applicable primarily to listed companies.

[2] This was evident in the period following the GFC, when cooperative banks (Mare, 2015) and medium-sized banks (Poli et al., 2024) were more vulnerable to macroeconomic shocks, contributing to negative spillovers across the broader banking sector in both Europe and the United States.

[3] Our findings are even more important in light of Santander's July 2025 announcement that it has agreed to acquire TSB for £2.65 billion, pending approval by TSB's current owner, Sabadell's, shareholders.

[4] Recent evidence by Khan et al. (2025) shows that the rise of digital credit providers (fintech), has reduced traditional banks' market power and eased financing constraints for smaller firms, underscoring how technological entrants can alter competition.

Finally, we examine the systemic importance of foreign-owned retail banks, a segment often excluded from national macro-prudential surveillance. Cross-border banking presents benefits for banks such as diversification and access to new markets, but it has also contributed significantly to the build-up of systemic risk before GFC (Hills and Hoggarth, 2013). Bakkar and Nyola (2021) finds that greater foreign complexity, measured by the number of countries in which a bank operates, is positively associated with systemic risk. Greater complexity can weaken supervisory oversight, reduce transparency, and delay the coordination of resolution strategies in times of crisis. In the UK, banks such as Santander UK operate within multinational groups, while Barclays and HSBC maintain large EU-based subsidiaries, linking UK financial stability to broader European financial markets. These risks are bidirectional: shocks can flow from the UK to parent banks and vice versa, especially if intra-group support weakens during crises.[5] Therefore, limited regulatory buffers available at the host-country level, represent systemic vulnerabilities often overlooked by standard risk metrics.

The rest of the paper is structured as follows: Section 2 presents the literature review, and Section 3 describes the data. Section 4 outlines the SRISK methodology for listed financial institutions, while Section 5 provides our estimates of systemic risk for non-listed banks and building societies. Section 6 discusses the robustness and comparison tests, and Section 7 concludes the paper.

2. Literature review

The results of this paper are primarily empirical and aim to contribute to both policy and academic literature. In terms of academic contributions, this study advances two key strands of research that are highly relevant for policymakers. Firstly, it enhances the growing literature on systemic risk estimation, which remains central to regulatory agendas focused on maintaining financial stability. The measurement of systemic risk has evolved significantly in response to the shortcomings exposed by the Global Financial Crisis (GFC). Silva et al. (2017) and Ellis et al. (2022) provide detailed, up-to-date surveys of systemic risk metrics, which can be categorized into five groups: early-warning indicators (Alessi and Detken, 2011; Duca and Peltonen, 2013), liquidity measures (Hu et al., 2013), contagion and connectedness measures (Lehar, 2005; Billio et al., 2012; Diebold and Yılmaz, 2014), network-based approaches (Covi et al., 2021), and capital market-based measures (Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017). Among these, capital market-based measures are the most widely used by policymakers, as they leverage firm-level financial market data, such as equity prices, volatility indices, and credit default swap (CDS) spreads, to provide forward-looking insights into financial vulnerabilities.

However, the reliance on firm-level market equity data limits the applicability of these measures to non-listed firms, which are integral to financial systems, but lack publicly traded financial instruments. To address this limitation, Dimitrov and van Wijnbergen (2023) extend systemic risk research by employing CDS data to evaluate systemic risk for non-listed European banks. Their approach highlights the importance of including non-listed entities in systemic risk assessments and reveals disparities in capital buffers across countries. Yet, the primary limitation of this method is the availability of CDS data, which is generally restricted to large, well-known institutions, leaving smaller banks and mutual entities underrepresented. More recently, and as we previously mentioned, Engle et al. (2024) develop an indirect method for measuring systemic risk in non-listed Euro Area banks. They map balance sheet characteristics to the risk profiles of listed firms and validate their results using EU-wide stress tests, demonstrating the reliability of balance sheet-based approximations.[6] These studies emphasize the value of leveraging balance sheet data for systemic risk estimation, especially in regions where non-listed entities play a substantial role.

To the best of our knowledge, this is the first study to quantify the systemic importance of building societies and digital-only challenger banks. The second strand of literature that this paper contributes to is on the risk-taking of financial institutions with non-standard ownership structures. Ownership structure and corporate governance have been documented to directly affect systemic risk-taking (Addo et al., 2021; Battaglia and Gallo, 2017). We focus on the aforementioned sectors due to their growing importance in maintaining financial stability. Building societies are a vital component of the UK financial system, promoting long-term stability and supporting local economies. They prioritise a customer-centric culture and responsible lending practices, ensuring that vulnerable groups, such as older borrowers and first-time buyers, who are often underserved by larger banks, receive appropriate support (Financial Conduct Authority, 2022). Despite their importance, the literature on building societies is very limited, since they are primarily associated with the UK alone, but they share key features with cooperative banks and credit unions worldwide. All operate on a mutual, member-owned, not-for-profit basis, reinvesting profits to benefit members rather than shareholders. Their focus is on supporting local communities through affordable lending and financial inclusion, with governance driven by member voting and participation. While credit unions and cooperative banks often focus on personal loans and basic banking services, building societies specialize in mortgage lending and savings products. However, deregulation in the 1980 s led to their deeper integration into the broader financial system. This shift exposed them to heightened competition from commercial banks, which were expanding their presence in the mortgage market (Casu, 2015).

Building societies, as mutual organizations, face limitations in raising external capital (FCA, 2024). Their capital primarily consists of retained earnings accumulated over time, which do not require remuneration and that presents both challenges and opportunities. This constraint typically leads building societies to adopt a more risk-averse approach and maintain conservative capital reserves (Casu, 2015). In addition, the lack of shareholders' pressure for high profits, makes them less prone to speculative investments

[5] Following the Global Financial Crisis (GFC), foreign state-owned banks reduced credit growth abroad in response to domestic banking crises, hereby transmitting shocks across borders through lending channels (Borsuk et al., 2024).

[6] Additionally, Altavilla et al. (2021) employ a similar approach to estimate the cost of equity for unlisted banks by regressing model-specific costs on listed bank characteristics, further demonstrating the versatility of balance sheet-based methods.

compared to shareholder-owned banks (Michie and Llewellyn, 2010). The literature on cooperative banks and credit unions provides empirical evidence to support the previous arguments. Loans provided by cooperative or mutual banks have a lower probability of default (Nitani and Legendre, 2021) and exhibit better loan quality and lower asset risk (Iannotta et al., 2007; Beck et al., 2009) than private sector banks. The low risk profile of savings and cooperative banks can be attributed to their reliance on customer deposits and retail-oriented activities, and they benefit from moderate diversification into non-interest income sources (Köhler, 2015). However, their stability can be compromised if they shift significantly towards non-deposit funding. Because of the lending policies stakeholder banks (and cooperative banks in particular) diminish the procyclicality of the banking sector (Meriläinen, 2016; Ferri et al., 2014). Similarly, Hesse and Čihák (2007) and Chiaramonte et al. (2015) find that the presence of cooperative banks is associated with greater financial stability in a financial crisis period. Recent evidence from Hartarska et al. (2025) further supports this view, showing that non-commercial microfinance institutions remain resilient during banking crises, whereas more commercialized entities experience mission drift and increased vulnerability. Overall, a financial system that is more diversified in terms of ownership, structure and business size, is better equipped to withstand the pressures of the typical business cycle (Ayadi et al., 2010; Ayadi et al., 2025).

While stakeholders banks and credit unions can enhance financial stability, some studies highlight potential risks. Hesse and Čihák (2007) argue that a high cooperative banks market share can weaken commercial banks, especially those already struggling to compete in retail markets dominated by non-profit-maximizing entities. Fonteyne (2007) further notes that cooperative banks, due to their focus on traditional financial intermediation, are more vulnerable to credit quality and interest rate shocks. Moreover, governance challenges stemming from their intergenerational endowment structure may lead to risks such as empire-building or misallocation of resources. Empirical evidence from the US credit unions and Goddard et al. (2008) suggest that their risk profile depends largely on their size and diversification strategy. Smaller credit unions face higher risk when diversifying into non-interest income activities due to increased volatility, limited expertise, and operational constraints. More recently, Gerken (2025) argues that building societies face persistent risks related to limited capital generation, IT transformation challenges, and structural inefficiencies due to lack of economies of scale. She also warns that underinvestment in risk management and digital infrastructure could pose a serious threat to long-term sustainability.

The literature that explores the risk level in building societies (Casu, 2015), small or cooperative banks (Hesse and Čihák, 2007; Ayadi et al., 2010; Köhler, 2015; Clark et al., 2018) and credit unions (Goenner, 2018; Naaman et al., 2021) uses the Z-score to capture the institution level of risk. While the Z-score reflects an institution's individual risk and its likelihood of insolvency, systemic risk measures the potential for an institution to contribute to instability across the broader financial system. This distinction is important because institutions with low individual risk (high Z-score) can still have significant systemic importance due to their size or degree of interconnectedness. In this paper, we examine the risk profile of building societies, focusing on their systemic importance, thereby contributing to the literature by extending the analysis beyond firm-level risk. A study closely related to our paper is by Pacelli et al. (2024) who examined the systemic risk in the Italian cooperative banks system using cluster analysis on data from 2018 to 2022 to examine the indicators related to interconnectedness and financial health. Their results show that cooperative banks have lower exposure to interbank markets and sovereign debt, making them less interconnected and less likely to propagate systemic risk. The results indicate that cooperative banks also exhibit healthier financial indicators, such as higher capital adequacy and liquidity. More specifically, as banks' systemic risk increases, the presence of cooperative banks decreases significantly, highlighting their role as buffers rather than amplifiers during crises.

Finally, this is one of the very first papers focusing on the risk profile of digital-only challenger banks. The sector often referred to as digital-only banks, neobanks, or fintech banks, represent a significant shift in the banking sector. According to the ECB (2025), the number of digital-only banks in the euro area reached approximately 60 by the end of 2024, with their market share rising to 3.9%. Similar trends are evident in the UK, where these banks have grown substantially in customer base and product offerings. Challenger banks initially garnered attention for their innovative and cost-efficient models. They provide banking services predominantly through digital channels, such as mobile apps and online platforms, without the reliance on traditional branch networks. Without the overhead of physical branches, these banks could theoretically offer competitive rates and superior customer experiences (Boot et al., 2021). Therefore, these banks have been positioned as competitors to traditional banking institutions, particularly in the wake of public distrust following the 2008 financial crisis. They aim to fill gaps left by incumbents, offering services to underserved markets, such as small businesses and niche consumer segments (Lu, 2017).

However, our data from UK digital-only banks' balance sheets and from ECB (2025) suggests that digital banks remain less profitable than traditional banks, but at the same time they exhibit unusually high liquidity buffers, which however, reflects defensive positioning rather than balance sheet strength. The literature also provides mixed evidence on the performance and risk profile of these institutions. Fuster et al. (2019) find that FinTech lenders have increased their mortgage market share without raising default rates. Conversely, Di Maggio and Yao (2021) report that FinTech lenders appear to target lower-quality borrowers in the personal loans market, often previously rejected by traditional banks. Similarly, evidence from European neobanks suggests that, while they charge sufficiently high interest rates to address information asymmetries, they face higher non-staff expenses and tend to underperform compared to traditional peers (Citterio et al., 2024). Additionally, the findings indicate that neobanks do not benefit from lower funding costs or generate higher fees and commissions, offering little support for the 'digital spatial capture' hypothesis (Boot et al., 2021; Citterio et al., 2024).

The digital revolution began long before the coronavirus pandemic, however, the COVID-19 pandemic significantly accelerated the adoption of digital banking services, creating opportunities for challenger banks to expand their market share. At the same time, the pandemic introduced additional risks for these banks, which often lack the extensive experience and operational resilience of traditional banks. This vulnerability was evident in issues such as freezing customer accounts without notice, which highlighted gaps in their crisis preparedness (Schmidt-Jessa, 2023). Moreover, challenges in building customer trust, coupled with reported operating losses driven by high costs and limited profitability, raise concerns about their long-term sustainability (Schmidt-Jessa, 2023). These factors underscore the importance of assessing the risk profiles of challenger banks to understand their potential systemic implications, particularly as traditional banks aggressively expand their digital offerings, further intensifying competition in the sector. Our paper addresses this gap in the literature by providing estimates of the systemic risk of the four largest challenger banks in the UK.

3. Data

For the purposes of our analysis we create a new building societies database based on data collected from unconsolidated financial statements provided by the Building Societies Association (BSA) and institution's finance report archive. Our sample consists of 43 building societies and the period 2008–2023.[7] During this period, building societies demonstrated resilience and growth and they have increased their share in the UK mortgage market as can be seen in Fig. 1. In 2023, building societies accounted for 27.2% of all gross mortgage lending, approving around 365,000 mortgages of total value above 64 billion pounds. Their gross lending share started at 18.8% in 2006, dropped to 15.4% in 2009 during the financial crisis, but rebounded significantly, peaking at 28.5% in 2013. Despite fluctuations, their gross lending share stabilized above 22% from 2017 onward, reaching 27.2% in 2023, reflecting their competitiveness in capturing new mortgage activity. Loans outstanding showed a upward trend, rising from 20.8% in 2006 to 23.1% in 2023. Although there was a slight dip to 20.1% in 2009, the share remained consistently above 21% after 2016, peaking at 23.2% in 2019. This growth reflects building societies' ability to compete with traditional banks, particularly in the aftermath of the financial crisis when banks adopted more cautious lending practices.

In addition, according to the latest BSA statistics, building societies have a strong presence in the savings market, building societies held 19% of UK retail savings deposits, totalling £362 billion. This growth continued even as the broader market experienced declines. Serving over 26 million members and employing around 42,500 staff, building societies also account for 38% of all bank and building society branches. In Fig. 2 we present the share of the largest building societies in terms of the sector's total assets as of the end of 2023. Nationwide accounts for more than half of the sector's total assets, followed by Coventry and Yorkshire building societies with around 12% and then by Skipton and Leeds building societies with 7.2% and 5.4%, respectively.

