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Central bank digital currency and systemic risk

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ABSTRACT

Central Bank Digital Currency (CBDC) is an emerging Financial Technology (FinTech) area. Several countries are involved in CBDC development at different stages and a few are already in the launching stage. We use the autoregressive distributed lag approach to explore the association between CBDC-related news and systemic risk in the short and long run by employing dynamic panel heterogeneity analysis. The results show that CBDC-related news has a significant negative association with systemic risk in the long run, indicating a positive reception by the global financial sector. Extended analysis shows that the long-run negative association is consistent across different income levels and geographical regions. However, countries in the advanced stages of CBDC development show a significant positive association between CBDC-related news and systemic risk warranting the utmost care in implementing CBDC initiatives.

1. Introduction

Over the past ten years, decentralized finance (DeFi) and financial technology (FinTech) have enhanced financial inclusion and permeated every aspect of the financial system (Fan et al., 2023; Awais et al., 2023; Zarrouk et al., 2021; Zhou et al., 2022). Due to FinTech disruptions, traditional financial institutions now face a higher likelihood that payment processing, investing, and banking will become decentralized and eliminate the need for intermediaries (Saengchote, 2023; Yuan et al., 2023). Real-time payments, online financing, and various financial services accessible via mobile devices are just a few examples of the many new developments in financial products and services that have experienced spectacular growth (Hassan et al., 2023; Lai and Langley, 2023; Savitha et al., 2022). The pandemic-induced digital transformation has also accelerated efforts to lower friction in the payment and financial domains (Allen et al., 2022). Even though there exist challenges of being a retail currency, digital currencies have the potential to act as a medium of exchange and offer an efficient payment system (Ong et al., 2023; Schwarcz, 2022). Furthermore, the issuance of stablecoins by unregulated banks also poses regulatory challenges (Gorton and Zhang, 2023). Due to these developments in technology-oriented payment systems, central banks of many countries are actively working on issuing digital currencies, widely known as Central Bank Digital Currency (CBDC) (Hoang et al., 2023; Bech et al., 2017).

The interest of central banks in CBDC is considered to be an important step towards financial innovation that aims to improve efficiency and financial inclusion significantly (Choi et al., 2021; Allen et al., 2022; Cullen, 2022) that may arise from safe storage of value and low maintenance cost compared to physical currency (Murray, 2019; Didenko et al., 2020). Potentially, it can replace the

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existing payment methods (Akin et al., 2023) by providing convenient and unambiguous payment modes and decreasing transaction costs (Fabris et al., 2019). Considering these positive outcomes, central banks of more than 100 countries are at different stages of CBDC development (Boar and Wehrli, 2021; Soderberg et al., 2022). However, issuing CBDCs might work as a double-edged sword as individuals and businesses might shift their deposits from banks to digital currency accounts, leading to instability in the banking sector (Hoang et al., 2023). Additionally, CBDC may lead to a reduction in the demand for bank loans, thus causing an 'asset-side' problem for the banking system (Temperini et al., 2024). In this context, the Efficient Market Hypothesis (EMH), markets incorporate all available information in asset prices (Fama, 1970), suggests that the financial sector may adjust in response to CBDC-related news. This study contributes to the literature by exploring such adjustments in systemic risk in the short- and long-run using a panel of countries.

Existing literature provides mixed findings as Dunbar (2023) shows that CBDC uncertainty is a risk transmitter to the financial sector, while Wang et al. (2022) demonstrates that CBDC Uncertainty and Attention indices have a negative relationship with the volatility of the MSCI World Banks Index. These mixed findings align with Knightian Uncertainty (Knight, 1921) which states that unusual business events lead to unpredictable changes in the asset markets. Knight (1921) emphasizes the difference between actual uncertainty and stochastic risk by stating that uncertainty "cannot by any method be reduced to an objective, quantitatively determinate probability [p. 321]." Since the digital currencies landscape, in general, and the implementation of CBDC, in particular, are in the evolving stages, investors, bank management, and regulators are uncertain due to ambiguous regulatory stances and unpredictable market responses. As the opacity surrounding CBDC developments deepens further, investors may manifest heightened levels of risk aversion, in line with Knightian uncertainty, leading to augmented market volatility (Mangee, 2024) and a discernible surge in due diligence practices, marked by a meticulous examination of banks' risk management strategies (Pritsker, 2013).

Bank managers – cognizant of the inherent ambiguities – respond with strategic acumen, implementing prudent risk management practices, embracing adaptability in operational paradigms, fostering collaborative networks, and prioritizing transparent communication channels (Shabir et al., 2023). In the intricate web of interactions among financial stakeholders, central banks assume a pivotal role in financial stability (Tomuleasa, 2015). By employing adaptive policy frameworks, rigorous stress testing methodologies, and scenario planning exercises, central banks may increase the resilience of the banking sector (Cornett et al., 2020). In such a case, CBDC-related developments may result in enhanced regulatory and market infrastructure, prudent investor behavior, and effective risk management practices by bank managers, leading to reduced systemic risks.

In contrast to the prevailing discourse on CBDC-related developments and their effects, an alternative theoretical perspective provides arguments favoring the potential escalation of systemic risk amid the ambiguity surrounding CBDC implementations. The theoretical foundations of behavioral economics can be particularly relevant in examining how psychological factors and cognitive biases influence economic decisions and market outcomes (Landry, 2021). This perspective posits that the opacity and uncertain regulatory landscape associated with CBDCs could endanger market stability (Dunbar, 2023) due to sub-optimal decision-making by market participants (Persakis and Iatridis, 2023), triggering herd behavior and excessive risk-taking (Luo et al., 2023) which prevails specifically in digital currency markets (Almeida and Gonçalves, 2023). Furthermore, as investors grapple with unclear information, liquidity concerns might arise, exacerbating market illiquidity (Lu and Wang, 2023). Considering the lack of standardized frameworks and divergent international regulatory approaches for FinTech (Xu and Bao, 2023), these challenges could compound and potentially lead to cross-border spillover effects and amplified systemic risks.

In this paper, we contribute to the growing literature by investigating the short- and long-run implications of CBDC-related news – captured by CBDC Uncertainty and Attention indices (Wang et al., 2022) – on systemic risk in a sample of 50 countries. We employ dynamic panel heterogeneity analysis, introduced by Pesaran et al. (1999), using the autoregressive distributed lag (ARDL) approach. Our baseline results show that an increase in CBDC indices is associated with a significant decrease in systemic risk in the long run whereas, in the short run, there is no significant association.

Further analysis reveals heterogeneity in this relationship based on the income level, stages of CBDC development, and geographical regions of the countries. For low, middle, and high-income countries, an increase in CBDC indices is associated with systemic stability in the long run, especially in low and high-income countries. In the short run, for low and middle-income countries, the relationship between CBDC indices and systemic risk is directionally cyclical, suggesting over-reaction and subsequent correction of systemic risk to CBDC-related news. Although existing literature, such as Luu et al. (2023), suggests that CBDC has more benefits for developing than developed countries, our findings imply benefits for high-income countries. Regarding the developmental stages of CBDC, we find that, in the long run, an increase in CBDC indices is associated with a decrease in systemic risk for countries in the status quo stage while an increase in systemic risk for countries in the research and pilot stages. Furthermore, in the proof of concept stage, we find a significant positive association between CBDC-related news and systemic risk in the short run. Finally, we find that CBDC indices have a significant negative long-run association with systemic risk across all the geographical regions but with some heterogeneity in the magnitude: South & East Asia and the Pacific region has the strongest association, followed by North & Latin America and Caribbean region and North & Sub-Saharan Africa and the Middle East region, and Europe and Central Asia region has the weakest association.

For the countries in the research and pilot stages of CBDC development, results are in line with the literature that suggests the possibility of disruptive outcomes of CBDC to the financial system and, therefore, central banks are advised to carefully design and implement the CBDCs (Hoang et al., 2023). As suggested by Allen et al. (2022), the success of CBDC very much depends on its level of adoption, and security and privacy risks are considered to be one of the major hurdles in the widespread acceptability of the digital currencies (Gupta et al., 2023; Tronnier et al., 2022). Therefore, central banks should devise strong cybersecurity guidelines and legislative frameworks to protect CBDC platforms and increase the confidence of market participants in the CBDC adaptation (Tian et al., 2023). Regulatory bodies should also work together to set strict online safety guidelines, ensuring that banks and tech companies follow industry best practices (Morales-Resendiz et al., 2021). Our results show that CBDC indices have system-wide implications that require countries to have backup plans and response procedures to quickly handle disruptions brought on by cyber-attacks and maintain public confidence in the financial system (Han et al., 2023; Poletykin and Promyslov, 2013). Furthermore, financial institutions must enhance their resilience and sustain stability in periods of increased demand for digital currencies by putting in place stress-testing procedures and flexible liquidity facilities (Bibi and Canelli, 2023).

The rest of the paper is structured as follows; Section 2 provides a review of the literature on CBDC and its implications for the financial system, Section 3 discusses the data, Section 4 presents the econometric methodology, Section 5 provides the results and discussion, and Section 6 concludes the paper.

2. Literature review

The literature on CBDC is growing and focuses on the motivation of central banks to issue and adopt digital currency, and its impact on financial inclusion, transaction efficiency, and cost reduction in traditional payment systems. Existing literature also links CBDC with cryptocurrency markets, volatility spillover on banks, and the overall financial sector's stability.

Alfar et al. (2023) explore several factors that may motivate central banks to issue CBDCs and find that CBDCs are being issued more actively by developing economies while regulatory policies, foreign direct investment, demographics, and countries' technical factors have a significant role in driving CBDC adoption. Similarly, Hoang et al. (2023) evaluate the reasons behind the adoption of CBDC in advanced and developing economies and conclude that advanced economies place more emphasis on financial stability and domestic payment efficiency while emerging countries prioritize financial inclusion and cross-border payments. Gupta et al. (2023) explore the relationship between perceived risks, benefits, trust, and the adoption of CBDC in India (digital rupee). The study analyzes six perceived risk factors (financial, regulatory, security, privacy and anonymity, operational and inertia), and four perceived benefits factors (usefulness, ease of use, awareness, and innovativeness) that influence CBDC adoption. Gupta et al. (2023) conclude that all the perceived factors influence readiness to accept digital currency except for usefulness. The study also highlights the moderating role of trust in promoting acceptance and desire to use CBDC.