We then construct an index of the Big 5 building societies that own more than 5% of the market each and provide consistent data series from 2008 up until 2023. Fig. 3 displays the year-on-year growth of total assets and the net profits for the five largest building societies. Asset growth for the five largest building societies has been consistently positive since 2013, indicating that these institutions have steadily increased in size. Despite fluctuations, net profits also grew significantly during this period, peaking at £2,743 million in 2022. The COVID-19 pandemic impacted these trends, with a temporary slowdown in asset growth to just 0.4% in 2020, reflecting economic uncertainty and disruptions to lending and housing markets. However, the strong rebound in 2021 and 2022 suggests that building societies adapted well, potentially benefiting from increased mortgage activity, low-interest rates, and a surge in housing market demand post-pandemic.

Table 1 presents the summary statistics for listed financial institutions and building societies over the period 2008–2023, allowing for a detailed comparison of financial performance and balance sheet composition. Listed financial institutions are significantly larger than non-listed ones, as evidenced by the difference in total assets. The mean size of listed institutions, measured by the natural logarithm of total assets, is 25.460, compared to 21.061 for non-listed institutions. This difference reflects the broader market reach and economies of scale typically associated with listed entities. However, listed institutions exhibit lower profitability, with an average net profit-to-assets ratio of 0.357%, compared to 0.754% for non-listed institutions. This difference may be explained by the greater regulatory scrutiny faced by listed firms and the persistent effects of the GFC on large systemically important financial institutions. Additionally, the higher profitability of building societies compared to banks may stem from their focus on lower-risk residential mortgage lending, whereas banks have a more diversified portfolio, and greater exposure to market volatility, all of which negatively impact their profitability. Non-listed financial institutions exhibit higher equity-to-assets and liquidity ratios than their listed counterparts, with means of 6.73% and 11.827%, respectively, compared to 5.176% and 8.189% for listed institutions. These differences reflect the conservative risk management strategies of non-listed institutions, which prioritize financial stability over growth. Their reliance on internal funding and limited access to capital markets further necessitate higher liquidity buffers. In contrast, listed institutions may rely more heavily on external capital and diversified funding sources, reducing the need for maintaining large liquid asset reserves.

Within the non-listed group, the five largest building societies represent a distinct category with unique characteristics. Large building societies, which are significantly larger than the average non-listed institution, placed between listed institutions and the broader group of non-listed entities. Their profitability, measured by the profit-to-assets ratio, is 0.389%, higher than that of listed institutions, but lower than the broader non-listed category. This elevated profitability, compared to banks, reflects the specialized focus of building societies on residential mortgage lending, which is generally low-risk but provides stable returns. Furthermore, the mutual ownership structure of building societies allows them to re-invest profits into operations rather than distribute them as dividends, enabling cost efficiencies and enhancing long-term profitability. Similarly, large building societies exhibit an equity-to-assets ratio of 5.52%, which is comparable to that of listed institutions but lower than the broader non-listed category. The higher equity and liquidity observed among smaller non-listed institutions can be attributed to their more conservative business models, which prioritize

[7] Appendix Table A1 presents all the building societies included in the analysis, the available data period for each institution, and their share of the total building society sector as of 2023 (measured as the percentage of total assets). It also reports estimates of systemic risk (SRISK), expressed both in logarithmic form and as a percentage of assets.

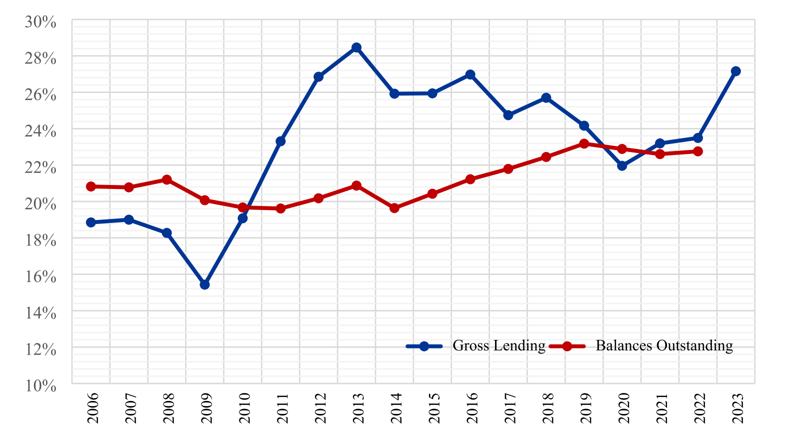


Fig. 1. Building societies mortgage market share.
Note: The figure presents the share of building societies in the UK mortgage market in terms of gross lending and balances outstanding. In December 2023, the largest market share is owned by banking institutions (67%) followed by other specialty mortgage providers that account for less than 10% of the market. The data are provided by the Bank of England (BoE) and the Building Society Association (BSA).

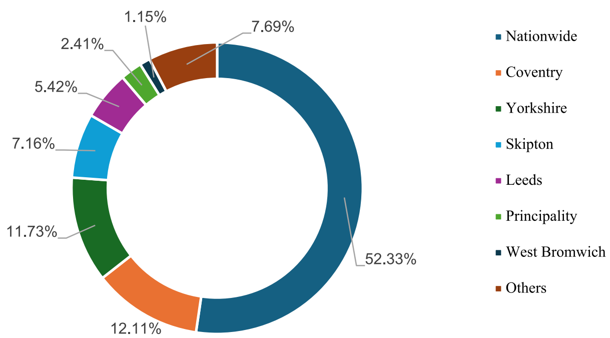


Fig. 2. Market shares in the building societies sector (2023).
Note: The figure illustrates the market share of the building societies sector in 2023, based on total assets. The data were obtained from the annual financial reports of individual building societies. The 2023 market consists of 42 building societies in total, however, only those with total assets exceeding 1% of the market are included in this figure.

stability and solvency. Smaller institutions are often more constrained in accessing external funding sources, requiring them to rely on internal capital and maintain higher levels of liquidity as a precaution against potential shocks.

4. Methodology

This section presents the main results of the analysis. It begins by detailing the *SRISK* methodology and presenting the estimates for UK listed financial institutions, followed by an examination of the primary balance sheet predictors associated with systemic risk.

4.1. Measuring systemic risk of listed companies

For the estimation of systemic risk we employ SRISK, a measure introduced by Brownlees and Engle (2017). SRISK captures the expected capital shortfall of a financial institution during a systemic financial crisis. The mathematical representation of capital shortfall $\left(CS_{i,t}\right)$ for financial institution i at time t is defined as:

$$CS_{i,t} = kA_{i,t} - MVE_{i,t} \tag{1}$$

In this Eq. (1), k is the prudential capital requirement ratio, typically set at 8%, $A_{i,t}$ is the value of Total Assets and $MVE_{i,t}$ is the market value of equity. The capital shortfall can be viewed as the inverse of the firm's working capital. When the capital shortfall is negative, that indicates a capital surplus. Alternatively, when the capital shortfall is positive, the firm faces financial distress (Brownlees and Engle, 2017). To account for systemic risk, SRISK represents the additional capital that a financial institution would need to maintain

Fig. 3. Building societies performance 2008–2023.
Note: Figure A displays the year-on-year percentage change in total assets for the period 2009–2023. Figure B illustrates the year-end net profits (in millions of £) over the same period. The data were sourced from annual financial reports of building societies. The Figure is based on the five largest building societies, namely Nationwide, Coventry Building Society, Yorkshire Building Society, Skipton Building Society and Leeds Building Society.

solvency under a systemic event scenario. Following Acharya et al. (2017), a systemic event is defined as a market decline below a threshold $C = 40\%$ over an horizon (h) of six months. To capture developments in the UK financial market, we use the EIKON Datastream DS Financials index (FIN) that includes banks, financial services firms, insurance companies and investment trusts. Based on the above, *SRISK* is defined as:

$$SRISK_{i,t} = E_t\left(CS_{i,t:t+h} \middle| FIN_{t:t+h} < C\right) \tag{2}$$

In Eq. (2), $CS_{i,t:t+h}$ and $FIN_{t:t+h}$ are the capital shortfall of financial institution i and the returns of the UK financial market index between time t and $t+h$. By combining Eqs. (1) and (2) we obtain the mathematical representation of SRISK as shown in Eq. (3). The estimation is based on annual data, with $Debt_{i,t}$ representing the financial institutions' total debt at year t and $MVE_{i,t}$ is the firm's market capitalisation at the same point in time.

$$SRISK_{i,t} = kDebt_{i,t} - (1-k)(MVE_{i,t})(1 - LRMES_{i,t}) \tag{3}$$

The final component, $LRMES_{i,t}$ stands for the Long-Run Marginal Expected Shortfall and captures the expected percentage loss in the firm's equity value if the market experiences a significant decline. *LRMES* measures the firm's sensitivity to systemic shocks and is estimated following Acharya et al. (2017), using a dynamic model based on daily equity return data. To align with the annual frequency of balance sheet variables, we compute LRMES on a monthly basis and then take the annual average for each firm-year observation.

$$LRMES_{i,t} = -E_t(FIN_{t+1:t+h} | FIN_{t+1:t+h} < C) \tag{4}$$

SRISK indicates the capital shortfall a financial institution is likely to face under systemic stress and may require additional capital to remain solvent. In other words, it quantifies the extent to which a firm is likely to experience distress in the event of a significant market downturn and the potential implications for the financial system as a whole. Larger SRISK values suggest that the institution

Table 1
Summary statistics.

Listed Financial Institutions	Obs	Mean	Std. dev.	Min	Max
Ln Total Assets	283	25.460	1.939	20.460	28.526
Profits / Assets	283	0.357	0.517	−1.393	2.191
Equity / Assets	283	5.176	2.542	0.571	14.701
Liquidity ratio	283	8.189	14.141	0.001	98.005
Large UK banks (4)	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Ln Total Assets	64	27.816	0.386	26.800	28.526
Profits / Assets	64	0.159	0.381	−1.393	0.756
Equity / Assets	64	5.520	1.258	2.134	8.218
Liquidity ratio	64	8.616	4.627	0.518	22.766
All Building Societies	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Ln Total Assets	688	11.633	8.057	4.441	26.330
Profits / Assets	688	0.754	7.276	−1.293	45.541
Equity / Assets	687	6.730	2.508	0.046	27.991
Liquidity ratio	688	11.827	11.175	0.004	78.553
Large Building Societies (5)	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Ln Total Assets	80	24.389	0.996	22.975	26.330
Profits / Assets	80	0.389	0.182	0.080	0.915
Equity / Assets	80	5.520	2.839	2.114	27.991
Liquidity ratio	80	7.178	3.235	0.020	13.622

Note: The table presents the summary statistics of the natural logarithm of Total Assets, Net Profits over Assets, Equity over assets and of the liquidity ratio (Cash and Liquid assets over assets) for our sample of listed and non-listed financial institutions. The sample period is 2008–2023 and all data are of annual frequency. Large UK banks include HSBC, Barclays, Lloyds Banking Group and NatWest. Large building societies include Nationwide, Coventry BS, Yorkshire BS, Skipton BS and Leeds BS. Data on listed companies are provided by Thomson Reuters EIKON Datastream, whereas the data on building societies are based on their annual reports.

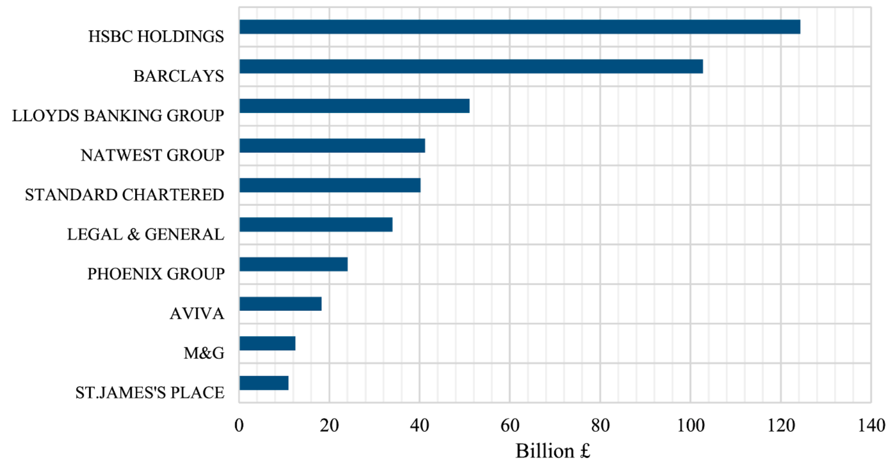
has higher systemic importance and a greater potential to contribute to financial instability. SRISK offers several advantages as a measure of systemic risk. It is forward-looking, as it incorporates expectations about potential future declines in equity value. Furthermore, it is firm-specific, accounting for each institution's leverage and sensitivity to market shocks. By highlighting institutions that pose significant risks to the broader financial system, *SRISK* provides valuable insight into systemic risk dynamics.

Based on Eq. (3), the calculation of SRISK relies on both balance sheet and market data, making it applicable only to publicly listed financial institutions. To ensure a sufficiently large dataset, we estimate SRISK for all listed UK financial institutions included in the DS Financials index, with a primary focus on banks, insurance companies, and investment trusts. In total, SRISK is calculated for 154 financial institutions. Among these, 28 institutions exhibit positive SRISK values[8] for 2023, with the four largest banks ("Big 4") leading the list. According to our findings, the SRISK values for the largest four systemic banks range between £40 billion and £124 billion. This indicates that, in the event of a financial crisis or systemic distress, these banks are estimated to face significant capital shortfalls to remain adequately capitalized. The high SRISK values are driven by their large balance sheets, which may amplify potential losses during a crisis, and their high leverage, which suggests that equity buffers may be insufficient relative to their liabilities.

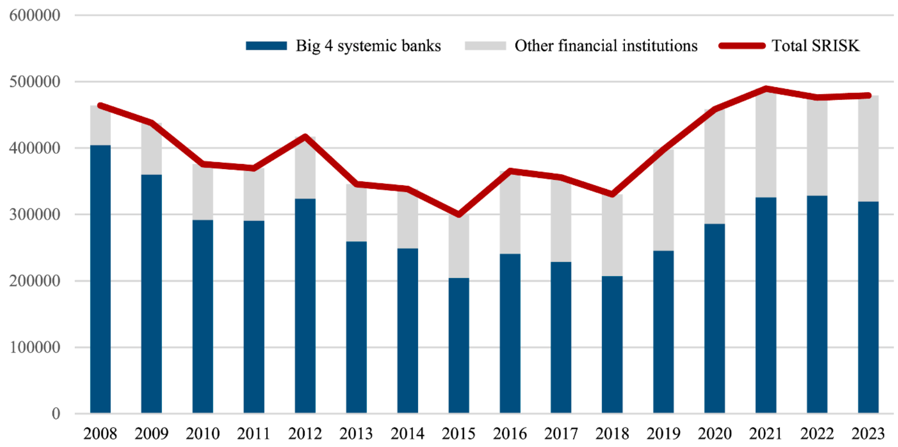
Fig. 4A presents the ten most systemically important UK financial institutions for 2023. Fig. 4B illustrates the evolution of UK aggregate SRISK from 2008 to 2023. Over this period, we observe a significant decline in the contribution of the "Big 4″ banks to total UK SRISK, from 87% in 2008 to 78% in 2010, and further down to 67% by 2023. This downward trend likely reflects a series of structural and regulatory changes introduced in the aftermath of GFC, aimed at reducing systemic importance and mitigating risk concentration among major financial institutions. Key drivers of this decline include the implementation of stricter capital adequacy requirements under Basel III, the development of resolution frameworks to address "*too big to fail*" concerns, and heightened regulatory oversight of systemically important financial institutions (FSB, 2021; BIS, 2022). In addition, banks have strengthened their balance sheets by increasing equity capital, reducing leverage, and adopting more prudent risk management practices.

The rise of non-bank financial institutions and the diversification of systemic risk across a broader set of entities have also contributed to the diminishing relative share of the largest banks in total SRISK. Aggregate UK SRISK aligns with expectations, peaking during the global financial crisis (2008–2009) and again at the onset of the COVID-19 pandemic (2020–2021). Notably, banks' SRISK reached its highest levels in 2008, while the aggregate SRISK of other financial institutions peaked in 2021. Furthermore, systemic risk levels also spiked during key periods of economic uncertainty, such as the Euro Area Sovereign Debt Crisis (2012) and the Brexit Referendum (2016).

[8] The results are consistent with the SRISK values presented by the New York University's V-LAB, where only 17 financial institutions present positive SRISK values as of December 2023. Negative SRISK values indicate that the examined financial institution is not expected to require additional capital in the event of a financial crisis or systemic distress. Therefore, it is unlikely to exacerbate systemic risk and it has the capacity to absorb shocks.



A. The ten highest $SRISK$ values for 2023



B. Evolution of UK $SRISK$ over time

Fig. 4. Systemic risk of listed financial institutions.
Note: Figure A presents the SRISK values for the ten most systemically important financial institutions in the UK in 2023. The estimation is based on 2023 data on total liabilities and market value of equity provided by Thomson Reuters EIKON Datastream, as well as LRMES values estimated using stock market returns for the examined financial institutions and the DS Financials Index over the period 2008–2023. The values are expressed in billions of GBP. Figure B shows the dynamic changes in UK aggregate SRISK for the period 2008–2023. The dark-shaded portion represents the contribution of the four largest UK banks, as detailed in Figure A. "Other financial institutions" include 24 large entities such as banks, insurance companies, and financial services firms.

4.2. SRISK predictors

As we mentioned beforehand, the estimation of SRISK for non-listed banks is based on an indirect approach and relies on leveraging balance sheet data to approximate systemic risk measures typically derived from market data. The approach involves using key financial metrics such as debt, size, and profitability, which are observable in the banks' financial statements. A statistical mapping model is developed using data from listed banks, where balance sheet variables are linked to SRISK values derived from market data. This model is then applied to non-listed banks, enabling the estimation of SRISK based on their financial characteristics. Although non-listed banks differ from publicly listed institutions in terms of ownership structure and governance, the SRISK framework remains conceptually suitable for assessing systemic vulnerability across different types of financial institutions since its core components are relevant regardless of listing status and can be proxied effectively using accounting data. SRISK has already been increasingly applied beyond the context of listed banks. For example, Brownlees and Engle (2017) include insurance firms, broker-dealers, and other financial institutions when first introduced the methodology, and more recent studies, such as Karlström (2025), estimate SRISK for investment and insurance firms, while Cincinelli et al. (2024) and Kladakis et al. (2025) extend the methodology to financial services and real estate firms. These applications support the broader use of SRISK across institutional forms. For our benchmark model we use only firms with positive SRISK values and we create a panel of 28 financial institutions with a total 283 annual observations.[9]

$$\ln SRISK_{i,t} = \beta X_{i,t} + a_t + \varepsilon_{i,t} \tag{5}$$

In addition to systemic risk values we incorporate data on balance sheet variables, such total assets to capture firms' size, total liabilities to account for its level of debt and net profits and cash over total assets to measure its ROA and level of liquidity. All variables are included in Eq. (5) within a panel regression model to estimate their ability to predict a firm's systemic risk. The dependent variable, measured as the natural logarithm of SRISK, is regressed on the predictors, along with year (a_t) fixed effects.[10] The choice of variables closely follows Engle et al. (2024). Table 2 presents the correlation plot of the four selected variables, namely the natural logarithm of Total Assets, and Net Income, Total Equity and Cash & Liquid Assets as percentage of Total Assets. The four variables exhibit low levels of correlation, thereby addressing any concerns about multicollinearity.

The panel regression results are reported in Table 3. The empirical findings are consistent, indicating that balance sheet variables are strongly correlated with financial institutions' systemic risk and can explain a significant portion of its variation. Firstly, the size of a financial institution is positively associated with SRISK, in line with our expectations since larger financial institutions play a central role in the financial system, making them systemically important and more interconnected with other institutions (Pais and Stork, 2013; Laeven et al., 2016; Varotto and Zhao, 2018; Buch et al., 2019). Their size is often associated with higher leverage, complex exposures, and a perception of being "*too big to fail*", which can encourage risk-taking and amplify systemic vulnerabilities. As a result, distress in larger institutions has a disproportionately higher potential to trigger widespread financial instability. Secondly, profitability, quantified as the ratio of net profits to total assets, demonstrates a negative association with systemic risk. This relationship may reflect the fact that more profitable institutions are better positioned to absorb losses and may be less vulnerable during periods of financial stress. Prior research includes profitability as a control variable and consistently finds a negative association with systemic risk (Varotto and Zhao, 2018; Davydov et al., 2021; Kladakis and Skouralis, 2024). Lang and Forletta (2020) provide complementary evidence, showing that increases in cyclical systemic risk predict declines in ROA. Profitability is typically associated with greater financial stability and reduced reliance on external funding, which aligns with a lower degree of interconnectedness and systemic exposure. Moreover, sustained profitability often signals effective management and operational efficiency, further mitigating systemic risk.

Kladakis and Skouralis (2024) also find that both strong profitability and capitalisation help reduce systemic vulnerabilities. These findings are in line with prior studies reporting a negative correlation between the equity (or capital) to assets ratio and systemic risk (Acharya and Thakor, 2016; Anginer et al., 2018; Davydov et al., 2021). Consistent with this literature, the negative coefficient for the equity over assets ratio highlights the advantages of robust equity financing. A high equity ratio signifies that a financial institution relies more heavily on its own capital rather than external borrowing to fund its operations. This lower dependence on debt reduces the institution's interconnectedness with other entities in the financial system, such as creditors and counterparties, who might otherwise amplify and transmit financial distress across the system. As a result, institutions with higher equity financing are less vulnerable to cascading failures and systemic risks during periods of market stress. This lower systemic exposure stems from their enhanced ability to absorb losses without triggering distress in connected institutions.

Beyond statistical significance, the estimated coefficients are also economically meaningful. For a financial institution with an SRISK of £1 billion, a 1% increase in total assets is associated with a 1.14% increase in SRISK, translating to an additional capital shortfall of approximately £11.4 million. Similarly, a 1 percentage point increase in the equity-to-assets ratio is associated with a 7.7% reduction in SRISK, equivalent to £77 million. Finally, a 1 percentage point improvement in profitability corresponds to a 28.5% decline in SRISK. These findings highlight the economic relevance of balance sheet fundamentals in explaining systemic risk.

In Models (2)-(4), we also include a liquidity ratio, defined as cash and liquid assets divided by total assets. The relationship between liquidity and systemic risk is complex (Davydov et al., 2021). On one hand, liquid assets serve as a buffer against sudden cash flow disruptions, enhancing an institution's resilience to shocks. On the other hand, a positive association between liquidity and SRISK could reflect regulatory requirements that compel banks, in particular, to maintain higher cash reserves, thereby inflating their cash-to-assets ratio even when systemic risks remain elevated. Engle et al. (2024) observed a positive relationship between liquidity and SRISK in a sample of European banks, however, their findings were inconsistent across model specifications and were not incorporated into further analyses. In our study, we find a negative but statistically insignificant relationship between liquidity and SRISK, which leads us to exclude liquidity from our benchmark model specification. For robustness, in Models (3) and (4), we also include the leverage (Debt/Assets), dividend payments, and cost of borrowing (measured as interest expenses on debt). However, as the estimated coefficients reported in Table 3 are not statistically significant, we exclude these variables from our benchmark model specification. Additional controls, such as the number of employees, the ratio of real estate assets to total assets, deposit levels, and the Net Interest Margin, were also tested but did not improve model performance.

Overall, the signs and significance levels of the predictors remain largely consistent across various model specifications. Engle et al. (2024) base their analysis on quarterly data and lagged predictors, where a one-quarter lag can meaningfully capture the next period's systemic risk, however our study relies on lower-frequency annual data. At this horizon, a one-year lag would be too distant to capture

[9] The analysis is based on an unbalanced panel, and no interpolation was applied to missing data. Instead, firms are allowed to enter or exit the sample based on data availability. In addition, financial institutions with fewer than three years of data were excluded.

[10] The regression model includes only time fixed effects, as firm fixed effects would absorb much of the variation in key explanatory variables (see Table A2). This approach is consistent with Engle et al. (2024), who include time and country fixed effects but not firm fixed effects.

Table 2
Correlation table.

	Ln Total Assets	Profits / Assets	Equity / Assets	Liquidity ratio
Ln Total Assets	1.000			
Profits / Assets	0.312	1.000		
Equity / Assets	−0.285	0.388	1.000	
Liquidity ratio	−0.080	0.056	0.045	1.000

Note: The table presents the correlation between the four explanatory variables (predictors) of our panel regression model. The sample consists of 28 listed financial institutions and 283 annual observations in total over the period 2008–2023.

Table 3
Panel Regression Results: Benchmark model.

Models:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_{t+1}$	$lnSRISK_{t+1}$	$lnSRISK_{t+1}$	$lnSRISK_{t+1}$
Ln Total Assets (t)	**1.144*****	**1.141*****	**1.140*****	**1.123*****	**1.081*****	**1.082*****	**1.084*****	**1.097*****
	(0.026)	(0.025)	(0.026)	(0.020)	(0.019)	(0.020)	(0.021)	(0.026)
Equity ratio (t)	**−0.077*****	**−0.076*****	**−0.083*****	**−0.076*****	**−0.027***	**−0.026***	−0.0216	−0.022
	(0.016)	(0.016)	(0.0168)	(0.020)	(0.014)	(0.015)	(0.0158)	(0.0247)
Profits / Assets (t)	**−0.284*****	**−0.287*****	**−0.276*****	**−0.366*****	**−0.345*****	**−0.346*****	**−0.349*****	**−0.406*****
	(0.055)	(0.055)	(0.0553)	(0.077)	(0.073)	(0.074)	(0.0745)	(0.105)
Liquidity ratio (t)		−0.045	−0.0203	−0.107		−0.069	−0.0635	−0.005
		(0.244)	(0.253)	(0.220)		(0.238)	(0.240)	(0.309)
Leverage (t)			0.335	**0.507***			−0.144	0.169
			(0.227)	(0.206)			(0.223)	(0.265)
Dividend (t)				0.020				**0.039***
				(0.016)				(0.022)
Cost of Debt (t)				−0.017				−0.006
				(0.029)				(0.049)
Constant	−6.380***	−6.296***	−6.325***	−5.945***	−4.638***	−4.678***	−4.716***	−5.418***
	(0.693)	(0.668)	(0.696)	(0.576)	(0.533)	(0.556)	(0.565)	(0.770)
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Firm Fixed Effects	NO	NO	NO	NO	NO	NO	NO	NO
Observations	283	283	283	179	270	270	270	166
No of firms	28	28	28	20	28	28	28	20
R^2	0.77	0.77	0.77	0.78	0.53	0.53	0.53	0.50

Note: The table reports the results from panel regressions using data from 28 listed financial institutions over the period 2008–2023. Data is sourced from Thomson Reuters EIKON Datastream. The dependent variable is the natural logarithm of SRISK at time t in Models (1)–(4), and at time t + 1 in Models (5)–(8). Ln Total Assets refers to the natural logarithm of annually reported total assets. Equity ratio is calculated as total equity divided by total assets. Profits/Assets and Liquidity ratio are computed using net income and cash plus liquid assets, respectively, as a share of total assets. Leverage is defined as total debt divided by total assets, and Cost of Debt is the ratio of interest expenses to total debt. All models include year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

short-term financial dynamics, as systemic risk is a forward-looking, market-based variable that can adjust rapidly to new information. Therefore, contemporaneous fundamentals provide a more appropriate alignment with SRISK. However, to ensure robustness, we present results using both contemporaneous and lagged independent variables. Lagged predictors mitigate concerns of endogeneity by addressing potential simultaneity bias, as past values of balance sheet characteristics, such as the debt-to-assets ratio and return on assets (ROA), are determined prior to the realization of current-period systemic risk. In Table 3, Models (5)-(8), we present the results using one-year-lagged predictors, and the findings remain consistent with our benchmark specification. Key variables, such as firm size and profitability, retain their expected signs and statistical significance, reinforcing the reliability of our baseline estimates. However, the explanatory power of the lagged models, as measured by the R^2, is notably lower than that of the contemporaneous specifications, which is why we retain Model (1) as our preferred specification in the main analysis.

Fig. 5 presents the observed aggregate SRISK against the estimated SRISK based on our results in Model (1). The latter closely tracks the actual SRISK over our examined period, underscoring the accuracy and reliability of the estimation methodology. The results reveal a sharp decline in systemic risk following the 2008 financial crisis, reflecting the recovery and stabilization of the UK financial sector during this period. From 2015 onwards, systemic risk begins to rise, likely driven by increasing economic and political uncertainties, including Brexit and the COVID-19 pandemic, which amplified market vulnerabilities. The strong alignment between estimated and aggregate SRISK, even during periods of heightened market stress, highlights the robustness of the approach and its ability to effectively capture systemic risk dynamics over time. These findings confirm that balance sheet-based systemic risk estimation provides a powerful tool for understanding and monitoring financial stability in UK-listed institutions, offering valuable insights for policymakers and regulators aiming to mitigate systemic vulnerabilities in the financial system.