Chen and Siklos (2023) study the global landscape of digital currencies and discuss the acceleration of retail digital currency plans by the central banks, especially in the context of the pandemic. The authors discuss how digitalization may lead to currency replacement and estimate the possibility of such a replacement using data from developed and developing economies. The authors also highlight the need for coordinated regulatory efforts for the effective implementation of CBDCs and propose that countries may be encouraged to adopt best practices in macroeconomic management through a flexible regulatory environment and cross-border CBDC holdings. In the context of CBDC becoming the medium of exchange in international trade, Kuehnlenz et al. (2023) report that the adoption of CBDCs might lead to the decentralization of the international payment system, however, CBDC will not completely replace the key currencies, such as the US dollar, of the international monetary framework. Concerns are also raised over how the issuance of CBDCs may affect commercial banks and how the effective payment mechanism may cause a disruption to conventional bank deposits. The existing literature uses a payment portfolio model to ascertain the crowding-out effect of CBDC on bank deposits. Bian et al. (2021) models the choice of economic agents from cash, deposits, and CBDC to optimize their utility while meeting payment needs. Their model shows that demand for CBDC may lead to a reduction in cash and deposit holdings, under certain conditions, suggesting that CBDC offers an efficient payment alternative, but it may create challenges for commercial banks and pose stability concerns.

So far, retail CBDCs have only been launched in a few countries. Among these, some were withdrawn (Finland and Ecuador) while others (The Bahamas, Jamaica, and Nigeria) received limited initial adoption in retail transactions (Dowd, 2024). Moreover, in its report, the UK Economic Affairs Committee concluded that there was no convincing case for the need of CBDC in the UK and, while there may be some potential advantages, a CBDC could pose challenges for financial stability. This indicates the possibility of non-adoption of retail CBDCs on a substantial scale, suggesting a limited impact of CBDCs on the conventional banking system.

Another strand of literature links CBDC with other cryptocurrencies. For instance, Helmi et al. (2023) explore the impact of CBDC news on financial and cryptocurrency markets and demonstrate that CBDC news negatively affects Bitcoin returns, especially during periods of increased CBDC-related news. Furthermore, CBDC news shocks positively influence cryptocurrency uncertainty, suggesting that widespread CBDC adoption could aid in regulating the Bitcoin market and conducting independent monetary policy. Scharnowski (2022) reports that positive CBDC news from central bank speeches increases the prices of cryptocurrencies, however, any negative news increases the volatility. Moreover, the market participants do not consider CBDC development news as a possible peril, but they consider it as a positive development in favor of all the digital currencies (Scharnowski, 2022).

Minesso et al. (2022) studied the open-economy implications of CBDC for shock transmission, optimum monetary policy, and welfare using a two-country DSGE model. Their simulations show the need for more reactive monetary policies, at national and international levels, as CBDC may reduce monetary policy autonomy in foreign economies. Their results also show that international linkages and shock spillovers are amplified and strengthened when a CBDC is present. They concluded that: (i) the magnitude of such an impact depends on how the CBDC is designed and (ii) the issuance of one country's CBDC diminishes the other economy's welfare and monetary policy autonomy. Consequently, they stress carefully designing the CBDCs as these can contribute to the asymmetry in the global monetary system. Mzoughi et al. (2022) conducted an event study to examine the impact of the Bahamas' SANDDollar and Nigeria's eNaira on the Bitcoin market. Authors report that the Bitcoin market showed a strong reaction towards the SANDDollar wherein Bitcoin investors shifted from Bitcoin to SANDDollar due to its safety and convertibility. However, considering a limited adoption of SANDDollar, compared to Bitcoin trade volume, these findings have significant limitations in terms of generalization.[1]

[1] In 2024, SANDDollar accounts for less than 1 percent of the currency in circulation in the Bahamas (Reuters).

Yousaf and Goodell (2023) explores the relationship between the CBDC Uncertainty index, cryptocurrency policy uncertainty, cryptocurrency price uncertainty, and digital payment stock returns and volatility. The findings indicate that external factors influence the CBDC Uncertainty index, while cryptocurrency policy and price uncertainties affect other variables. The authors report that most digital payment stocks are impacted, except major players like VISA, MasterCard, and American Express. Interestingly, weak connections were found between uncertainty indices and digital payment stocks, highlighting the ability of stocks to hedge against CBDC and cryptocurrency market uncertainties. In another study, Castrén et al. (2022) analyzes the effects of CBDC on financial accounts and network structure and demonstrates that the introduction of CBDC leads to funding shortages in banks, triggering adjustments in balance sheets across sectors and influencing securities prices and financial network structure. Furthermore, they extend their analysis to include the introduction of stablecoins and further provide a comprehensive understanding of the potential implications of various digital financial assets.

Allen et al. (2022) reviews the literature on multiple dimensions of CBDC and discusses the exponential expansion of cryptoassets and its effects on investments, wealth management, and payments. The authors conclude that CBDCs, especially e-CNY, could become a mainstream currency in the global financial system if the regulatory framework provides incentives and protection to the market participants. The authors also discussed important factors to consider while creating legislation for cryptocurrencies and stated that CBDC introduction could potentially resolve the inherent problems of traditional financial systems if it becomes the mainstream currency. However, the authors' conclusions are drawn from a single country's CBDC experience, which may have limited generalizability.

Finally, a stream of literature focuses on the implications of CBDC for the financial sector's stability. Chen and Siklos (2022) highlights various challenges faced by CBDC related to legal, technological, and political considerations. They studied CBDC under two versions; a narrow version in which CBDC may replace physical notes and coins and a broader version that has a deposit feature. Through historical data analysis and simulations, Chen and Siklos (2022) finds that while CBDC may not contribute to higher inflation, the financial sector's stability remains a concern. Similarly, Son et al. (2023) also highlights that CBDC issuance might work as a double-edged sword by providing benefits like payment choices but increasing the risk for financial intermediaries through higher costs and lower margins. Bindseil (2020) raises similar concerns by highlighting the risk implications arising from CBDC in the form of possible structural disintermediation of banks, centralization of credit allocation within central banks, and facilitation of systemic runs on banks in crises.

Contrary to the aforementioned literature, the empirical findings show the financial system stabilizing benefits of CBDC-related developments. For instance, Wang et al. (2022) conducted a comprehensive analysis of CBDC-related news and proposed CBDC Uncertainty and Attention indices. Their results show that these indices are negatively related to the volatility of banking sectors and stock markets. Similarly, Luu et al. (2023) reports that CBDC adoption increases the financial stability of the banking sector and emerging economies tend to have greater benefits from CBDC adoption compared to the developed economies. Regarding retail and wholesale CBDC, Luu et al. (2023) find that retail CBDC enhances whereas wholesale CBDC dampens financial stability. Li et al. (2022) examine CBDC signals from central banks on the FinTech sector. Using a signal index of CBDC, the authors report that CBDC news positively impacts the FinTech sector, however, this impact is prevalent in the short term and decreases over the long term. The contrasting evidence on the stabilizing role of CBDC for the financial sector provides a gap that can help investors, policymakers, regulators, and the broader group of stakeholders to understand CBDC's impact on systemic risk. Our study contributes to this body of literature by investigating the short and long-run association of CBDC Uncertainty and Attention indices with systemic risk using a panel of 50 countries.

3. Data

To examine the association between CBDC-related news and systemic risk, we focus on countries involved in CBDC development and were listed on CBDC Tracker database at the time of acquiring the data. We use CATFIN to measure systemic risk for the countries in our sample which was introduced by Allen et al. (2012) who shows that it can forecast macroeconomic downturns six months into the future. Moreover, Giglio et al. (2016) shows that CATFIN is among the best-performing individual measures of systemic risk in its ability to forecast macroeconomic downturns.[2]

CATFIN is the average of three different estimates of the financial sector's Value-at-Risk (VaR). Following Giglio et al. (2016), we use the non-parametric version because the three VaR estimates are strongly correlated with each other (Allen et al., 2012).[3] Daily CATFIN is estimated using stock price data of banks and financial institutions of sample countries.[4,5] We did not include countries with stock price data on less than three banks and financial institutions available on Refinitiv Eikon. Our final sample consisted of 50 countries and Appendix A provides details about the number of banks and financial institutions used for each country. We took the weekly average of the estimated CATFIN to match it with the weekly data on the CBDC Uncertainty Index ($CBDC^{UI}$) and Attention Index ($CBDC^{AI}$) developed by Wang et al. (2022), acquired from the authors' onlineresource. The sample period starts from the first week of 2015 and ends in the last week of 2022.

2 Ahmad et al. (2021) also highlight the predictive power of CATFIN in forecasting downturns in Total Industrial Production, Financial Stress Index, and Chicago Fed National Activity Index for the US.

3 The non-parametric version of VaR is based on the cutoff point for the lower α percentile of the excess return.

4 Non-parametric CATFIN was estimated using the Systemic Risk repository by Belluzzo (2023) and standardized at the country level for ease of interpretation.

5 For countries with many banks and financial institutions, e.g., the US, the sample was restricted to the 50 largest banks and financial institutions based on the total reported assets.

Table 1
The eigenvalues, proportion of variance explained by the components, and eigenvectors for the principal component analysis and descriptive statistics.

	Component 1	Component 2	Statistic	$CBDC^{UI}$	$CBDC^{AI}$	$CBDC^{PCA}$
Eigenvalue	1.9140	0.0860	Obs.	416	416	416
Proportion	0.9570	0.0430	Mean	100.48	100.49	0.00
Eigenvectors			Std. Dev.	1.4275	1.4607	1.3834
$CBDC^{UI}$	0.7071	0.7071	Min.	99.1167	99.4419	−1.1584
$CBDC^{AI}$	0.7071	−0.7071	Max.	106.1566	106.0224	5.3353

Note: This table provides the eigenvalues, proportion of variance explained by the components, and eigenvectors for the principal component analysis using the uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices to construct their first principal component ($CBDC^{PCA}$). The table also reports the descriptive statistics for $CBDC^{UI}$, $CBDC^{AI}$, and $CBDC^{PCA}$.