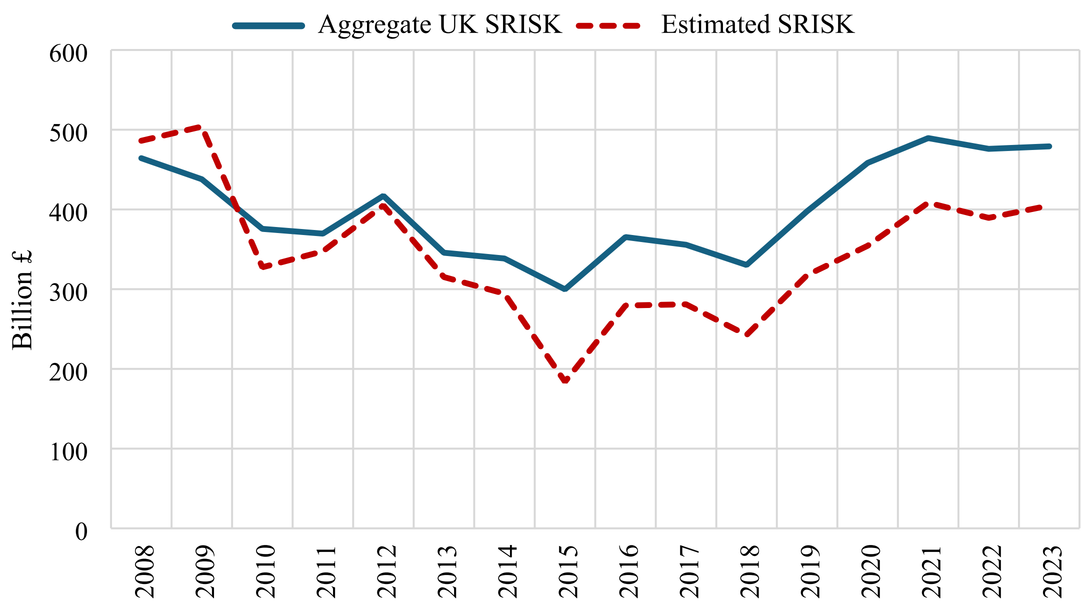


Fig. 5. Observed and estimated *SRISK* for listed financial institutions.
Note: The figure depicts the actual observed aggregate SRISK for the UK. The index is based on the sum of SRISK of 28 large UK financial institutions and its estimation is based on the period 2008–2023. The Estimated SRISK is based the indirect estimation of SRISK based on a set of balance sheet characteristics such as total Assets, Total Equity/Total Assets and Net Profits/Total Assets.

5. Empirical results

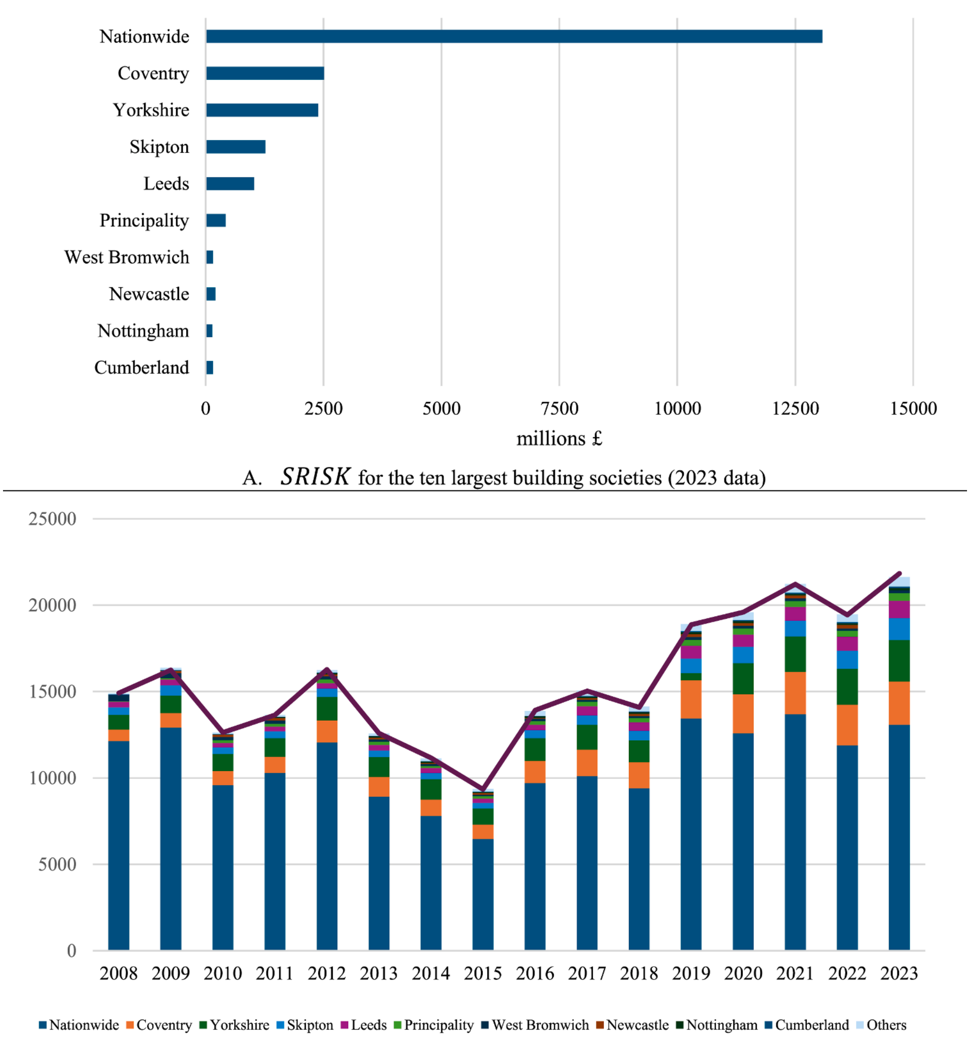
5.1. Systemic risk in building societies

Having established the relationship between balance sheet characteristics and SRISK, we now proceed with the estimation of systemic risk for non-listed financial institutions. The results, presented in Fig. 6A, highlight the significant heterogeneity in systemic importance among UK building societies in 2023. Nationwide Building Society, as the largest in the sector, unsurprisingly emerges as the most systemically important institution, with an estimated SRISK of £13.1 billion.[11] This value places Nationwide among the ten most systemically important financial institutions in the UK for 2023, ranking just above M&G and following the five large UK banks, Legal & General, Phoenix Group, and Aviva. Coventry and Yorkshire Building Societies follow as the next most systemically important, each with an SRISK of approximately £2.5 billion, positioning them 13th and 14th on the UK's list of systemically important financial institutions. Skipton and Leeds Building Societies exhibit moderately lower SRISK values, estimated between £1 to £1.3 billion each, reflecting their smaller size and systemic footprint compared to their larger peers. Beyond the "Big Five" building societies, other institutions, such as Principality Building Society, display much smaller SRISK values, with Principality estimated just above £420 million and the remaining institutions around or below £200 million. These results emphasize the concentration of systemic risk among the largest building societies, while smaller institutions contribute comparatively less to systemic vulnerabilities, accounting for approximately 1.7% of the sector's and only 0.09% of the overall market's SRISK.

Fig. 6B shows the evolution of systemic risk for UK building societies from 2008 to 2023, broken down by individual institutions. Nationwide Building Society has consistently dominated, accounting for 80% of the sector's SRISK in 2008. However, this share declined steadily over time to 71% in 2013 and further to 60% in 2023. This decline in Nationwide's dominance has been accompanied by an increase in the systemic importance of other building societies. Notably, Coventry and Yorkshire increased their contributions from 4% and 6%, respectively, in 2008 to 11%-12% in the post-pandemic period. Similarly, Skipton and Leeds also saw notable growth in their systemic importance, with Skipton rising from 2.8% to 5.8% and Leeds increasing from 2.1% to 4.7% between 2008 and 2023. The trend in SRISK reveals a significant peak during the 2008–2009 global financial crisis, reflecting heightened vulnerabilities across the sector. While systemic risk declined during the recovery period up to 2015, it has risen steadily since then, particularly in the post-pandemic period. This recent increase underscores the relevance of our results, as it highlights the growing systemic importance of institutions beyond Nationwide, which is already included in the Bank of England's stress tests.

Overall, our findings regarding systemic risk among UK building societies carry significant implications for policymakers,

[11] Similar results are obtained using the estimated coefficients in Model (5), where the predictors are lagged. In that case, Nationwide also ranks among the top 10 systemically important institutions in the UK, with its SRISK value estimated at £14.8 billion.



A. *SRISK* for the ten largest building societies (2023 data)

B. Decomposition of the UK Building society *SRISK*

Fig. 6. Estimated *SRISK* for UK building societies.
Note: Figure A presents the ranking of systemic importance for the ten largest building societies as of the end of 2023. Figure B illustrates the dynamic evolution of each building society's contribution to the sector aggregate. SRISK is estimated indirectly, based on a set of balance sheet characteristics, including total assets, the equity ratio, and net profits over total assets for the period 2008–2023. Data is sourced from the annual reports of the building societies.

particularly as traditional systemic risk approaches often overlook non-listed institutions. The building societies' sector accounted for 4.33% of the UK's aggregate SRISK in 2023, marking the highest share in the period examined and an increase of 1.08 percentage points from 3.05% in 2008. This trend underscores the growing systemic importance of non-listed financial institutions, driven by shifts in the distribution of risk across the sector. Our results not only highlight the contribution of building societies to systemic vulnerabilities, but also emphasize the importance of incorporating non-listed mutual financial institutions, such as credit unions, cooperative banks, and other member-owned deposit-taking entities, into systemic risk frameworks. By addressing this gap, policymakers and regulators can ensure a more comprehensive approach to safeguarding financial stability, particularly as the role of non-listed institutions continues to grow within the broader financial system.

5.2. Systemic risk in digital-only challenger banks

In addition, we extend our analysis to include the systemic risk associated with digital-only banks, commonly referred to as challenger banks or neobanks. In the UK, challenger banks began to emerge around the mid-2010s, spurred by regulatory support, technological innovation, and a growing demand for user-friendly digital financial solutions. These institutions have significantly transformed the financial landscape, experiencing substantial growth in recent years. The movement was initiated in 2014 with the launch of Atom Bank, the UK's first mobile-only bank, which focused on mortgages and savings products. Around the same time, Starling Bank entered the market, offering current accounts and payment solutions. The subsequent growth phase between 2015 and 2017 witnessed the entry of key players such as Monzo and Revolut. Monzo began as a prepaid card service before obtaining a full banking license in 2017, enabling it to offer a broader range of banking services. Revolut, initially launched as a currency exchange app, similarly evolved into a challenger bank, providing an extensive suite of financial products.

We analyse data from the annual reports of the four largest challenger banks for the period 2020 to 2023. Fig. 7A. illustrates the total assets of these institutions. Over the examined period, their total assets grew by an impressive 172%, increasing from £1.7 billion in 2020 to £4.6 billion in 2023. This remarkable growth highlights the rising consumer preference for digital banking solutions and the transformative impact of challenger banks on the UK's financial services sector. Using the estimates from Table 3, Model (1), we indirectly calculate the systemic risk (SRISK) of these challenger banks. The predicted SRISK values are presented in Fig. 7B. Our findings reveal that Starling Bank, despite being the second-largest challenger bank after Revolut, is the most systemically important, with an estimated SRISK of £402 million, compared to £302 million for Revolut. This can be attributed to Starling's lower equity ratio relative to other institutions. In 2023, the systemic risk for the other two challenger banks was estimated at £339 million for Monzo and £244 million for Atom Bank. The systemic risk for these two banks is primarily driven by the losses they incurred over recent years. Collectively, the aggregate SRISK for the challenger bank sector in 2023 is estimated at £1.3 billion, remaining at the same level as in 2022 but representing a significant 14.9% increase compared to 2020.

Table 4 presents the summary statistics for challenger banks' balance sheet. Despite the rapid growth of the challenger banks sector and its persistent losses over the past year, our estimates indicate that these institutions are not a significant source of systemic risk. This conclusion is primarily driven by their relatively small size compared to traditional large financial institutions and their relatively high equity ratios, which provide a buffer against financial shocks. Additionally, challenger banks' business models and market positioning contribute to their lower systemic importance, as they typically avoid large-scale interbank lending, complex financial transactions, and other activities that heighten contagion risk within the financial system. Instead, their operations are largely focused

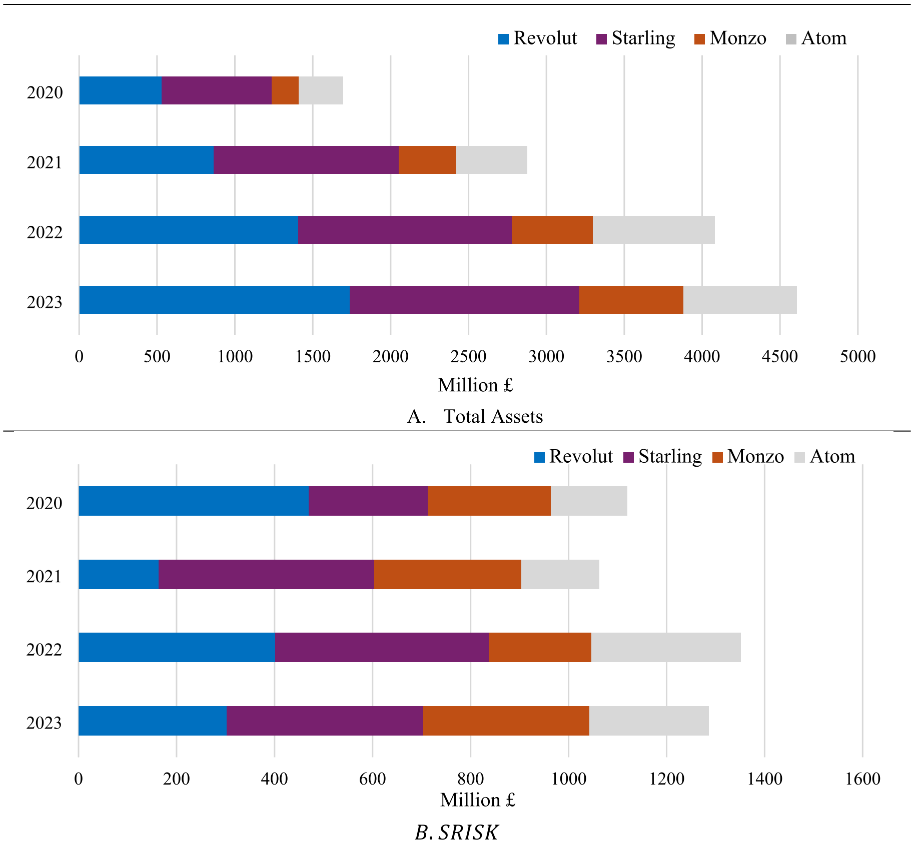


Fig. 7. Size and systemic risk estimates for challenger banks.
Note: Figure A illustrates the total assets (in millions of £) for four selected UK challenger banks, namely Revolut, Starling, Monzo, and Atom Bank over the period 2020–2023. Figure B presents the indirectly estimated SRISK (in millions of £) for the same banks and period. SRISK is calculated based on a set of balance sheet characteristics, including total assets, the equity ratio, and profits over assets, covering the period 2008–2023. All data are sourced from the annual reports of the selected challenger banks.