Wang et al. (2022) developed these indices by collecting data on news stories related to CBDC. The authors conducted multiple searches in the LexisNexis database by combining different keywords related to CBDC. To account for news stories in different countries and languages, authors also used keywords in non-English languages. By doing so, authors collected 663,881,640 news items between January 2015 and June 2021 and constructed $CBDC^{UI}$ and $CBDC^{AI}$ as follows:

$$\begin{aligned} CBDC_t^{UI} &= \frac{N_{1t}-\mu_1}{\sigma_1}+100 \\ CBDC_t^{AI} &= \frac{N_{2t}-\mu_2}{\sigma_2}+100 \end{aligned} \tag{1}$$

where N_{1t} and N_{2t} are the number of news articles related to CBDC uncertainty and attention on LexisNexis observed for week t, μ_1 and μ_2 are the means of N_{1t} and N_{2t}, and σ_1 and σ_2 are the standard deviations of N_{1t} and N_{2t}, respectively. According to the authors, $CBDC^{AI}$ is based on the number of weekly news articles observed on LexisNexis related to CBDC whereas $CBDC^{UI}$ is based on only those weekly news items where the term 'uncert!' is added in the search keywords with the link of 'and'. Hence, the former measures the attention given to CBDC while the latter shows the element of uncertainty surrounding the CBDC.

Although there is a difference in how these two indices are defined, statistically, we found that indices are strongly correlated (91.39%). Therefore, to capture information from both indices, we conducted principal component analysis (PCA) and used the first principal component of $CBDC^{UI}$ and $CBDC^{AI}$ as our main variable of interest, which is referred to as $CBDC^{PCA}$. It is worth mentioning that the $CBDC^{PCA}$ is not necessarily a measure showing inherent risks in CBDC rather it shows how much news coverage CBDC is receiving globally.

Table 1 presents the output of PCA and the descriptive statistics for $CBDC^{UI}$, $CBDC^{AI}$, and $CBDC^{PCA}$. The table shows that the eigenvalue for the first component is safely above 1 and it explains 95.70% of the variance. The eigenvectors show that $CBDC^{UI}$ and $CBDC^{AI}$ are positively associated with and equally important for the first component. Fig. 1 plots $CBDC^{PCA}$ against $CBDC^{UI}$ and $CBDC^{AI}$, which shows that the two CBDC indices depict similar movements and the first principal component is strongly correlated with these indices.

4. Econometric methodology

In this section, we provide the econometric methodology used to establish the short- and long-run relationship between $CBDC^{PCA}$ and systemic risk.[6] GMM estimators proposed by Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) are frequently used for macro panel data (Samargandi et al., 2015). However, Roodman (2009) points out that in situations with small N and large T, the GMM estimators can produce spurious results. In our context, we have 50 countries, and the number of observations ranges from 336 to 416, which suggests that the GMM estimators may not be reliable or consistent. Moreover, these estimators pool individual groups and only allow intercepts to vary across groups, thus, imposing homogeneity on coefficients of lagged dependent variables, which could result in biases unless coefficients are identical across the groups (Pesaran, 1997; Im et al., 2003; Pesaran et al., 1997, 1999).

We utilize dynamic panel heterogeneity analysis, introduced by Pesaran et al. (1999), which can be used to estimate non-stationary dynamic panel models that allow heterogeneous parameters across groups. These estimators have been used to establish long-term relationships; see Frank et al. (2005), Samargandi et al. (2015), and Sohag et al. (2015). We denote the autoregressive distributed lag approach with p and q lags of dependent and independent variables as ARDL(p,q), which is given as:

$$\Delta CATFIN_{i,t} = \mu_i + \sum_{j=1}^{p} \gamma_{i,j} CATFIN_{i,t-j} + \sum_{j=0}^{q} \delta_{i,j} CBDC_{t-j}^{PCA} + \epsilon_{i,t} \tag{2}$$

In Eq. (2), i represents the country, t represents time at a weekly frequency, and μ_i is the intercept. In the error correction form, ARDL(p,q) can be rewritten as:

$$\Delta CATFIN_{i,t} = \mu_i + \sum_{j=1}^{p-1} \alpha_{i,j} \Delta CATFIN_{i,t-j} + \sum_{j=0}^{q-1} \beta_{i,j} \Delta CBDC_{t-j}^{PCA}$$

[6] As a robustness check, we examine how $CBDC^{UI}$ and $CBDC^{AI}$ are individually related to systemic risk in Appendix C.1.

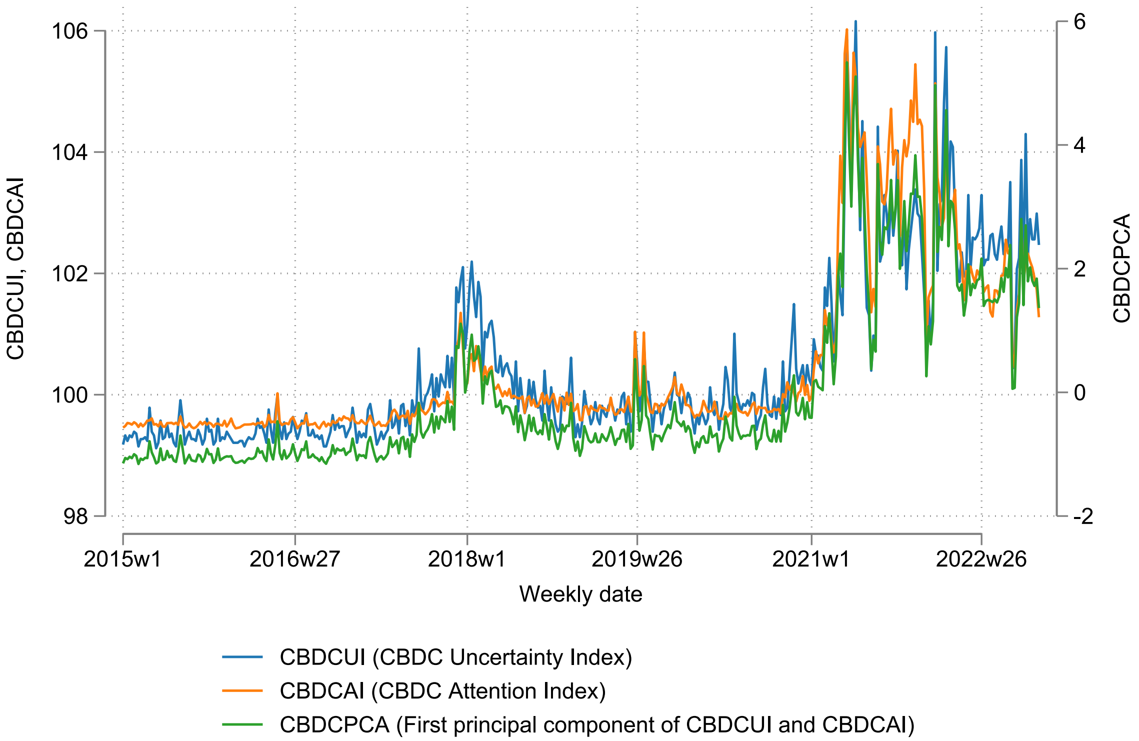

Fig. 1. CBDC indices and their first principal component.
Note: The figure shows the weekly observations of CBDC Uncertainty and Attention indices (left axis) in blue and orange lines, respectively, and their first principal component (right axis) in green line. The observations range from the first week of 2015 to the last week of 2022. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$+ \phi_i \left(CATFIN_{i,t-1} - \theta_i CBDC_t^{PCA} \right) + \epsilon_{i,t} \tag{3}$$

In Eq. (3), $\alpha_{i,j}$'s and $\beta_{i,j}$'s are the short-run coefficients for the lagged dependent and independent variables, respectively, Δ represents the first difference, ϕ_i is the error correction term (speed of adjustment to the long-run), and θ_i represents the long-run impact of $CBDC^{PCA}$ on systemic risk and we have the following:

$$\alpha_{i,j} = -\sum_{m=j+1}^{p} \gamma_{i,j}$$

$$\beta_{i,j} = -\sum_{m=j+1}^{q} \delta_{i,m}$$

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \gamma_{i,j}\right)$$

$$\theta_i = -\frac{1}{\phi_i} \sum_{j=0}^{p} \delta_{i,j}$$

One benefit of the ARDL model is that it is applicable even when variables have different orders of integration as long as the variables are $I(0)$ or $I(1)$ (Pesaran et al., 1995). Using the Augmented Dickey–Fuller (ADF) test for each country in the sample, we show that $CATFIN$ and $CBDC^{PCA}$ have an order of integration of either $I(0)$ or $I(1)$ since the null hypothesis of a unit root is rejected for all countries for the first differences of these variables (Table B.1). Eq. (3) can be estimated using three different estimators and we briefly discuss these here.

Pooled mean group (PMG):. The PMG estimator, introduced by Pesaran et al. (1999), assumes common long-run coefficients across countries and allows heterogeneity in short-run coefficients, intercepts, speed of adjustment, and error variances among countries. This is suitable in our context because we expect the long-run relationship between CBDC and systemic risk to be similar across countries due to cross-country spillovers (McLemore et al., 2022). The validity, consistency, and efficiency of the PMG estimator require that the speed of adjustment term is negative and not lower than −2, residuals are serially uncorrelated, explanatory variables are treated as exogenous, and N and T should be large (Samargandi et al., 2015).

Table 2
The estimated coefficients for the baseline estimation.

Variable	PMG	MG	DFE
Error correction	−0.0626***	−0.0647***	−0.0564***
	(0.0025)	(0.0026)	(0.0023)
$\Delta CBDC^{PCA}$	0.0077	0.0057	0.0048
	(0.0145)	(0.0161)	(0.0130)
$\Delta^2 CBDC^{PCA}$	0.0205	0.0229	0.0234
	(0.0228)	(0.0247)	(0.0213)
$\Delta^3 CBDC^{PCA}$	−0.0171	−0.0186	−0.0182
	(0.0151)	(0.0160)	(0.0157)
$\Delta^4 CBDC^{PCA}$	0.0050	0.0053	0.0052
	(0.0039)	(0.0040)	(0.0044)
COVID-19	0.0903***	0.0912***	0.0858***
	(0.0090)	(0.0100)	(0.0086)
$CBDC^{PCA}$	−0.2431***	−0.2300***	−0.2335***
	(0.0385)	(0.0371)	(0.0437)
Constant	0.1661	0.1908**	0.2218**
	(0.1033)	(0.0948)	(0.1078)
Observations	20,520	20,520	20,520
Countries	50	50	50
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−1.794	−0.0707

Note: This table presents the estimated coefficients for Eq. (3). $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Mean group (MG):. Pesaran and Smith (1995) introduced the MG estimator, which does not impose any restrictions on short- and long-run coefficients across countries. The consistency and validity of this estimator require sufficiently large T and at least 20–30 countries (Samargandi et al., 2015). Since we have 50 countries and the number of observations ranges from 336 to 416, we expect this estimator to be appropriate in our context as well.

Dynamic fixed effects (DFE):. The DFE estimator allows country-specific intercepts but restricts the speed of adjustment and the short- and long-run coefficients across countries.

Among the PMG, MG, and DFE estimators, we select the appropriate estimator using the Hausman test for which the null hypothesis is that the difference between PMG and MG or PMG and DFE estimation is not significant. If we are unable to reject the null hypothesis, then the PMG estimation is recommended owing to its efficiency. Aside from selecting an appropriate estimator, we also need to determine the ARDL lag structure, for which we rely on the Bayesian Information Criterion (BIC).[7]

5. Results and discussion

In this section, we first present the baseline results, which are then extended by exploring heterogeneity impacts based on the country's income level, development status of CBDC, and geographical region. Then, we discuss the results.

5.1. Baseline results

The estimated coefficients for Eq. (3), with the inclusion of a dummy for COVID-19 and time trend (Pesaran et al., 1999), are provided in Table 2. Regarding estimator selection, the negative value of the Hausman χ^2, which is strong evidence that the null hypothesis cannot be rejected, suggests that the PMG estimation is recommended. Furthermore, according to BIC, the selected lag order for the estimation is ARDL(1, 4). We find a negative and significant long-run association between $CBDC^{PCA}$ and systemic risk across all estimators with similar magnitudes. This is in line with the existing literature suggesting that CBDC Uncertainty and Attention indices are negatively related to financial sector volatility (Wang et al., 2022). The baseline results show that $CBDC^{PCA}$ has no association with systemic risk in the short-run as the coefficients of $\Delta^d CBDC^{PCA}$, where d represents the differencing order, are insignificant across all estimators.[8] Significance in the long run and insignificance in the short run suggest

[7] The maximum lags on $CBDC_t^{PCA}$ are capped at four for the lag selection. Appendix C.2 shows that our results are robust to the choices of information criteria for lag selection and maximum lags allowed.

[8] Appendix C.1 shows a statistically significant but directionally inconclusive short-run association between $CBDC^{UI}$ and systemic risk whereas $CBDC^{AI}$ mirrors the baseline findings.

Table 3
The categorization of sample countries into low, middle, and high income countries.

Low-income	Middle-income	High-income
Brazil	Argentina	Australia
China	Chile	Austria
Egypt	Cyprus	Belgium
India	Czech Republic	Canada
Indonesia	France	Denmark
Jordan	Greece	Finland
Lebanon	Hungary	Hong Kong
Malaysia	Israel	Ireland
Mexico	Italy	Netherlands
Morocco	Japan	Norway
Nigeria	Oman	Singapore
Pakistan	Poland	Sweden
Peru	Portugal	Switzerland
Philippines	Saudi Arabia	UAE
Russia	South Korea	UK
South Africa	Spain	USA
Thailand	Turkey	
[1473.86, 11223.15]	[12402.49, 40802.14]	[42535.97, 88966.67]

Note: This table presents the countries categorized as low, middle, and high income using terciles of real GDP per capita (constant 2015 US$). The bottom row presents the real GDP per capita range for the three categories.

that market participants do not immediately react to CBDC-related news rather they incorporate the informational content over the longer horizon. In line with the existing literature (Rizwan et al., 2022, 2020), the coefficient of COVID-19 is significant and positive suggesting the systemic instability costs of the COVID-19 pandemic. We also find that the speed of adjustment is negative and significant for all estimators, which validates our estimations (Samargandi et al., 2015).

5.2. Heterogeneity of impacts

This subsection explores heterogeneity in the impact of $CBDC^{PCA}$ on systemic risk by estimating Eq. (3) across income levels, CBDC developmental stages, and geographical regions of countries.[9] Such an analysis is motivated by the existing literature showing that the impact of different regulatory and financial factors on systemic risk depends on income-level (Rizwan, 2021) and institutional environment of countries (Rizwan et al., 2023), and regional interconnectedness (Fang et al., 2019). Furthermore, market participants may react differently to CBDC-related news based on the level of the country's CBDC development.

5.2.1. Income level

First, we explore how the association of $CBDC^{PCA}$ with systemic risk might vary based on the income level of countries. The countries were categorized as low, middle, and high-income using terciles of the real GDP per capita in 2021.[10] Table 3 lists the countries and the range of real GDP per capita in low, middle, and high-income categories.

Table 4 shows the estimation results of Eq. (3) for low-income countries with a lag structure of ARDL$(1,4)$, based on BIC, and PMG as the recommended estimator according to the Hausman test. The estimated results show a highly significant negative association between $CBDC^{PCA}$ and systemic risk in the long run. In the short run, $CBDC^{PCA}$ has a mixed association with systemic risk, as seen by the opposing signs of the significant differenced terms. This suggests that, even though CBDC news has systemic stability benefits in the long run, it has a mixed role in the short run.

For middle-income countries, BIC recommends a lag structure of ARDL$(1,4)$ and the recommended estimator is PMG, as shown in Table 5. The estimated results show a significant and negative long-run association between $CBDC^{PCA}$ and systemic risk. Directionally, this long-run association is similar to low-income countries, but it is not as strong as shown by its smaller magnitude and significance level of 10%. The short-run coefficients for middle-income countries are consistently significant but directionally cyclical, similar to low-income countries.

The estimated results for high-income countries are provided in Table 6 where ARDL$(1,0)$ structure is used based on BIC and PMG is the recommended estimator according to the Hausman test. The estimated results show that $CBDC^{PCA}$ has a significant negative association with systemic risk in the long run with a magnitude similar to low-income countries.

In summary, the income-level-based sub-sample analysis shows that the long-run association between $CBDC^{PCA}$ and systemic risk is consistently negative and significant. This suggests that market participants, irrespective of the country's income level, consider CBDC-related developments as a positive sign for the long-term sustainability of the financial system. In terms of magnitude,

[9] The sub-sample analysis in this sub-section has fewer panels, however, we draw confidence from the fact that Pesaran et al. (1999) provide two empirical applications of the PMG estimator with (i) $N = 24$ and $T = 31$ and (ii) $N = 10$ and $T = 17$.

[10] Instead of using income classification of countries by the World Bank, we rely on terciles of GDP per capita in 2021 to ensure that we have a reasonable number of countries for each sub-sample.

Table 4
The estimated coefficients for low income countries.

Variable	PMG	MG	DFE
Error correction	−0.0617***	−0.0645***	−0.0577***
	(0.0040)	(0.0041)	(0.0040)
$\Delta CBDC^{PCA}$	0.0525**	0.0500**	0.0495**
	(0.0247)	(0.0237)	(0.0228)
$\Delta^2 CBDC^{PCA}$	−0.0633	−0.0607	−0.0605
	(0.0385)	(0.0383)	(0.0372)
$\Delta^3 CBDC^{PCA}$	0.0444*	0.0430	0.0444
	(0.0267)	(0.0267)	(0.0274)
$\Delta^4 CBDC^{PCA}$	−0.0120*	−0.0117*	−0.0122
	(0.0063)	(0.0063)	(0.0078)
COVID-19	0.0718***	0.0724***	0.0698***
	(0.0149)	(0.0166)	(0.0147)
$CBDC^{PCA}$	−0.3116***	−0.2689***	−0.2941***
	(0.0676)	(0.0768)	(0.0739)
Constant	−0.1314	−0.1025	−0.0656
	(0.1572)	(0.1383)	(0.1860)
Observations	6924	6924	6924
Countries	17	17	17
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		0.244	1
Hausman χ^2		1.359	−0.0755

Note: This table presents the estimated coefficients for Eq. (3) for low income countries. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 5
The estimated coefficients for middle income countries.

Variable	PMG	MG	DFE
Error correction	−0.0674***	−0.0692***	−0.0602***
	(0.0046)	(0.0048)	(0.0041)
$\Delta CBDC^{PCA}$	−0.0490**	−0.0478	−0.0458*
	(0.0239)	(0.0321)	(0.0239)
$\Delta^2 CBDC^{PCA}$	0.1187***	0.1177***	0.1130***
	(0.0341)	(0.0435)	(0.0392)
$\Delta^3 CBDC^{PCA}$	−0.0812***	−0.0807***	−0.0771***
	(0.0203)	(0.0245)	(0.0288)
$\Delta^4 CBDC^{PCA}$	0.0205***	0.0204***	0.0194**
	(0.0058)	(0.0064)	(0.0082)
COVID-19	0.0783***	0.0806***	0.0794***
	(0.0174)	(0.0196)	(0.0156)
$CBDC^{PCA}$	−0.1158*	−0.1492**	−0.1328*
	(0.0669)	(0.0605)	(0.0758)
Constant	0.2828	0.2790	0.3129
	(0.2413)	(0.2074)	(0.1994)
Observations	7004	7004	7004
Countries	17	17	17
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−1.384	−0.0743

Note: This table presents the estimated coefficients for Eq. (3) for middle income countries. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 6
The estimated coefficients for high income countries.