Table 4
Summary statistics: Challenger banks.

	Obs	Mean	Std. dev.	Min	Max
Ln Total Assets	16	22.665	0.643	21.266	23.577
Profits / Assets	16	−0.887	2.387	−6.611	1.982
Equity / Assets	16	6.226	3.078	1.183	12.478

Note: The table presents the summary statistics of the natural logarithm of Total Assets, Net Profits over Assets and Equity over assets for our sample of challenger banks. The sample period is 2020–2023 and all data is of annual frequency. Data is provided by banks' annual reports.

on retail banking services, which are less interconnected with the systemic core of the financial sector. However, traditional systemic risk metrics, including SRISK predominantly assess capital adequacy and macroeconomic-level risks, potentially overlooking the operational disruptions that could arise from the failure of a challenger bank. Given their expanding customer base the collapse of one of these banks could still lead to significant disruptions, particularly for consumers who rely heavily on digital-only banking solutions. Therefore, while challenger banks do not currently pose a systemic threat to the financial system, their increasing market presence and potential expansion into more complex financial activities warrant ongoing regulatory scrutiny to ensure the stability of their operations and customer-facing services.

5.3. Foreign-owned non-listed banks

In addition, we assess the systemic importance of other international banking institutions that account for a share of the UK market, but they are not listed on the London Stock Exchange. A primary challenge in this evaluation is the limited availability of detailed data, as these banks often do not publish annual reports dedicated solely to their UK operations. Our focus is on large banking institutions that provide retail banking services rather than investment banking. This focus reflects their critical role in deposit-taking, consumer lending, and payment systems, which makes their failure a significant threat to the UK's financial stability. In addition, international investment banks operating in the UK typically do not release separate reports on their UK-specific assets. Consequently, we prioritize retail-focused banks and, using market share data from the BoE, identify two prominent institutions, Santander and TSB Bank (owned by Banco Sabadell), as potentially systemically important.[12] These banks hold substantial market shares in key areas such as mortgage lending and deposit-taking, highlighting the need to understand their contribution to systemic risk. The data are extracted from annual reports covering the period 2008–2023 for Santander and 2014–2023 for TSB Bank. Santander manages £275 billion in UK assets, making it comparable to the largest UK banks, with an average return on assets (ROA) of 0.5% and an equity ratio of 5% over the last three years. In contrast, TSB's asset book amounts to just under £48 billion.

Both banks are currently unlisted, and therefore the traditional SRISK estimation based on market data is not applicable. Instead, we adopt a similar approach to the one used in previous sections of this paper, estimating the systemic risk of these banking institutions using the methodology outlined by Engle et al. (2024) and the estimated coefficients from Table 3, Model (1). Our results indicate that Santander's SRISK for 2023 is approximately £14.2 billion,[13] ranking it as the 9th most systemically important financial institution in the UK. Fig. 8A presents an updated list of financial institutions with the highest SRISK values in 2023, including both Santander and Nationwide. For TSB, its SRISK is estimated at £1.8 billion, placing it 19th on the list of UK systemically important institutions.

Fig. 8B illustrates the time evolution of UK aggregate SRISK, including estimates for Santander, TSB, building societies, and challenger banks over the past ten years. The systemic risk shares remain relatively stable over time. According to our data, the five largest listed UK banks collectively account for 61.7% of the total UK SRISK, followed by other financial institutions, such as insurance companies and investment trusts, which contribute 30.9 %. The aggregate SRISK of the ten largest building societies is estimated at 4.1% of the UK total, with Nationwide contributing two-thirds of the sector's systemic risk. Santander accounts for 2.8%, while TSB contributes 0.4%. Lastly, challenger banks make a minimal contribution, collectively representing only 0.25% of the UK's total SRISK in 2023, and are barely visible in the figure.

Finally, Fig. 9 presents SRISK scaled by total assets over the period 2008–2023, offering a more comparable measure of systemic vulnerability across different types of UK financial institutions (Brownlees and Engle, 2017; Engle et al., 2024). The SRISK-to-assets ratio for the four largest and systemically important UK banks (SIBs) fluctuates between 6% and 7% in the aftermath of the Global Financial Crisis, declines to just under 5% by 2015, and then rises steadily from 2018 onwards, reaching approximately 6% by 2023. In that year, the highest SRISK-to-assets ratios are observed for Barclays (7%), followed by NatWest (6%), Lloyds (5.8%), and HSBC (5.2%). This upward trend in systemic risk intensity is consistent with the pattern observed in Fig. 8, indicating an overall increase in systemic vulnerabilities across the sector.

Santander and Nationwide closely mirror the variation seen among the SIBs, with SRISK-to-assets ratios of 5.2% and 4.8%, respectively, in 2023. This suggests that, despite not being listed in London Stock Exchange, both institutions exhibit systemic profiles comparable to the largest UK banks. In contrast, the broader building society sector demonstrates consistently lower systemic risk, with

[12] Other foreign-owned banks active in the UK operate mainly as branches rather than subsidiaries and therefore do not publish separate UK balance sheets or hold a significant share of the UK retail market. As a result, these institutions are excluded from the analysis.

[13] Similar results are obtained using the estimated coefficients in Model (5), where the predictors are lagged. In that case, Santander is also ranked the 8th most systemically important institutions in the UK, with its SRISK value estimated at £15.1 billion.

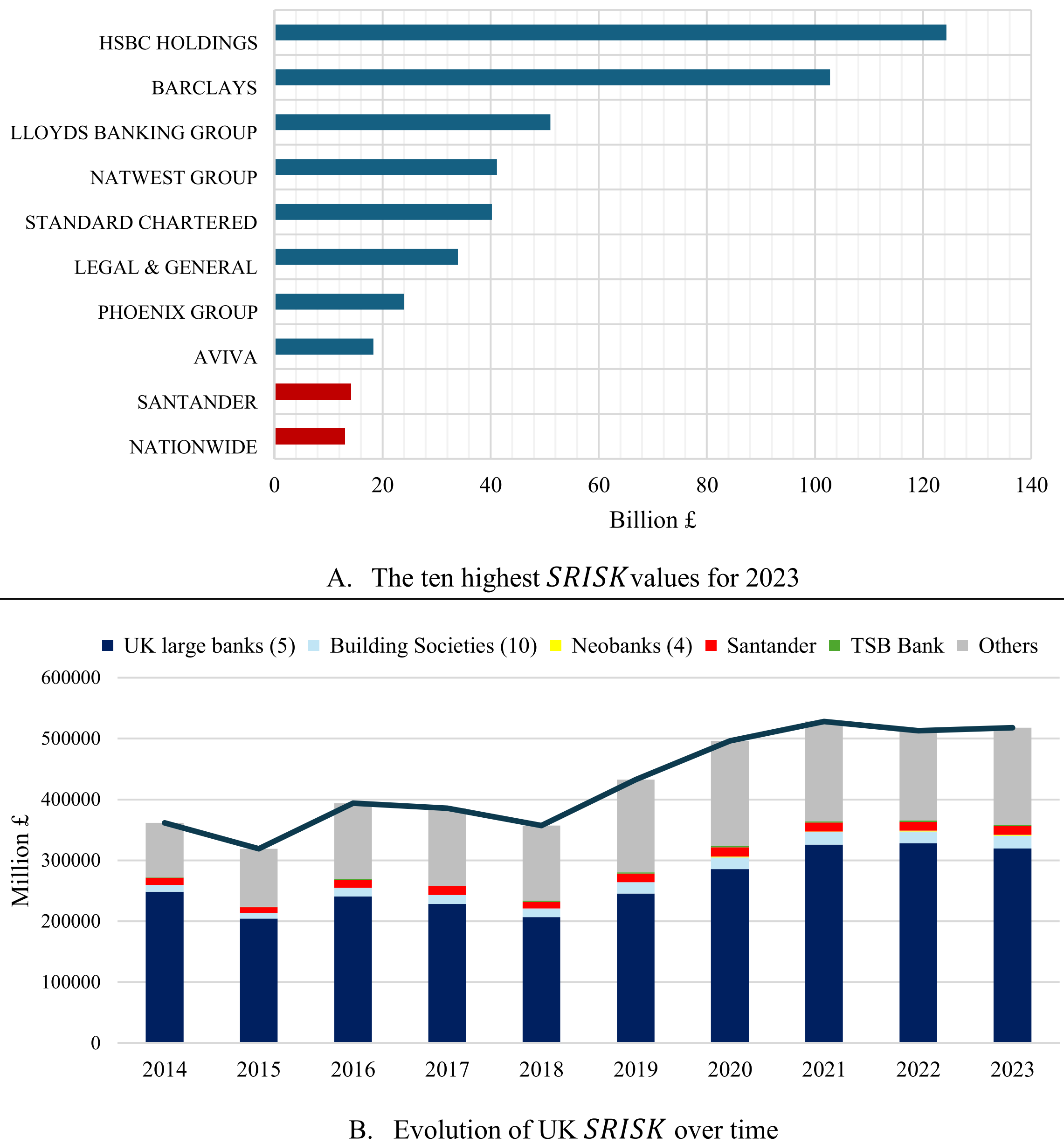


Fig. 8. Systemic risk of listed and non-listed financial institutions.
Note: Figure A presents the SRISK values for the UK ten most systemically important listed and non-listed financial institutions in 2023. For listed companies, the estimation is based on 2023 data on Total liabilities and Market value of equity provided by Thomson Reuters EIKON Datastream and LRMES estimated based on stock market returns for the examined financial institutions and the DS Financials index in the period 2008–2023. For non-listed, SRISK is estimated indirectly, based on a set of balance sheet characteristics, including total assets, the equity ratio and profits over assets for the period 2008–2023 and data is sourced from the annual reports of the building societies. The values are expressed in billions of GBP.

SRISK-to-assets ratios excluding Nationwide ranging from approximately 2.5% to 4% over the period. These findings reinforce the conclusions drawn from Fig. 8 and confirm that systemic risk has not only increased in absolute terms, but also as a proportion of institutional balance sheets highlighting persistent vulnerabilities across both listed and non-listed financial institutions in the UK.

6. Robustness

To ensure the robustness and reliability of our findings, this section conducts a series of empirical checks. We test the sensitivity of our results to alternative model specifications, measurement approaches, sample definitions, and risk metrics. We also assess their validity of our results by comparing our SRISK estimates with the Bank of England's stress testing outcomes.

6.1. Alternative model specification

6.1.1. Testing for Nonlinearities

Firstly, we alter our benchmark model specification to account for non-linearities in the relationship between the predictors and SRISK. The results are presented in Table 5, and they indicate a possible nonlinear relationship between systemic risk and the financial institutions' size and capitalization. The positive coefficient for the logarithm of total assets suggests that larger institutions are associated with higher systemic risk, consistent with their greater systemic importance and potential impact on the financial system. However, the negative coefficient for the squared term of total assets implies diminishing marginal effects, potentially reflecting diversification benefits or heightened regulatory targeting systemic risk metrics for those larger entities. For the equity-to-assets ratio, the negative coefficient suggests that higher capitalization is associated with lower systemic risk. However, in Models (3) and (4) that include the squared terms, the equity-to-assets coefficient becomes positive while the squared term is negative, indicating a nonlinear relationship. This suggests that higher equity-to-assets ratios are initially associated with greater systemic risk, but at very high levels, the effect is negative again, pointing to a hump-shaped relationship.

In addition, the inclusion of the liquidity ratio and leverage in Model (4) does not materially change the results, and both variables are not statistically significant across specifications. Moreover, Models (5) and (6) extend this analysis by incorporating lagged nonlinear terms alongside liquidity and leverage controls. The findings confirm that lagged firm size and profitability remain significant predictors of systemic risk, whereas the lagged equity ratio, and its squared term, are statistically insignificant, suggesting that the effect of capitalization is primarily contemporaneous. Importantly, the lagged models do not outperform their contemporaneous counterparts in terms of within R-squared, indicating no substantial gain in explanatory power from using lagged specifications. Therefore, since the models with and without the squared terms yield very similar R^2, the more parsimonious specification is preferred, as it avoids overfitting. In addition, as we discuss in Section 6.1.4, the model with lagged predictors performs worse in the out-of-sample testing.

6.1.2. Alternative SRISK specifications

In this section, we provide robustness tests using alternative SRISK specifications. First, we confirm our results by using SRISK over assets instead of its logarithmic transformation. This is the transformation used in Engle et al. (2024) and our results (Table 6, Model 1) are in line with the coefficients they obtain for a large panel of Euro area banks. However, we chose not to proceed with the approach because of the weaker explanatory power of the model ($R^2 = 0.47$). In addition, we consider three alternative specifications in the estimation SRISK. In Model 2, we use a historical beta provided by Thomson Reuters EIKON Datastream for the estimation of *LRMES* instead of the approach proposed by Brownlees and Engle (2017). In Model 3, we set the capital adequacy threshold *k* to 5.5% instead of the standard 8%, following other studies in the Euro Area (Engle, 2018; Buch et al., 2019). Finally, in Model (4) we compute SRISK using the FTSE 100 index as the market benchmark, instead of a EIKON DS Financials index. In all three cases, the results remain quantitatively similar to our benchmark model, reinforcing the robustness of our main findings.