Variable	PMG	MG	DFE
Error correction	−0.0581***	−0.0598***	−0.0515***
	(0.0046)	(0.0044)	(0.0038)
COVID-19	0.1198***	0.1203***	0.1053***
	(0.0127)	(0.0130)	(0.0143)
$CBDC^{PCA}$	−0.2726***	−0.2378***	−0.2419***
	(0.0601)	(0.0663)	(0.0696)
Constant	0.4032***	0.4484***	0.4456***
	(0.0912)	(0.1011)	(0.1651)
Observations	7472	7472	7472
Countries	16	16	16
Lag order	ARDL(1, 0)	ARDL(1, 0)	ARDL(1, 0)
Time trend	Yes	Yes	Yes
Hausman *p*-value		0.221	1
Hausman χ^2		1.498	−0.291

Note: This table presents the estimated coefficients for Eq. (3) for high income countries. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman *p*-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 7
The yearly breakdown of the number of countries by CBDC stages.

Stage of CBDC	2014	2015	2016	2017	2018	2019	2020	2021	2022
Status quo	50	50	48	45	41	38	32	26	13
Research	0	1	4	8	10	14	14	22	22
Proof of concept	0	0	0	1	1	5	9	11	12
Pilot	0	0	0	0	0	2	5	8	8

Note: This table presents the yearly breakdown of the number of countries in different CBDC stages. In any year, the sum of countries across the different stages can exceed 50 as the status of a country can change during the listed year.

systemic risk shows a stronger association with $CBDC^{PCA}$ in low and high-income countries compared to middle-income countries. However, the results show over-reaction and subsequent correction of systemic risk to CBDC-related developments in the short-run for low and middle-income countries.

5.2.2. CBDC development stages

In this subsection, we discuss the results of the heterogeneity of association of $CBDC^{PCA}$ with systemic risk based on the status of CBDC development.[11] We collected time-variant data on a country's CBDC development stage from CBDCTracker database. The developmental stages are categorized as (i) research, which includes countries that have conducted their first explanatory CBDC research, (ii) proof of concept, which includes countries in the advanced research stage and have published a proof of concept, (iii) pilot, which includes countries that have developed a CBDC that is tested in a real environment, and (iv) status quo, which includes countries before conducting any explanatory CBDC research. Table 7 shows the yearly breakdown of the number of countries in various stages of CBDC development. It is noteworthy that the sum of rows can exceed 50 as the development stage of some countries changes during the given year.

To have sufficient observations for each panel, we include only those countries that have at least 30 observations for each stage. We have 49, 31, 12, and 8 countries for the status quo, research, proof of concept, and pilot sub-samples, respectively. The estimated results for the status quo stage of CBDC are presented in Table 8. Based on the Hausman test, the PMG estimator is recommended. The estimated results are similar to our findings from the baseline estimation wherein $CBDC^{PCA}$ has a significant negative long-run association with systemic risk but is insignificant in the short-run.

For the research stage of CBDC, the estimated results are presented in Table 9. At the 5% significance level, we accept PMG as the appropriate estimator for this stage with a lag structure of ARDL(1, 2) based on BIC. Contrary to the status quo stage, $CBDC^{PCA}$ has a significant positive association with systemic risk in the long run for countries in the research stage of CBDC development. Meanwhile, similar to the status quo stage, $CBDC^{PCA}$ does not have any short-run association with systemic risk.

Table 10 presents the estimated results for the proof of concept stage of CBDC. We use a lag order of ARDL(1, 4) based on BIC. For this stage, we find a negative and significant long-run association between $CBDC^{PCA}$ and systemic risk and no significant short-run

[11] Since COVID-19 may not have occurred in some sub-samples and be ever present in others, we do not include it as a dummy variable for the estimations in this subsection.

Table 8
The estimated coefficients for countries in the status quo stage of CBDC.

Variable	PMG	MG	DFE
Error correction	−0.0599***	−0.0628***	−0.0527***
	(0.0051)	(0.0054)	(0.0028)
$\Delta CBDC^{PCA}$	0.0314	0.0973	−0.0130
	(0.0666)	(0.0778)	(0.0219)
$\Delta^2 CBDC^{PCA}$	−0.0298	−0.0978	0.0426
	(0.1068)	(0.1114)	(0.0359)
$\Delta^3 CBDC^{PCA}$	0.0209	0.0561	−0.0243
	(0.0704)	(0.0717)	(0.0264)
$\Delta^4 CBDC^{PCA}$	−0.0083	−0.0159	0.0058
	(0.0181)	(0.0184)	(0.0075)
$CBDC^{PCA}$	−0.1336**	−0.4479	−0.2034***
	(0.0548)	(0.4161)	(0.0703)
Constant	−0.9393*	−0.9831*	−0.5153***
	(0.5256)	(0.5523)	(0.1107)
Observations	13,944	13,944	13,944
Countries	49	49	49
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		0.447	1
Hausman χ^2		0.577	−1.899

Note: This table presents the estimated coefficients for Eq. (3) for countries in the status quo stage of CBDC. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 9
The estimated coefficients for countries in the research stage of CBDC.

Variable	PMG	MG	DFE
Error correction	−0.0746***	−0.0819***	−0.0606***
	(0.0085)	(0.0120)	(0.0053)
$\Delta CBDC^{PCA}$	−0.0023	0.0180	0.0210
	(0.0151)	(0.0232)	(0.0131)
$\Delta^2 CBDC^{PCA}$	0.0057	−0.0025	−0.0044
	(0.0071)	(0.0107)	(0.0077)
$CBDC^{PCA}$	0.2068***	−0.2199	0.0111
	(0.0655)	(0.2636)	(0.0844)
Constant	2.1244	2.7399	−0.4128
	(1.7666)	(3.0686)	(0.2955)
Observations	3903	3903	3903
Countries	31	31	31
Lag order	ARDL(1, 2)	ARDL(1, 2)	ARDL(1, 2)
Time trend	Yes	Yes	Yes
Hausman p-value		0.0983	1
Hausman χ^2		2.733	−10.37

Note: This table presents the estimated coefficients for Eq. (3) for countries in the research stage of CBDC. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

association for PMG estimation. However, for the MG estimation, which is preferred over PMG estimation based on the Hausman test at the 5% significance level, there is no significant long-run association of $CBDC^{PCA}$ with systemic risk, but it does show a significant positive association in the short-run.

For the pilot stage of CBDC, the estimated results are provided in Table 11. Based on the Hausman test, we find that the PMG estimator is recommended and we use a lag structure of ARDL(1, 0) according to BIC. The estimated results indicate a significant positive association between $CBDC^{PCA}$ and systemic risk in the long run for PMG.

Overall, the results of this subsection indicate that countries in the advanced stages of CBDC development face adverse systemic implications from CBDC-related news. This is in line with Chen and Siklos (2022) who raised macroeconomic stability concerns of CBDCs.

Table 10
The estimated coefficients for countries in the proof of concept stage of CBDC.

Variable	PMG	MG	DFE
Error correction	−0.0643***	−0.0660***	−0.0517***
	(0.0109)	(0.0108)	(0.0073)
$\Delta CBDC^{PCA}$	0.0365	−0.0724	−0.0259
	(0.0370)	(0.0479)	(0.0331)
$\Delta^2 CBDC^{PCA}$	−0.0126	0.1097	0.0708
	(0.0628)	(0.0707)	(0.0531)
$\Delta^3 CBDC^{PCA}$	−0.0009	−0.0685	−0.0489
	(0.0386)	(0.0437)	(0.0387)
$\Delta^4 CBDC^{PCA}$	0.0011	0.0156*	0.0114
	(0.0081)	(0.0089)	(0.0109)
$CBDC^{PCA}$	−0.2295**	0.7469	−0.0651
	(0.0963)	(0.4869)	(0.1498)
Constant	4.3113*	2.9034*	0.0247
	(2.2942)	(1.6276)	(0.6323)
Observations	1,483	1,483	1,483
Countries	12	12	12
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		0.0432	1
Hausman χ^2		4.087	−3.615

Note: This table presents the estimated coefficients for Eq. (3) for countries in the proof of concept stage of CBDC. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 11
The estimated coefficients for countries in the pilot stage of CBDC.

Variable	PMG	MG	DFE
Error correction	−0.0426***	−0.0429***	−0.0334***
	(0.0103)	(0.0103)	(0.0088)
$CBDC^{PCA}$	0.3262*	2.1394	0.1649
	(0.1832)	(1.8204)	(0.2537)
Constant	0.6659	0.4205	1.3558
	(1.6387)	(1.5473)	(0.8411)
Observations	983	983	983
Countries	8	8	8
Lag order	ARDL(1, 0)	ARDL(1, 0)	ARDL(1, 0)
Time trend	Yes	Yes	Yes
Hausman p-value		0.318	1
Hausman χ^2		0.996	−0.908

Note: This table presents the estimated coefficients for Eq. (3) for countries in the pilot stage of CBDC. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

5.2.3. Geographical regions

To assess the role of regional interconnectedness in the association of CBDC-related news and systemic risk, the sample countries are categorized into four geographical regions, provided in Table 12. These geographical regions are based on the region classification of the World Bank wherein we combined nearby regions, e.g., North America (2 countries) and Latin America and the Caribbean (5 countries), to ensure a reasonable number of countries in each sub-sample.

Table 13 provides the estimated coefficients for Europe and Central Asia. At the 5% (10%) significance level of the Hausman tests, PMG (MG) estimation is preferred. Nonetheless, the conclusions under the two estimations are similar, i.e., $CBDC^{PCA}$ and systemic risk have a significant negative association for countries in the Europe and Central Asia region in the long run whereas the association is directionally cyclical in the short-run.

Table 14 presents the estimated results for countries in North & Latin America and the Caribbean. We cannot reject the null hypothesis of the Hausman tests and, therefore, PMG is the preferred estimation. Results show that $CBDC^{PCA}$ is significantly negatively associated with systemic risk in the long run for the North & Latin America and Caribbean region. It is noteworthy that the long-run impact for North & Latin America and the Caribbean is almost twice as much as the estimated coefficient for the Europe and Central Asia region.

Table 12
The geographical categorization of countries.

Region	No. of countries
Europe and Central Asia	21
North & Latin America and Caribbean	7
North & Sub-Saharan Africa and Middle East	10
South & East Asia and Pacific	12

Note: This table presents the four geographical regions the countries are categorized into and lists the number of countries in each region.

Table 13
The estimated coefficients for countries in Europe and Central Asia.

Variable	PMG	MG	DFE
Error correction	−0.0680***	−0.0694***	−0.0607***
	(0.0039)	(0.0041)	(0.0036)
$\Delta CBDC^{PCA}$	−0.0288	−0.0318	−0.0324
	(0.0245)	(0.0287)	(0.0206)
$\Delta^2 CBDC^{PCA}$	0.0922***	0.0961**	0.0953***
	(0.0353)	(0.0395)	(0.0337)
$\Delta^3 CBDC^{PCA}$	−0.0735***	−0.0759***	−0.0749***
	(0.0202)	(0.0212)	(0.0248)
$\Delta^4 CBDC^{PCA}$	0.0211***	0.0216***	0.0214***
	(0.0051)	(0.0050)	(0.0070)
COVID-19	0.1121***	0.1125***	0.1024***
	(0.0136)	(0.0160)	(0.0139)
$CBDC^{PCA}$	−0.1450***	−0.1154**	−0.1213*
	(0.0561)	(0.0581)	(0.0647)
Constant	0.4137**	0.4393***	0.4256**
	(0.1774)	(0.1548)	(0.1717)
Observations	8652	8652	8652
Countries	21	21	21
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		0.0585	1
Hausman χ^2		3.579	−0.205

Note: This table presents the estimated coefficients for Eq. (3) for countries in Europe and Central Asia. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively.

Table 14
The estimated coefficients for countries in North & Latin America and the Caribbean.

Variable	PMG	MG	DFE
Error correction	−0.0603***	−0.0628***	−0.0552***
	(0.0073)	(0.0074)	(0.0061)
COVID-19	0.0451	0.0451	0.0569**
	(0.0284)	(0.0337)	(0.0227)
$CBDC^{PCA}$	−0.2474**	−0.2489**	−0.2470**
	(0.1000)	(0.1025)	(0.1120)
Constant	−0.2764	−0.2455	−0.1242
	(0.3492)	(0.2485)	(0.2873)
Observations	3269	3269	3269
Countries	7	7	7
Lag order	ARDL(1, 0)	ARDL(1, 0)	ARDL(1, 0)
Time trend	Yes	Yes	Yes
Hausman p-value		0.950	1
Hausman χ^2		0.00399	−1.86e−05

Note: This table presents the estimated coefficients for Eq. (3) for countries in North & Latin America and the Caribbean. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

The estimated results for the North & Sub-Saharan Africa and Middle East region are provided in Table 15. PMG is the preferred estimation since we are unable to reject the null hypothesis of the Hausman tests. Again, we find a statistically significant negative

Table 15
The estimated coefficients for countries in North & Sub-Saharan Africa and the Middle East.

Variable	PMG	MG	DFE
Error correction	−0.0650***	−0.0668***	−0.0629***
	(0.0044)	(0.0048)	(0.0055)
$\Delta CBDC^{PCA}$	0.0791**	0.0823**	0.0911***
	(0.0376)	(0.0355)	(0.0312)
$\Delta^2 CBDC^{PCA}$	−0.1173**	−0.1219**	−0.1351***
	(0.0576)	(0.0567)	(0.0511)
$\Delta^3 CBDC^{PCA}$	0.0846**	0.0875**	0.0986***
	(0.0414)	(0.0413)	(0.0376)
$\Delta^4 CBDC^{PCA}$	−0.0209**	−0.0216**	−0.0244**
	(0.0103)	(0.0104)	(0.0107)
COVID-19	0.0618***	0.0631***	0.0657***
	(0.0144)	(0.0145)	(0.0200)
$CBDC^{PCA}$	−0.2180**	−0.2442***	−0.2553***
	(0.0886)	(0.0549)	(0.0924)
Constant	−0.0494	−0.0510	−0.0360
	(0.1914)	(0.2064)	(0.2521)
Observations	4040	4040	4040
Countries	10	10	10
Lag order	ARDL$(1,4)$	ARDL$(1,4)$	ARDL$(1,4)$
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−0.143	−0.199

Note: This table presents the estimated coefficients for Eq. (3) for countries in North & Sub-Saharan Africa and the Middle East. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table 16
The estimated coefficients for countries in South & East Asia and the Pacific.

Variable	PMG	MG	DFE
Error correction	−0.0524***	−0.0536***	−0.0468***
	(0.0051)	(0.0049)	(0.0041)
COVID-19	0.0990***	0.0986***	0.0898***
	(0.0151)	(0.0153)	(0.0156)
$CBDC^{PCA}$	−0.4201***	−0.3621***	−0.3800***
	(0.0735)	(0.0629)	(0.0860)
Constant	0.2252**	0.2641**	0.3178*
	(0.1107)	(0.1118)	(0.1852)
Observations	5604	5604	5604
Countries	12	12	12
Lag order	ARDL$(1,0)$	ARDL$(1,0)$	ARDL$(1,0)$
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−2.336	−0.329

Note: This table presents the estimated coefficients for Eq. (3) for countries in South & East Asia and the Pacific. $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

association between $CBDC^{PCA}$ and systemic risk in North & Sub-Saharan Africa and Middle East countries. Moreover, the estimated long-run impact has roughly the same magnitude as for North & Latin America and Caribbean countries. In the short run, we find a directionally cyclical association between $CBDC^{PCA}$ and systemic risk.

Finally, Table 16 presents the estimations for the South & East Asia and the Pacific region. PMG is the preferred estimation according to the Hausman tests. $CBDC^{PCA}$ has a statistically significant and negative long-run association with systemic risk.

Interestingly, in terms of magnitude, the estimated long-run coefficient is almost twice as much as for the North & Latin America and Caribbean and North & Sub-Saharan Africa and Middle East regions.

Overall, the results of this subsection highlight that there is heterogeneity in the long-run association between $CBDC^{PCA}$ and systemic risk based on geographical regions where South & East Asia and the Pacific has the strongest long-run association, North & Latin America and the Caribbean, and North & Sub-Saharan Africa and Middle East regions have roughly similar long-run association, and Europe and Central Asia has the lowest long-run association. In terms of the short run, countries in Europe, Central Asia, North & Sub-Saharan Africa, and the Middle East exhibit directional cyclicality, which suggests over-reaction and subsequent correction in the response of systemic risk to CBDC-related news.

5.3. Discussion

As the evolving literature on CBDCs and their implications for the financial sector provides mixed evidence, our analysis of the short- and long-run association between CBDC-related news and systemic risk offers a significant contribution. Our baseline results show that CBDC-related news has a significant negative association with systemic risk, which aligns with Wang et al. (2022) and Luu et al. (2023). This observed stabilizing role of CBDC-related news might be explained by Knightian Uncertainty (Knight, 1921) where the financial system is increasing its level of risk aversion and due diligence practices owing to developments related to CBDC.

Interesting findings emerge from the extended analysis, highlighting the heterogeneity in the association between CBDC-related news and systemic risk across income levels, CBDC development stage, and geographical regions of the countries. Luu et al. (2023) show that developing countries may have higher benefits from CBDC, however, our findings indicate that market participants in low and high-income countries respond similarly to CBDC-related news in the long run. In terms of short-run association, low and middle-income countries show directional cyclicality which might be evidence of over-reaction and subsequent correction of systemic risk to CBDC-related news. These findings suggest that regulators and policymakers of low and middle-income countries should be attentive to advancements in CBDC even in the short run.

Even though the baseline results indicate a negative association between CBDC-related news and systemic risk, analysis across developmental stages of CBDCs shows a different picture. Our findings show that status quo countries drive the negative association in the baseline results. Meanwhile, countries in the advanced stages of CBDC development show a positive association. Countries in the research and pilot stages exhibit a long-run whereas those in proof of concept show a short-run positive association between CBDC-related news and systemic risk. These findings align with Chen and Siklos (2022) and Son et al. (2023) who highlight macroeconomic concerns arising from the introduction of CBDCs.

We also find heterogeneity in the association between CBDC-related news and systemic risk across geographical regions. The long-run association is qualitatively identical, but there is variation in the magnitudes. Furthermore, countries in Europe, Central Asia, North & Sub-Saharan Africa, and the Middle East have short-term volatility in systemic risk arising from CBDC-related news.

These findings highlight the need for stringent risk management strategies (Pritsker, 2013), building cooperative networks and emphasizing thorough communication among bank management (Shabir et al., 2023), and local and international regulators. In particular, central banks of countries in advanced developmental stages of CBDC must play a proactive role in maintaining systemic stability within the complex network of interactions (Tomuleasa, 2015). For this purpose, a thorough implementation of adaptive policy frameworks, rigorous stress testing procedures, and scenario planning exercises (Cornett et al., 2020) may play a crucial role. The proactive approach of regulators in improving market and regulatory frameworks, encouraging cautious behavior from investors, and helping bank managers implement efficient risk management techniques can buffer the uncertainties created by CBDC in the short run. Moreover, effectively enforcing regulatory compliance and identifying irregularities early on with the help of a real-time transaction monitoring system may help diffuse the negative effects of CBDC uncertainty (Shabbir et al., 2022).

6. Concluding remarks

In this study, we investigate the association between CBDC-related news and systemic risk in 50 countries by employing dynamic panel heterogeneity analysis using the ARDL approach. This provides an initial understanding of the market participants' reaction to CBDC-related developments, which can be further enhanced with more progress in CBDC development and implementation. We also explore the heterogeneity in association based on income levels, developmental stage of CBDCs, and geographical region of the sample countries. Our results indicate that, in general, CBDC-related news has a significant negative association in the long run but is insignificant in the short run with systemic risk. This might indicate that CBDC-related news permeates the systemic framework with some delay.

Our heterogeneity analysis indicates that the association between CBDC-related news and systemic risk differs across income levels, CBDC developmental stages, and geographical regions of countries. Notably, baseline results might not be instrumental for policymakers in the advanced stages of CBDC development. These countries show a significant positive association between CBDC-related news and systemic risk. Regulators of these countries should consider issues such as structural disintermediation of banks, centralization of credit allocation within central banks, and facilitation of bank runs (Bindseil, 2020) while implementing CBDCs. However, the true impact of CBDCs in shaping the traditional banking systems will be governed by the extent of its (non-)adoption.