6.1.3. Estimated coefficients stability

This section presents several additional robustness checks to assess the stability and validity of the baseline results. First, we examine whether the estimated relationships vary across institutional types. While we acknowledge that structural characteristics, such as ownership and governance, may differ across banks, we argue that such features are more likely to influence the levels of key financial variables rather than the relationships between these variables and SRISK. To investigate this empirically, we re-estimate our baseline specification using a restricted sample comprising the four largest UK banks. The results, shown in Table 7, Model (2), alongside the benchmark model in Model (1), indicate that the signs and magnitudes of the coefficients remain consistent despite the smaller sample size. Moreover, the confidence intervals for each predictor overlap across the two specifications, suggesting that the core relationships between balance sheet characteristics and systemic risk are robust across institutional structures. In addition, in Model (3), we extend the (listed companies) sample to include banks that exited the market, such as delisted or failed institutions, to address potential survivorship bias. By incorporating these observations, we ensure that the results are not driven by the exclusion of distressed or failed institutions.[14] The findings indicate that the estimated levels of systemic risk remain quantitatively similar, reinforcing the robustness of our benchmark model. Notably, the estimated coefficients remain within the same confidence intervals as those in Model (1), further mitigating concerns related to survivorship bias.

Furthermore, in Model (4), we re-estimate the benchmark model using robust standard errors clustered at the firm level to account for potential heteroskedasticity and serial correlation in the error structure. While standard errors increase modestly, the statistical significance and economic interpretation of the coefficients are unchanged, indicating that the results are not sensitive to error distributional assumptions. Model (5) introduces a lag of the dependent variable, ln(SRISK), to capture the persistence of systemic risk and allow for potential dynamics. The coefficient on the lagged dependent variable is positive and highly significant, confirming the

[14] To ensure comparability across institutions, we include only those with at least three years of observations and consistent, positive SRISK estimates. At this point, we would also like to note that the time period examined is constrained by data availability. Annual reports for most building societies are not consistently available prior to 2008, and most challenger banks were established after 2010. As a result, our sample of de-listed firms excludes institutions that failed during or immediately after the Global Financial Crisis.

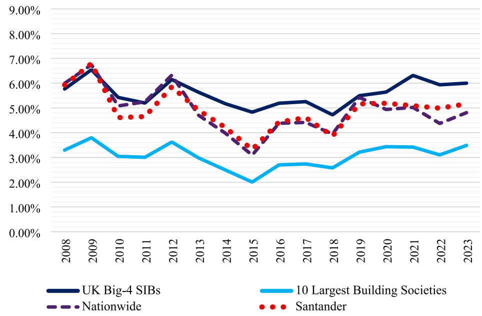


Fig. 9. SRISK / Total Assets (Period 2008–2023).
Note: The figure presents the ratio of SRISK to total assets for selected UK financial institutions over the period 2008–2023. The UK Big-4 Systemically Important Banks (SIBs) presents the average of HSBC, Barclays, Lloyds Banking Group, and NatWest Group. SRISK estimates for building societies (including Nationwide) and Santander are derived using the indirect estimation method based on balance sheet characteristics such as total assets, equity ratio, and profitability. The building society sector aggregate is based on the ten largest institutions for which SRISK is estimated to be positive.

persistence of SRISK over time. Notably, the contemporaneous effects of firm fundamentals remain significant, suggesting these variables have explanatory power above and beyond SRISK's autoregressive nature. Model (6) presents a fully lagged specification, where all explanatory variables are lagged by one year. This specification mitigates concerns about simultaneity and allows for a more forward-looking interpretation. The key coefficients remain stable, indicating that lagged size and profitability are strong predictors of future systemic risk. Taken together, the results confirm the robustness of the baseline findings to alternative samples, dynamic specifications, and adjustments for heteroskedasticity, serial correlation, and firm exit.

In addition, we test whether the relationship between balance sheet characteristics and SRISK could plausibly vary over time due to major structural shifts such as the Global Financial Crisis, Euro area sovereign debt crisis, Brexit, or the COVID-19 pandemic. To empirically test this, we re-estimated our model allowing the impact of the predictors to vary across years. More specifically, we interact each of the three predictors with year dummies to examine whether their association with systemic risk changes over time. This approach enables us to assess both stability and potential structural breaks in the predictor-SRISK relationship across the full sample period. The results, reported in Table 8, show that while a few interaction terms are individually significant, the vast majority are statistically insignificant and the overall effects of the core variables remain stable. Importantly, the baseline coefficients are

Table 5
Regression Results with Non-Linearities.

Models:	(1)	(2)	(3)	(4)	(5)	(6)
	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_{t+1}$	$lnSRISK_{t+1}$
Ln Total Assets (t)	3.311***	3.339***	3.457***	3.479***	2.848***	2.856***
	(0.557)	(0.550)	(0.460)	(0.488)	(0.469)	(0.450)
Equity ratio (t)	−0.0673***	−0.0724***	0.118**	0.110**	−0.00853	−0.0146
	(0.0168)	(0.0170)	(0.0373)	(0.0396)	(0.0148)	(0.0380)
Profits / Assets (t)	−0.276***	−0.268***	−0.273***	−0.255***	−0.349***	−0.351***
	(0.0535)	(0.0540)	(0.0503)	(0.0514)	(0.0716)	(0.0711)
Ln Total Assets squared (t)	−0.0432***	−0.0439***	−0.0465***	−0.0469***	−0.0352***	−0.0353***
	(0.0111)	(0.0110)	(0.00917)	(0.00972)	(0.00934)	(0.00894)
Equity ratio squared (t)			−0.0145***	−0.0147***		0.000366
			(0.00291)	(0.00304)		(0.00299)
Liquidity ratio (t)		−0.0141		−0.119		
		(0.256)		(0.217)		
Leverage (t)		0.374		0.348		
		(0.224)		(0.203)		
Constant	–33.40***	–33.74***	−35.43***	−35.70***	−26.75***	−26.81***
	(6.964)	(6.884)	(5.773)	(6.114)	(5.887)	(5.645)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO
Observations	283	283	283	283	270	270
R^2	0.78	0.78	0.79	0.79	0.54	0.54

Note: The table reports the results from panel regressions using data from 28 listed financial institutions over the period 2008–2023. Data is sourced from Thomson Reuters EIKON Datastream. The dependent variable is the natural logarithm of SRISK at time t in Models (1)–(4), and at time t + 1 in Models (5)–(6). Ln Total Assets refers to the natural logarithm of annually reported total assets. Equity ratio is calculated as total equity divided by total assets. Profits/Assets and Liquidity ratio are computed using net income and cash plus liquid assets, respectively, as a share of total assets. Leverage is defined as total debt divided by total assets. All models include year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Alternative SRISK Specifications.

Models:	(1)	(2)	(3)	(4)
	$SRISK/TA_t$	$lnSRISK_{beta,t}$	$lnSRISK_{k=5.5\%,t}$	$lnSRISK_{FTSE100,t}$
Ln Total Assets (t)	0.497***	1.077***	1.201***	1.145***
	(0.083)	(0.019)	(0.055)	(0.026)
Equity ratio (t)	−0.209***	−0.038**	−0.070*	−0.070***
	(0.046)	(0.012)	(0.037)	(0.017)
Profits / Assets (t)	−0.670***	−0.197***	−0.269**	−0.235***
	(0.136)	(0.041)	(0.110)	(0.059)
Constant	−6.771***	−4.744***	−8.770***	−6.393***
	(2.160)	(0.511)	(1.428)	(0.697)
Year Fixed Effects	YES	YES	YES	YES
Firm Fixed Effects	NO	NO	NO	NO
Observations	283	283	255	283
R^2	0.47	0.82	0.51	0.72

Note: The table reports the results from panel regressions using data from 28 listed financial institutions over the period 2008–2023. Data is sourced from Thomson Reuters EIKON Datastream. The dependent variable differs across the four models. In Model (1), the dependent variable is SRISK scaled by total assets. In Models (2)–(4), alternative specifications of SRISK are employed: Model (2) uses SRISK estimated based on the historical beta provided by EIKON Datastream; Model (3) adjusts the prudential capital requirement (k) to 5.5% instead of 8% used in the benchmark specification; and Model (4) replaces the Datastream (DS) Financials index with the FTSE 100 index as the market benchmark. Ln Total Assets refers to the natural logarithm of annually reported total assets. Equity ratio is calculated as total equity divided by total assets and Profits/Assets is computed using net income as a share of total assets. All models include year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Robustness.

Models:	(1)	(2)	(3)	(4)	(5)	(6)
	Benchmark	Big 5 SIBs	Incl. Delisted	Clustered Robust se	Incl. lagged lnSRISK	
	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_t$	$lnSRISK_{t+1}$
Ln Total Assets (t)	1.144***	1.206***	1.165***	1.144***	0.825***	0.621***
	(0.0264)	(0.0915)	(0.0255)	(0.0248)	(0.0588)	(0.0936)
Equity ratio (t)	−0.0771***	−0.0879*	−0.0745***	−0.0771***	−0.0274**	−0.0132
	(0.0164)	(0.0402)	(0.0165)	(0.0220)	(0.00990)	(0.0128)
Profits /Assets (t)	−0.284***	−0.237**	−0.300***	−0.284***	−0.263***	−0.169*
	(0.0547)	(0.0783)	(0.0607)	(0.0714)	(0.0482)	(0.0699)
Ln SRISK (t-1)					0.238***	
					(0.0510)	
Ln SRISK (t)						0.403***
						(0.0839)
Constant	−6.380***	−8.232**	−6.950***	−6.380***	−3.577***	−2.148***
	(0.693)	(2.646)	(0.664)	(0.659)	(0.461)	(0.625)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	NO	NO	NO	NO	NO	NO
Observations	283	64	298	283	250	250
R^2	0.77	0.89	0.75	0.77	0.76	0.58

Note: The table reports the results from panel regressions using data from 28 listed financial institutions over the period 2008–2023. Data is sourced from Thomson Reuters EIKON Datastream. The dependent variable is the natural logarithm of SRISK. Ln Total Assets refers to the natural logarithm of annually reported total assets. The equity ratio is calculated as total equity divided by total assets, and Profits/Assets is computed as net income divided by total assets. Model (1) is the benchmark model. Model (2) restricts the sample to the five largest UK banks. Model (3) extends the sample to include de-listed financial institutions. Model (4) returns to the original sample of 28 listed institutions, but incorporates clustered standard errors. Finally, Models (5) and (6) include lagged values of SRISK as explanatory variables. All models include year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

quantitatively similar to those from our original specification, indicating that the main drivers of SRISK are consistent over time. These findings suggest that while macroeconomic and institutional conditions may evolve, the relationship between systemic risk and its key accounting-based predictors remains robust.

6.1.4. Out-of-sample testing

To assess the practical relevance and predictive validity of our benchmark specification, we conduct an out-of-sample forecasting exercise for the period 2022–2023. The goal of this analysis is to evaluate whether the identified predictors (log total assets, equity ratio, and profitability) can reliably predict future SRISK values beyond the estimation sample. We compare the benchmark model, which includes contemporaneous explanatory variables, against several alternative forecasting strategies. First, we employ a firm-level historical average benchmark, which assumes that a firm's future systemic risk contribution reverts to its 2008–2021 average. Second, we consider a random walk model based on a rolling average of SRISK. In addition, we employ the benchmark model using lagged fundamentals (Table 3, Model 5), and finally, we evaluate a non-linear specification that includes squared terms for size and capitalisation (Table 5, Model 3) to capture potential non-linearities in the SRISK-generating process.

Forecast performance is evaluated using three standard metrics: the Mean Error (ME), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), calculated over the holdout sample (2022–2023). As shown in Table 9, the benchmark model performs strongly, with a low ME (0.09) and the lowest MAE (0.40) among all specifications, suggesting accurate and unbiased predictions. Its RMSE (0.55) is nearly identical to that of the random walk model (0.58), which, despite its simplicity, performs reasonably well due to the high persistence of SRISK. In contrast, the historical average benchmark yields significantly higher errors (MAE = 0.71; RMSE = 0.93), reflecting its inability to accommodate time-varying risk exposures. The lagged fundamentals and non-linear models also exhibit higher prediction errors (MAEs of 0.56 and 0.43, respectively), suggesting that contemporaneous firm characteristics remain more informative for SRISK forecasting than either lagged or transformed variables. These results highlight the out-of-sample robustness of the benchmark model, which offers a reliable framework for monitoring systemic risk buildup at the firm level.

Table 8
Stability of Estimated Coefficients Test.