Table A.1
The number of banks and financial institutions across countries for CATFIN estimation.

Country	Banks/financial inst.	Country	Banks/financial inst.
Argentina	9	Malaysia	33
Australia	50	Mexico	20
Austria	9	Morocco	10
Belgium	12	Netherlands	10
Brazil	35	Nigeria	21
Canada	50	Norway	46
Chile	20	Oman	23
China	50	Pakistan	50
Cyprus	14	Peru	15
Czech Republic	4	Philippines	33
Denmark	24	Poland	50
Egypt	42	Portugal	3
Finland	16	Russia	18
France	42	Saudi Arabia	17
Greece	11	Singapore	21
Hong Kong	50	South Africa	30
Hungary	5	South Korea	50
India	50	Spain	11
Indonesia	47	Sweden	48
Ireland	3	Switzerland	43
Israel	50	Thailand	49
Italy	39	Turkey	49
Japan	48	UAE	28
Jordan	38	UK	49
Lebanon	8	USA	50

Note: This table presents the number of banks and financial institutions (inst.) included to estimate CATFIN for each country in the sample.

CRediT authorship contribution statement

Muhammad Suhail Rizwan: Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Ghufran Ahmad:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Anum Qureshi:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization.

Appendix A. Banks and financial institutions

The banks and financial institutions are selected using the Global Industry Classification Standard (GICS) codes 4010 (Banks) and 4020 (Diversified Financials). Table A.1 presents the number of banks and financial institutions included to estimate CATFIN for each country in the sample. For countries with a large number of banks and financial institutions, we only included the top 50 banks and financial institutions based on the total reported assets.

Appendix B. Unit root tests

We provide the p-values for the Augmented Dickey–Fuller test for the levels and first differences of $CATFIN$ and $CBDC^{PCA}$ to determine the order of integration. The p-values indicate that for all of the sample countries, both $CATFIN$ and $CBDC^{PCA}$ have an order of integration of either $I(0)$ or $I(1)$.

Appendix C. Robustness check

C.1. Individual indices

As a robustness check, we provide the baseline results by separately using $CBDC^{UI}$ and $CBDC^{AI}$, instead of $CBDC^{PCA}$, in Eq. (3).[12] The estimated results are provided in Tables C.1 and C.2, which indicate that the PMG estimation is recommended with a lag structure of ARDL(1, 4). The estimates are similar to the baseline results provided in Table 2 as we find that the $CBDC^{UI}$ and $CBDC^{AI}$ have a negative association with systemic risk in the long-run with similar magnitudes. Moreover, the estimates of the speed of adjustment are similar to the baseline results and the coefficient of COVID-19 is positive and significant. The only difference between the individual indices is that $CBDC^{UI}$ is significantly associated with systemic risk even in the short run. This suggests that uncertainty-related CBDC news results in a short-term reaction to systemic risk.

[12] We take $CBDC^{UI}$ and $CBDC^{AI}$ separately to avoid potential issues with multicollinearity since the two variables are highly correlated (91.39%).

Table B.1
The p-values of the Augmented Dickey–Fuller test.

Country	$CATFIN$	$\Delta CATFIN$	$CBDC^{PCA}$	$\Delta CBDC^{PCA}$	Country	$CATFIN$	$\Delta CATFIN$	$CBDC^{PCA}$	$\Delta CBDC^{PCA}$
Argentina	0.0002	0	0.0025	0	Malaysia	0.1087	0	0.0025	0
Australia	0.3049	0	0.0025	0	Mexico	0.0266	0	0.0025	0
Austria	0.0102	0	0.0025	0	Morocco	0.048	0	0.0025	0
Belgium	0.0008	0	0.0025	0	Netherlands	0.0085	0	0.0025	0
Brazil	0.0488	0	0.0025	0	Nigeria	0.0217	0	0.0025	0
Canada	0.292	0	0.0025	0	Norway	0.0585	0	0.0025	0
Chile	0.0269	0	0.0025	0	Oman	0.0035	0	0.0025	0
China	0.0402	0	0.0025	0	Pakistan	0.0007	0	0.0025	0
Cyprus	0.0002	0	0.0025	0	Peru	0.0005	0	0.0025	0
Czech Republic	0.0033	0	0.0025	0	Philippines	0.0221	0	0.0025	0
Denmark	0.0079	0	0.0025	0	Poland	0.0095	0	0.0025	0
Egypt	0.0001	0	0.0025	0	Portugal	0.0388	0	0.0025	0
Finland	0.0554	0	0.0025	0	Russia	0.1286	0	0.0025	0
France	0.0017	0	0.0025	0	Saudi Arabia	0.063	0	0.0025	0
Greece	0.0368	0	0.0025	0	Singapore	0.0623	0	0.0025	0
Hong Kong	0.1651	0	0.0025	0	South Africa	0.0081	0	0.0025	0
Hungary	0.0162	0	0.0025	0	South Korea	0.0187	0	0.0025	0
India	0.0688	0	0.0025	0	Spain	0.0001	0	0.0025	0
Indonesia	0.0918	0	0.0025	0	Sweden	0.0665	0	0.0025	0
Ireland	0.0117	0	0.0025	0	Switzerland	0.0563	0	0.0025	0
Israel	0.0079	0	0.0025	0	Thailand	0.0411	0	0.0025	0
Italy	0.0154	0	0.0025	0	Turkey	0.014	0	0.0025	0
Japan	0.0753	0	0.0025	0	UAE	0.0427	0	0.0025	0
Jordan	0	0	0.0025	0	UK	0.0235	0	0.0025	0
Lebanon	0.0187	0	0.339	0	USA	0.15	0	0.0025	0

Note: This table presents the p-values of the Augmented Dickey–Fuller test for which the null hypothesis is that the variable contains a unit root and the alternative is that the variable is stationary. $CATFIN$ is a measure of systemic risk and $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices.

Table C.1
The estimated coefficients when the uncertainty index ($CBDC^{UI}$) is used instead of the first principal component ($CBDC^{PCA}$).

Variable	PMG	MG	DFE
Error correction	−0.0616***	−0.0635***	−0.0558***
	(0.0025)	(0.0025)	(0.0023)
$\Delta CBDC^{UI}$	0.0116	0.0092	0.0084
	(0.0102)	(0.0114)	(0.0115)
$\Delta^2 CBDC^{UI}$	0.0180	0.0206	0.0211
	(0.0159)	(0.0174)	(0.0181)
$\Delta^3 CBDC^{UI}$	−0.0192*	−0.0207*	−0.0203
	(0.0109)	(0.0116)	(0.0128)
$\Delta^4 CBDC^{UI}$	0.0060**	0.0063**	0.0062*
	(0.0028)	(0.0030)	(0.0035)
COVID-19	0.0864***	0.0872***	0.0828***
	(0.0087)	(0.0094)	(0.0085)
$CBDC^{UI}$	−0.2369***	−0.2177***	−0.2267***
	(0.0397)	(0.0377)	(0.0448)
Constant	1.6040***	1.5198***	1.4706***
	(0.1058)	(0.2333)	(0.2273)
Observations	20,520	20,520	20,520
Countries	50	50	50
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−2.500	−0.0740

Note: This table presents the estimated coefficients for Eq. (3) where the first principal component ($CBDC^{PCA}$) is replaced with the uncertainty index ($CBDC^{UI}$). PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table C.2
The estimated coefficients when the attention index ($CBDC^{AI}$) is used instead of the first principal component ($CBDC^{PCA}$).

Variable	PMG	MG	DFE
Error correction	−0.0630***	−0.0652***	−0.0567***
	(0.0025)	(0.0027)	(0.0023)
$\Delta CBDC^{AI}$	0.0069	0.0055	0.0046
	(0.0161)	(0.0177)	(0.0126)
$\Delta^2 CBDC^{AI}$	0.0017	0.0037	0.0046
	(0.0249)	(0.0267)	(0.0212)
$\Delta^3 CBDC^{AI}$	0.0034	0.0021	0.0020
	(0.0166)	(0.0172)	(0.0163)
$\Delta^4 CBDC^{AI}$	−0.0014	−0.0011	−0.0011
	(0.0043)	(0.0044)	(0.0048)
COVID-19	0.0919***	0.0929***	0.0870***
	(0.0092)	(0.0104)	(0.0087)
$CBDC^{AI}$	−0.2142***	−0.2095***	−0.2071***
	(0.0340)	(0.0328)	(0.0387)
Constant	1.5763***	1.5355***	1.4470***
	(0.1079)	(0.2451)	(0.2152)
Observations	20,520	20,520	20,520
Countries	50	50	50
Lag order	ARDL(1, 4)	ARDL(1, 4)	ARDL(1, 4)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−0.313	−0.0491

Note: This table presents the estimated coefficients for Eq. (3) where the first principal component ($CBDC^{PCA}$) is replaced with the attention index ($CBDC^{AI}$). PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to the Bayesian Information Criterion (BIC). Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table C.3
The Akaike and Bayesian information criteria for different lags.

CBDC index	Lags	0	1	2	3	4	5	6	7	8
$CBDC^{PCA}$	AIC	7246.78	7239.63	7226.16	7201.33	7175.82	7081.89	7018.38	7005.58	7017.7
	BIC	7287.05	7287.25	7281.7	7264.78	7247.18	7161.16	7105.55	7100.64	7120.65
$CBDC^{UI}$	AIC	7256.02	7236.58	7224.86	7212.45	7191.37	7097.73	7028.99	7017.39	7030.77
	BIC	7296.29	7284.2	7280.4	7275.9	7262.73	7176.99	7116.15	7112.45	7133.72
$CBDC^{AI}$	AIC	7242.19	7245.69	7228.69	7178.97	7153.25	7083.66	7024.83	7010.93	7016.64
	BIC	7282.46	7293.31	7284.23	7242.42	7224.62	7162.93	7112	7105.99	7119.59

Note: This table presents the Akaike (AIC) and Bayesian (BIC) information criteria for CBDC uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and their first principal component ($CBDC^{PCA}$), allowing a maximum of eight lags. The lag structure with the minimum value of the chosen information criterion is selected for estimation.