Models:	(1)	(2)	(3)
Ln Total Assets (t)	**1.038*****	**1.115*****	**1.107*****
	(0.059)	(0.013)	(0.013)
Equity ratio (t)	**−0.051*****	0.039	**−0.051*****
	(0.105)	(0.071)	(0.011)
Profits /Assets (t)	**−0.326*****	**−0.308*****	0.150
	(0.053)	(0.054)	(0.487)
Interactions with Year:	Ln Total Assets × Year	Equity ratio × Year	Profits/Assets × Year
× 2009	−0.048	−0.030	−0.093
	(0.078)	(0.097)	(0.509)
× 2010	0.112	**−0.236*****	**−1.333*****
	(0.079)	(0.087)	(0.518)
× 2011	0.092	**−0.166***	−0.743
	(0.074)	(0.091)	(0.610)
× 2012	0.034	−0.082	−0.430
	(0.074)	(0.087)	(0.528)
× 2013	0.019	−0.101	−0.221
	(0.080)	(0.086)	(0.514)
× 2014	0.045	−0.099	−0.451
	(0.085)	(0.086)	(0.537)
× 2015	**0.279*****	**−0.177****	**−0.971***
	(0.075)	(0.082)	(0.580)
× 2016	0.108	−0.077	**−0.935***
	(0.078)	(0.083)	(0.537)
× 2017	0.033	−0.068	−0.356
	(0.080)	(0.082)	(0.522)
× 2018	0.096	−0.085	−0.501
	(0.080)	(0.082)	(0.547)
× 2019	0.098	−0.092	−0.449
	(0.073)	(0.078)	(0.521)
× 2020	0.069	−0.031	−0.185
	(0.075)	(0.079)	(0.522)
× 2021	0.088	−0.086	−0.373
	(0.073)	(0.076)	(0.504)
× 2022	0.100	−0.107	−0.700
	(0.073)	(0.075)	(0.500)
× 2023	0.024	−0.066	−0.350
	(0.074)	(0.077)	(0.497)
Constant	−3.696**	−6.008***	−5.728***
	(1.546)	(0.449)	(0.452)
Year FE	YES	YES	YES
Observations	283	283	283
R^2	0.810	0.787	0.806

Note: The table presents the results from panel regressions testing the stability of key coefficient estimates over time, using data from 28 listed financial institutions over the period 2008–2023. The dependent variable is the natural logarithm of SRISK. Ln Total Assets refers to the natural logarithm of annually reported total assets. The equity ratio is calculated as total equity divided by total assets, and Profits/Assets is computed as net income divided by total assets. Models (1)–(3) sequentially interact each of the core financial variables with year dummies from 2009 to 2023 to capture potential time variation in their effects. All models include year fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

6.2. Alternative aspects of systemic risk

To complement our main empirical analysis of systemic risk contributions, we examine the underlying co-movements in building societies' balance sheet dynamics using Principal Component Analysis (PCA) of year-on-year asset growth rates over the period 2009–2023. This methodological approach is based on the literature that links the synchronicity of financial institutions' behaviours with systemic vulnerability. Billio et al. (2012) develop several econometric tools to capture interconnectedness across financial sectors, including a PCA framework applied to a broad set of banks, insurance companies, and hedge funds. In their interpretation, the proportion of variance explained by the first few principal components serves as a proxy for systemic connectivity. A higher share indicates that firms are predominantly driven by common underlying factors, which increases the likelihood of joint stress episodes due to synchronised exposures and behaviours. Similarly, Kritzman et al. (2011) propose a PCA-based indicator of systemic risk, emphasising that a rise in the explanatory power of leading principal components reflects heightened market integration and vulnerability. In both frameworks, an elevated concentration of variance among the top components signals that systemic shocks are more likely to propagate across institutions through shared macro-financial dependencies. Consistent with the literature, we use PCA to identify synchronised exposures and common macro-financial drivers. Importantly, the analysis captures systemic vulnerability arising from co-movement rather than bilateral transmission of shocks.

We begin by analysing the ten largest building societies by total assets, with results reported in Table 10. The PCA indicates that the first principal component (PC1) explains 31.8% of the total variance in year-on-year asset growth, while the top three components together account for 69.9% of the total variation. These results suggest a strong degree of synchronisation across the largest societies and indicate that their asset expansion is strongly influenced by common drivers, such as macro-financial cycles. We then repeat the exercise for the ten most systemically important financial institutions as identified in the previous analysis (see Fig. 4). For this group, PC1 explains 39.8% of the variance, while the top three components together account for 70.4%. To further explore systemic connectivity across different institutional types, we apply PCA to a combined sample of the five largest building societies and the five largest UK SIFs. The results indicate that PC1 explains 43.7% of the variance, with PC2 and PC3 explaining an additional 23.2% and 11.2%, respectively. The ordering of explanatory power, highest for the mixed sample and lowest for the building societies, is intuitive. Building societies are more heterogeneous, reflecting their regional focus, conservative lending strategies, and limited access to wholesale funding. By contrast, SIFs display stronger co-movement due to their shared exposure to global financial cycles. When the two groups are combined, the common factor becomes more pronounced, as both domestic housing-credit dynamics and international financial conditions contribute jointly to the variance captured by the principal components. Overall, the results underscore that the largest building societies, particularly when analysed alongside SIFs, exhibit substantial co-movement, which reinforces their potential contribution to systemic risk through exposure to shared economic shocks.

The findings from Table 10 suggest that the largest building societies exhibit meaningful co-movement with UK banks, supporting the view that they are integrated into the broader financial system. Table 11 reports the correlation matrix between Nationwide, Santander, and the four major UK systemically important banks (SIBs). As expected, the degree of correlation is generally higher within the SIB group. Notably, Lloyds and NatWest exhibit a particularly strong correlation (88.7%), reflecting their shared focus on the domestic UK market. In contrast, HSBC demonstrates a higher correlation with Barclays (73%), likely attributable to their similar international exposure and diversified operations. When we focus on the two major non-listed financial institutions. Nationwide shows strong positive correlations with Lloyds Banking Group and NatWest, but weak or even negative correlations with HSBC and Barclays, which highlights its alignment with domestically oriented banks. Conversely, Santander displays more balanced correlations across all four SIBs, with stronger links to internationally focused institutions such as Barclays and HSBC.

Overall, the PCA and correlation analysis reveal that the largest building societies exhibit strong co-movement in asset growth both among themselves and with major UK banks, indicating shared exposure to macro-financial shocks and heightened systemic vulnerabilities. These findings are consistent with our earlier results and reinforce the case for extending macroprudential oversight to

Table 9
Out-of-sample Test.

Model:	Mean Error (ME)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
Benchmark Model	0.09	0.40	0.55
Historic Average	0.54	0.71	0.93
Random Walk Model	0.38	0.45	0.58
Lagged Benchmark Model	0.18	0.56	0.67
Non-linear Model	0.13	0.43	0.55

Note: The table reports the forecast performance of five models evaluated over the out-of-sample period 2022–2023. Forecast errors are assessed using three standard metrics: the Mean Error (ME), which captures directional bias, the Mean Absolute Error (MAE), which reflects average forecast accuracy and the Root Mean Square Error (RMSE), which penalises larger errors more heavily and is sensitive to outliers. The Benchmark Model uses contemporaneous firm-level predictors (log total assets, equity ratio, and profitability) estimated over the in-sample period 2008–2021. The Historic Average model assumes that each firm's future SRISK reverts to its pre-pandemic average over the same in-sample period. The Random Walk Model applies a five-year rolling average of lagged SRISK values to generate forecasts, capturing persistence but excluding any structural or forward-looking information. The Lagged Benchmark Model uses the same predictors as the benchmark model but lagged by one period/year, testing whether past fundamentals are predictive. The Non-linear Model extends the benchmark specification by including squared terms for size and capitalisation to account for potential non-linearities in the relationship between firm characteristics and systemic risk exposure.

Table 10
PCA Results: Explained Variance in Asset Growth (2009–2023).

Sample:	PC1 (%)	PC2 (%)	PC3 (%)	Cumulative (PC1-PC3)
10 Largest Building Societies	31.81 %	21.13 %	17.00 %	69.94 %
10 Listed SIFs	39.84 %	16.37 %	14.15 %	70.36 %
5 Largest Building Societies & 5 UK Listed SIFs	43.74 %	23.16 %	11.16 %	78.07 %

Note: The table reports the percentage of total variance explained by the first three principal components (PC1–PC3) from a Principal Component Analysis of annual asset growth rates over the period 2009–2023. A higher share of variance explained by the top components indicates stronger co-movement and higher interconnectedness across institutions. The analysis is conducted separately for three samples: (i) the ten largest building societies (Nationwide, Coventry, Yorkshire, Skipton, Leeds, Principality, West Bromwich, Newcastle, Nottingham, and Cumberland) (ii) the ten most systemically important listed financial institutions (SIFs) identified in our earlier analysis, where Investec is included in place of M&G due to data availability and (iii) a combined group of the five largest building societies (Nationwide, Coventry, Yorkshire, Skipton, and Leeds) and the five largest SIFs (Lloyds, Barclays, NatWest, HSBC, and Standard Chartered).

large mutual institutions.

6.3. Comparison with BoE stress testing

Engle et al. (2024) assess the performance of their indirect SRISK estimation by comparing their results with the European Banking Authority's (EBA) EU-wide stress tests. Although the EBA relies on supervisory balance sheet data and applies regulatory scenarios, they find that the ranking of firms by systemic risk and the scale of capital shortfalls are broadly consistent with their SRISK results. Based on that, Engle et al. (2024) argue that the indirect SRISK offer a valuable complement to traditional stress-testing frameworks and can enhance systemic risk regulatory surveillance.

In the UK, the BoE stress test simulates severe conditions involving high inflation, rising interest rates, deep recessions, and sharp declines in asset prices, examines the robustness of major UK banks. In line with Engle et al. (2024), our estimates of SRISK closely align with the BoE's 2022/23 stress test findings, offering complementary insights into the systemic risk profiles of major UK financial institutions. HSBC and Barclays exhibit the highest SRISK values, reflecting their significant expected capital shortfalls in a systemic crisis. This is consistent with their relatively large CET1 ratio drawdowns and lower low-point CET1 ratios observed in the BoE stress test (HSBC: 10.7%; Barclays: 8.5%). Lloyds Banking Group and NatWest Group represent institutions with relatively moderate systemic risk. Their resilience in the stress test, characterized by smaller CET1 drawdowns and low-point CET1 ratios just above 11%, reflects their focus on UK retail banking, which insulates them from some international risks.

Finally, Santander and Nationwide are estimated to carry the lowest systemic risk among the BoE-examined institutions. While these institutions appear robust, their roles in key segments of the UK financial system, particularly mortgage lending and deposit-taking, justify continued supervisory attention. This aligns with their strong stress test performance, particularly Nationwide, which maintained the highest low-point CET1 ratio of 20.4%. As noted earlier, there are several structural reasons why building societies (similarly to cooperative banks or credit unions) tend to exhibit lower risk profiles. These include maintaining higher capital ratios, focusing on low-risk residential mortgage lending, and having limited exposure to commercial real estate, trading activities, or complex derivatives. These characteristics closely align with the key drivers of resilience identified in the Bank of England's stress test, notably the strength of mortgage portfolios, reliance on deposit-based funding, and reduced exposure to volatile asset classes (BoE, 2023b). It is notable that the Bank of England's 2022/23 stress test includes only one building society, Nationwide, despite the presence of other building societies that play a significant role in the UK mortgage market. Our analysis suggests a potential gap in the existing regulatory stress testing framework, since it covers broader set of non-listed institutions, including additional building societies, online challenger banks, and foreign-owned banks such as Santander UK and TSB, several of these institutions exhibit non-negligible SRISK values.

Our findings carry several important implications for the stress testing framework, particularly in light of the BoE (2024) updated approach. First, the results highlight the need to broaden the core stress testing cohort to include large non-D-SIBs,[15] such as building societies, and challenger banks. Although not formally designated as systemically important institutions, these entities exhibit material levels of systemic risk, especially under adverse conditions. This recommendation aligns with the BoE's stated objective to assess system-wide resilience, rather than focusing solely on the largest banks.

Second, the study underscores the value of incorporating tail-risk metrics, such as SRISK, into future stress testing exercises. These measures offer additional insight beyond traditional capital adequacy metrics and are particularly relevant in identifying hidden vulnerabilities among institutions that appear robust under baseline assumptions. Given the BoE's commitment to exploratory scenario analysis and the integration of alternative methodologies, these tools could meaningfully enhance the identification of systemic fragilities. BoE's stress tests assess resilience under pre-specified macroeconomic scenarios, SRISK measures the expected capital shortfall conditional on a market-wide shock. Consequently, a building society may appear resilient under the BoE stress test but, still exhibit a

[15] Importantly, our SRISK estimates are not intended to serve as the sole basis for Domestic Systemically Important Bank (D-SIB) designation. The Basel Committee's D-SIB framework encompasses multiple dimensions of systemic importance (size, interconnectedness, substitutability, and complexity) that extend beyond the capital shortfall concept captured by SRISK. Instead, SRISK provides a complementary, market-consistent indicator that can help identify potential blind spots in the current macroprudential monitoring framework.

Table 11
Correlation Matrix of Year-on-Year Asset Growth.

	Lloyds BG	Barclays	NatWest	HSBC	Santander	Nationwide
Lloyds BG	100 %					
Barclays	66.3 %	100 %				
NatWest	88.7 %	73.8 %	100 %			
HSBC	32.0 %	73.0 %	32.9 %	100 %		
Santander	35.4 %	37.9 %	19.6 %	37.5 %	100 %	
Nationwide	39.6 %	−3.8 %	29.4 %	5.9 %	16.9 %	100 %

Note: The table shows the Pearson correlation coefficients (in %) of year-on-year asset growth between four major UK banks and Nationwide and Santander. The estimation is based on the period 2010–2023.

non-trivial SRISK value due to its leverage or exposure to aggregate shocks. The two approaches should therefore be viewed as complementary rather than contradictory.

Third, the results suggest that capital buffer calibration may need to be reconsidered for institutions currently outside the D-SIB perimeter, both in the UK and internationally. In particular, the behaviour of the very large mutual financial institutions during stress events raises questions about whether existing buffers, such as the countercyclical capital buffer or systemic risk buffer, are adequately capturing their contribution to overall financial stability risk. Fourth, enhancing transparency around the participation and performance of non-D-SIBs in annual stress testing publications would provide market participants and policymakers with a clearer understanding of their systemic importance. This is consistent with the BoE's stated goal of increasing accountability and public communication in stress testing. Collectively, these recommendations point to three practical directions for policy: broadening institutional coverage in the stress testing framework, incorporating tail-risk indicators such as SRISK into supervisory monitoring, and revisiting the calibration of capital buffers for large non-listed institutions. Implementing such measures would strengthen the BoE's capacity to identify, assess, and mitigate systemic risk in the UK banking system.

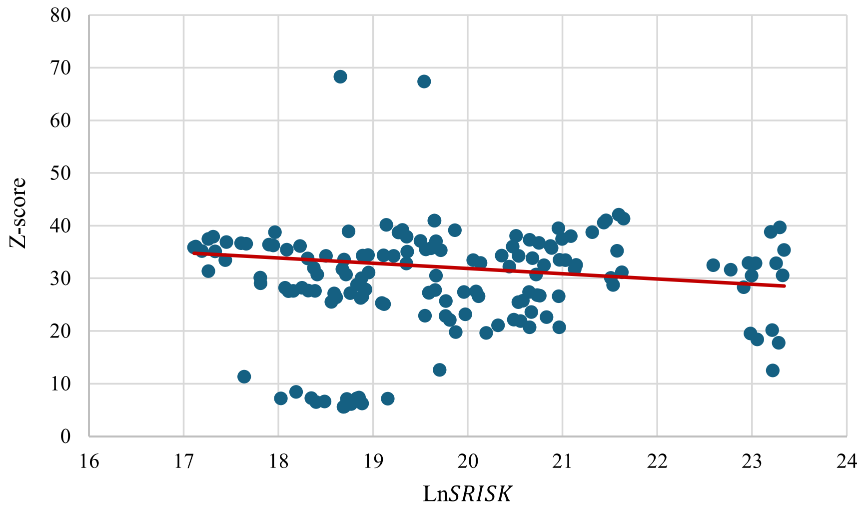
6.4. Comparison with alternative measures of risk

As we mentioned beforehand, the literature already provides some insights into the risk profile of building societies and cooperative and saving banks. However, these studies (Hesse and Čihák, 2007; Ayadi et al., 2010; Casu, 2015; Köhler, 2015; Clark et al., 2018) employ Z-score as a measure of bank risk. SRISK provides different information and captures a distinct aspect of risk compared to the Z-Score, offering complementary insights into financial stability and systemic vulnerabilities. While the Z-Score is widely used in the literature to assess an individual institution's risk of insolvency, it focuses on firm-specific risks and reflects the likelihood of a single institution's failure based on its historical profitability, capitalization, and earnings volatility. It provides a static and backward-looking measure of stability, quantifying how much "distance" the institution has from insolvency under normal operating conditions. In contrast, SRISK shifts the focus to systemic risk by estimating the expected capital shortfall of an institution during a systemic crisis. Unlike the Z-Score, which assumes isolated firm failure, SRISK explicitly accounts for the interconnected nature of financial institutions and their vulnerability under extreme macroeconomic stress scenarios. For example, two institutions with similar Z-Scores might have vastly different SRISK values if one is significantly larger or more leveraged. The Z-Score, while effective for measuring financial soundness, does not capture this systemic dimension or consider the spillover effects of a crisis.

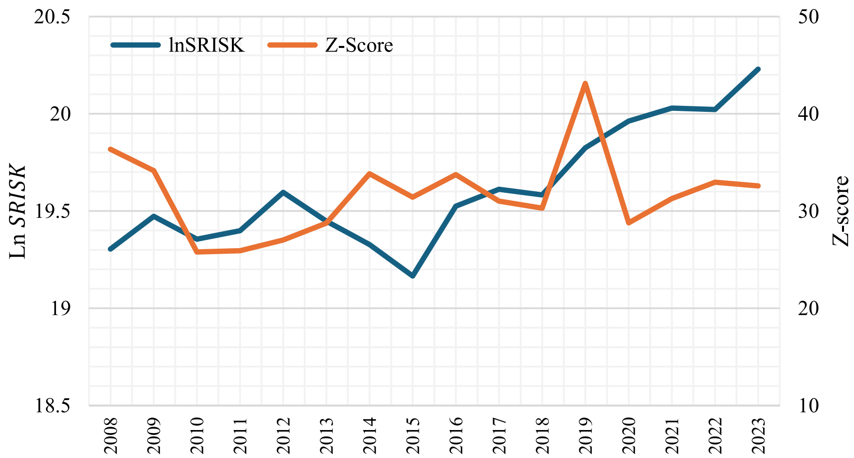
In this section, we provide an empirical comparison of the two metrics. Our estimates for 2023 indicate that, on average, the four largest UK banks have a Z-score of 23.4, compared to 32.7 for the five largest building societies, suggesting that building societies exhibit greater financial stability. This result aligns with previous studies, such as Casu (2015), who found that during the period 2000–2014, building societies in the UK displayed significantly higher Z-scores than banks, indicative of their more conservative risk profiles. Similarly, Köhler (2015) reports that smaller EU banks consistently demonstrate higher Z-scores, averaging 35%, compared to 26% for larger banks. By looking at individual building societies, the three larger and most systemically important institutions exhibit high levels of z-score of above 40%, whereas the lowest values (and less stable institutions) are Newcastle building society and Cambridge building society, which are ranked 8th and 13th in terms of systemic risk.

Fig. 10A illustrates the relationship between the natural logarithm of SRISK and the Z-Score for the ten largest building societies over the period 2008–2023. The scatterplot reveals a weak negative correlation between the two measures of risk, as expected, indicating that they capture distinct dimensions of financial risk. This divergence is evident in the dispersion of data points, where institutions with similar SRISK values often exhibit widely varying Z-Scores. Such patterns suggest that individual stability and systemic importance are influenced by different factors, including size, leverage, and interconnectedness, which *SRISK* captures more effectively. The clustering of data points and the presence of outliers highlight the heterogeneity among institutions in terms of risk profiles. For instance, institutions with high Z-Scores may still exhibit significant SRISK due to their systemic relevance, size, or exposure to correlated risks, factors not reflected in the Z-Score. Conversely, institutions with lower Z-Scores may display low SRISK values, indicating limited systemic importance despite weaker individual financial health. These findings underscore the complementary nature of SRISK and the Z-Score, emphasizing the value of using both metrics for a comprehensive assessment of financial risks.

In addition, Fig. 10B presents the average SRISK and Z-Score for the ten largest building societies over the period 2008–2023. The dynamics observed during this period suggest a generally negative relationship between the two metrics, reflecting their distinct yet complementary perspectives on financial risk. This negative relationship is particularly evident during the post-GFC recovery, where rising Z-Scores correspond to declining SRISK values, indicating that improvements in capitalization and profitability contributed to reduced systemic risk. However, periods of divergence are noticeable, especially after 2017. SRISK exhibits a pronounced increase from 2020 onwards, highlighting persistent vulnerabilities in the financial system despite stronger individual financial health. This suggests that systemic risk can escalate independently of individual financial stability, driven by factors such as increased interconnectedness, higher leverage, or macroeconomic uncertainties. From a policy perspective, these findings emphasize the limitations of relying solely on individual-level risk measures to assess systemic vulnerabilities, underscoring the importance of incorporating systemic risk metrics for a more comprehensive evaluation of financial stability.



A. Correlation chart



B. Dynamic Comparison of *SRISK* and Z-Score

Fig. 10. *SRISK* and Z-score for UK Financial Institutions (2008–2023).
Note: Figure A shows the correlation between the Z-score and the natural logarithm of SRISK (lnSRISK) for a sample of the ten largest building societies over the period 2008–2023. SRISK is indirectly estimated based on a set of balance sheet characteristics, including total assets, the equity ratio and profitability, with data sourced from the annual reports of the building societies. Smaller institutions are excluded as their SRISK values are close to zero, providing limited additional information. Figure B presents the dynamic average SRISK and Z-score for the same sample of building societies over the examined time period.

7. Conclusions

This paper provides novel estimates of systemic risk for UK non-listed financial institutions, focusing on three key segments: building societies, digital-only challenger banks, and foreign-owned banks not listed on the London Stock Exchange. Our findings offer important insights into the diverse risk profiles within these sectors and their implications for financial stability. First, we analyse building societies, which play a crucial role in the UK mortgage market and broader financial system. Among these, Nationwide emerges as the 10th most systemically important financial institution in the UK, with other significant building societies estimated to have *SRISK* values ranging from 1 to 2.5 billion GBP in 2023. The sector as a whole contributed 4.33% to aggregate UK SRISK in 2023, its highest share during the period analysed, highlighting a rising systemic footprint. These results highlight the need for targeted monitoring of this sector, given its systemic importance and concentration in mortgage lending. Second, we evaluate challenger banks, a rapidly expanding sector both in the UK and globally.

Our analysis reveals that UK digital-only banks such as Revolut, Monzo, and Starling exhibit relatively low systemic risk, with SRISK values below 500 million GBP. This is attributable to their high equity ratios and smaller balance sheet sizes compared to traditional banks. However, these estimates should be interpreted as a snapshot of their current systemic footprint rather than a prediction of their long-term relevance. These institutions have operated for only a few years and have not yet been tested through a full credit cycle or a period of systemic stress. Their present business models (focused primarily on retail deposits and payments) limit their interconnectedness with the broader financial system, but rapid growth, increased lending activity, or greater reliance on wholesale funding could meaningfully alter their systemic footprint over time. Continuous monitoring is therefore warranted to assess how the expansion and maturation of digital-only banks may affect their contribution to systemic risk in the future. Finally, we examine foreign-owned banks operating in the UK, but not listed on the London Stock Exchange. Our findings indicate that Santander holds significant systemic importance, with an SRISK value of 14.2 billion GBP, ranking it as the 9th most systemically important financial institution and the 6th most important bank in the UK.

In addition to the direct estimates of SRISK, we show that systemic vulnerabilities are also reflected in co-movements in asset growth and risk dynamics. PCA indicates a high degree of synchronicity between building societies and systemically important banks, reinforcing their potential to act as amplifiers of systemic shocks. Furthermore, we compare SRISK with traditional Z-scores and find that the two metrics capture different dimensions of financial fragility, underscoring the value of incorporating systemic risk measures alongside institution-level solvency indicators. Overall, our findings call for a broader regulatory perimeter. Non-listed institutions should be systematically monitored and their risk profiles integrated into the macroprudential framework. We recommend that the BoE, and other central banks, should expand its stress-testing perimeter to include large building societies, challenger banks, and foreign-owned subsidiaries. In addition, incorporating forward-looking metrics such as SRISK would enhance system-wide resilience assessments. Addressing these gaps is essential for safeguarding financial stability in an increasingly interconnected and diversified financial system.

CRediT authorship contribution statement

Alexandros Skouralis: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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Appendix

Table A1
Building societies detailed summary statistics.

Building Societies:	Sample Period From	To	Market Share (%)	SRISK 2023 LnSRISK	SRISK/Assets
Nationwide Building Society	2008	2023	52.3 %	23.294	4.81 %
Coventry Building Society	2008	2023	12.1 %	21.645	3.99 %
Yorkshire Building Society	2008	2023	11.7 %	21.594	3.92 %
Skipton Building Society	2008	2023	7.2 %	20.960	3.40 %
Leeds Building Society	2008	2023	5.4 %	20.751	3.65 %
Principality Building Society	2008	2023	2.4 %	19.865	3.38 %
West Bromwich Building Society	2008	2023	1.2 %	18.880	2.64 %
Newcastle Building Society	2010	2023	1.2 %	19.155	3.35 %
Nottingham Building Society	2011	2023	0.9 %	18.760	3.14 %
Cumberland Building Society	2008	2023	0.6 %	18.230	2.57 %
Family Building Society	2016	2023	0.5 %	17.890	2.37 %
Progressive Building Society	2009	2023	0.4 %	17.493	2.01 %
Cambridge Building Society	2008	2023	0.4 %	17.485	2.07 %
Monmouthshire Building Society	2014	2023	0.3 %	17.504	2.47 %
Newbury Building Society	2012	2023	0.3 %	17.346	2.21 %
Saffron Building Society	2014	2023	0.3 %	17.481	2.72 %
Leek Building Society	2008	2023	0.3 %	17.294	2.47 %
Furness Building Society	2008	2023	0.3 %	17.249	2.38 %
Darlington Building Society	2016	2023	0.2 %	16.887	2.34 %
Hinckley & Rugby Building Society	2019	2023	0.2 %	16.818	2.45 %
Suffolk Building Society	2013	2023	0.2 %	16.813	2.31 %
Marsden Building Society	2016	2023	0.1 %	16.554	2.07 %
Melton Mowbray Building Society	2008	2023	0.1 %	16.771	2.50 %
Market Harborough Building Society	2018	2023	0.1 %	•	•
Scottish Building Society	2013	2023	0.1 %	16.413	2.08 %
Dudley Building Society	2020	2023	0.1 %	16.509	2.32 %
Tipton & Coseley Building Society	2017	2023	0.1 %	16.122	1.66 %
Swansea Building Society	2020	2023	0.1 %	15.642	0.93 %
Mansfield Building Society	2016	2023	0.1 %	16.138	1.94 %
Hanley Economic Building Society	2008	2023	0.1 %	16.224	2.15 %
Loughborough Building Society	2008	2023	0.1 %	16.372	2.42 %
Vernon Building Society	2016	2023	0.1 %	16.047	2.02 %
Teachers Building Society	2019	2023	0.1 %	16.002	2.12 %
Bath Building Society	2008	2023	0.1 %	15.213	1.09 %
Buckinghamshire Building Society	2015	2023	0.1 %	15.744	1.81 %
Chorley & District Building Society	2021	2023	0.1 %	16.015	2.22 %
Harpenden Building Society	2016	2023	0.1 %	15.535	1.65 %
Ecology Building Society	2015	2023	0.1 %	15.641	2.00 %
Stafford Railway Building Society	2015	2023	0.1 %	15.360	1.52 %
Beverley Building Society	2014	2023	0.0 %	15.076	1.71 %
Manchester Building Society	2011	2022	0.0 %	•	•
Earl Shilton Building Society	2008	2023	0.0 %	14.875	1.60 %
Penrith Building Society	2008	2023	0.0 %	14.315	1.27 %

Note: The table presents the 43 building societies included in the analysis. It reports the first and last year for which data are available for each institution, as well as their share of the sector Total Assets in 2023. The final two columns present the natural logarithm of predicted SRISK and the ratio of SRISK to total assets, both for the year 2023.

Table A2
Fixed effects vs. random effects.

Model:	Fixed Effects (FE) Coefficient	Std. Error	Random Effects (RE) Coefficient	Std. Error
Ln Total Assets (t)	1.213***	(0.070)	1.144***	(0.026)
Equity ratio (t)	–0.071**	(0.028)	–0.077***	(0.016)
Profits / Assets (t)	–0.227***	(0.060)	–0.284***	(0.055)
Year Fixed Effects	Yes		Yes	
Observations	283		283	
Number of Firms	28		28	
R-squared (Within)	0.769		0.767	

(*continued on next page*)

Table A2 (*continued*)

Model:	Fixed Effects (FE) Coefficient	Std. Error	Random Effects (RE) Coefficient	Std. Error
Hausman Test				
Test Statistic (χ^2)	5.96			
p-value	0.996			

Note: The table compares the results from fixed effects (FE) and random effects (RE) panel regressions using data from 28 listed financial institutions over the period 2008–2023. The dependent variable is the natural logarithm of SRISK. Ln Total Assets refers to the natural logarithm of annually reported total assets. The equity ratio is calculated as total equity divided by total assets, and Profits/Assets is computed as net income divided by total assets. All models include year fixed effects. Robust standard errors are reported in parentheses. The Hausman test compares the consistency of the RE model relative to the FE model. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Data availability

Data will be made available on request.

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