C.2. Lag selection

In our empirical estimation, the selection of the lag structure is based on BIC. A maximum of four maximum lags on CBDC indices are used. Here, we show that the baseline results are unaffected by the choice of the information criterion and the number of maximum lags allowed.

Table C.3 shows that when we allow a maximum of eight possible lags, the optimal lag structure uses seven lags of CBDC indices and their first principal component regardless of which selection criterion is used. This is because the Akaike information criterion (AIC) and BIC are both minimum when the lag structure incorporates seven lags of the CBDC indices.

Tables C.4, C.5, and C.6 show that even with ARDL(1, 7) lag structure the results remain largely unchanged: (i) PMG estimation is still preferred over MG and DFE estimators, (ii) the error correction terms remain largely unchanged, and (iii) CBDC indices and their first principal component continue to decrease systemic risk in the long run, however, the magnitude is somewhat stronger. The results of this alternative lag structure exhibit a significant association between CBDC-related news and systemic risk in the short run for all CBDC indices. However, we still use the parsimonious lag structure as the baseline.

Data availability

Data will be made available on request.

Table C.4
The estimated coefficients for the baseline estimation with an alternative lag structure.

Variable	PMG	MG	DFE
Error correction	−0.0625***	−0.0647***	−0.0569***
	(0.0025)	(0.0025)	(0.0023)
$\Delta CBDC^{PCA}$	0.0754***	0.0715***	0.0677***
	(0.0197)	(0.0200)	(0.0202)
$\Delta^2 CBDC^{PCA}$	−0.2018***	−0.1926***	−0.1822***
	(0.0722)	(0.0704)	(0.0650)
$\Delta^3 CBDC^{PCA}$	0.2734**	0.2607*	0.2428**
	(0.1395)	(0.1354)	(0.1177)
$\Delta^4 CBDC^{PCA}$	−0.1613	−0.1505	−0.1318
	(0.1453)	(0.1413)	(0.1268)
$\Delta^5 CBDC^{PCA}$	0.0190	0.0134	0.0021
	(0.0867)	(0.0845)	(0.0817)
$\Delta^6 CBDC^{PCA}$	0.0184	0.0200	0.0236
	(0.0286)	(0.0279)	(0.0294)
$\Delta^7 CBDC^{PCA}$	−0.0054	−0.0056	−0.0060
	(0.0041)	(0.0040)	(0.0046)
COVID-19	0.0925***	0.0931***	0.0872***
	(0.0092)	(0.0099)	(0.0087)
$CBDC^{PCA}$	−0.3000***	−0.2720***	−0.2860***
	(0.0398)	(0.0363)	(0.0450)
Constant	0.1198	0.1462	0.1730
	(0.1012)	(0.0953)	(0.1110)
Observations	20,370	20,370	20,370
Countries	50	50	50
Lag order	ARDL(1, 7)	ARDL(1, 7)	ARDL(1, 7)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−3.002	−0.140

Note: This table presents the estimated coefficients for Eq. (3). $CBDC^{PCA}$ is the first principal component of uncertainty ($CBDC^{UI}$) and attention ($CBDC^{AI}$) indices and COVID-19 is a dummy variable to identify the COVID-19 pandemic. PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to both Akaike (AIC) and Bayesian Information Criteria (BIC) while allowing a maximum of eight lags. Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table C.5
The estimated coefficients when the uncertainty index ($CBDC^{UI}$) is used instead of the first principal component ($CBDC^{PCA}$) with an alternative lag structure.

Variable	PMG	MG	DFE
Error correction	−0.0619***	−0.0640***	−0.0565***
	(0.0025)	(0.0025)	(0.0023)
$\Delta CBDC^{UI}$	0.0864***	0.0821***	0.0785***
	(0.0172)	(0.0182)	(0.0184)
$\Delta^2 CBDC^{UI}$	−0.2261***	−0.2162***	−0.2064***
	(0.0612)	(0.0630)	(0.0576)
$\Delta^3 CBDC^{UI}$	0.3155***	0.3018***	0.2841***
	(0.1137)	(0.1160)	(0.1018)
$\Delta^4 CBDC^{UI}$	−0.2194*	−0.2077*	−0.1885*
	(0.1167)	(0.1189)	(0.1072)
$\Delta^5 CBDC^{UI}$	0.0663	0.0602	0.0483
	(0.0691)	(0.0704)	(0.0676)
$\Delta^6 CBDC^{UI}$	−0.0015	0.0003	0.0041
	(0.0225)	(0.0230)	(0.0238)
$\Delta^7 CBDC^{UI}$	−0.0021	−0.0023	−0.0028
	(0.0032)	(0.0033)	(0.0036)
COVID-19	0.0886***	0.0893***	0.0844***
	(0.0089)	(0.0094)	(0.0086)
$CBDC^{UI}$	−0.3164***	−0.2850***	−0.3026***
	(0.0416)	(0.0370)	(0.0467)
Constant	2.0180***	1.9307***	1.8301***
	(0.1150)	(0.2287)	(0.2369)

(*continued on next page*)

Table C.5 (*continued*).

Variable	PMG	MG	DFE
Observations	20,370	20,370	20,370
Countries	50	50	50
Lag order	ARDL(1, 7)	ARDL(1, 7)	ARDL(1, 7)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−2.804	−0.125

Note: This table presents the estimated coefficients for Eq. (3) where the first principal component ($CBDC^{PCA}$) is replaced with the uncertainty index ($CBDC^{UI}$). PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to both Akaike (AIC) and Bayesian Information Criteria (BIC) while allowing a maximum of eight lags. Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

Table C.6
The estimated coefficients when the uncertainty index ($CBDC^{AI}$) is used instead of the first principal component ($CBDC^{PCA}$) with an alternative lag structure.

Variable	PMG	MG	DFE
Error correction	−0.0627***	−0.0649***	−0.0569***
	(0.0025)	(0.0026)	(0.0023)
$\Delta CBDC^{AI}$	0.0498**	0.0467**	0.0442**
	(0.0209)	(0.0206)	(0.0196)
$\Delta^2 CBDC^{AI}$	−0.1273*	−0.1199*	−0.1145*
	(0.0721)	(0.0671)	(0.0635)
$\Delta^3 CBDC^{AI}$	0.1545	0.1443	0.1395
	(0.1368)	(0.1268)	(0.1161)
$\Delta^4 CBDC^{AI}$	−0.0547	−0.0462	−0.0444
	(0.1435)	(0.1337)	(0.1274)
$\Delta^5 CBDC^{AI}$	−0.0338	−0.0382	−0.0379
	(0.0876)	(0.0821)	(0.0838)
$\Delta^6 CBDC^{AI}$	0.0322	0.0335	0.0331
	(0.0297)	(0.0280)	(0.0307)
$\Delta^7 CBDC^{AI}$	−0.0070	−0.0072*	−0.0071
	(0.0043)	(0.0041)	(0.0049)
COVID-19	0.0939***	0.0945***	0.0884***
	(0.0094)	(0.0103)	(0.0088)
$CBDC^{AI}$	−0.2415***	−0.2237***	−0.2317***
	(0.0348)	(0.0325)	(0.0397)
Constant	1.7420***	1.6871***	1.5834***
	(0.1128)	(0.2256)	(0.2195)
Observations	20,370	20,370	20,370
Countries	50	50	50
Lag order	ARDL(1, 7)	ARDL(1, 7)	ARDL(1, 7)
Time trend	Yes	Yes	Yes
Hausman p-value		1	1
Hausman χ^2		−2.038	−0.0894

Note: This table presents the estimated coefficients for Eq. (3) where the first principal component ($CBDC^{PCA}$) is replaced with the attention index ($CBDC^{AI}$). PMG, MG, and DFE are pooled mean group, mean group, and dynamic fixed effects, respectively. Standard errors are reported in parenthesis. ***, **, and * correspond to p-values less than 1, 5, and 10%, respectively. Lag order provides the lags selected according to both Akaike (AIC) and Bayesian Information Criteria (BIC) while allowing a maximum of eight lags. Hausman p-value and χ^2 are for the Hausman test, which suggests using the PMG estimation (owing to its efficiency) if we are unable to reject the null hypothesis of no difference between the two estimators.

References

Ahmad, G., Rizwan, M.S., Ashraf, D., 2021. Systemic risk and macroeconomic forecasting: A globally applicable copula-based approach. J. Forecast. 40 (8), 1420–1443.

Akin, I., Khan, M.Z., Hameed, A., Chebbi, K., Satiroglu, H., 2023. The ripple effects of CBDC-related news on bitcoin returns: Insights from the DCC-GARCH model. Res. Int. Bus. Finance 66, 102060.

Alfar, A.J., Kumpamool, C., Nguyen, D.T., Ahmed, R., 2023. The determinants of issuing central bank digital currencies. Res. Int. Bus. Finance 64, 101884.

Allen, L., Bali, T.G., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Rev. Financ. Stud. 25 (10), 3000–3036.

Allen, F., Gu, X., Jagtiani, J., 2022. Fintech, cryptocurrencies, and CBDC: Financial structural transformation in China. J. Int. Money Finance 124, 102625.

Almeida, J., Gonçalves, T.C., 2023. A systematic literature review of investor behavior in the cryptocurrency markets. J. Behav. Exp. Finance 100785.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Rev. Econ. Stud. 58 (2), 277–297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econometrics 68 (1), 29–51.

Awais, M., Afzal, A., Firdousi, S., Hasnaoui, A., 2023. Is fintech the new path to sustainable resource utilisation and economic development? Resour. Policy 81, 103309.

Bech, M.L., Shimizu, Y., Wong, P., 2017. The quest for speed in payments. BIS Q. Rev..

Belluzzo, T., 2023. Systemic risk. URL https://github.com/TommasoBelluzzo/SystemicRisk/releases/tag/v3.6.0.

Bian, W., Ji, Y., Wang, P., 2021. The crowding-out effect of central bank digital currencies: A simple and generalizable payment portfolio model. Finance Res. Lett. 43, 102010.

Bibi, S., Canelli, R., 2023. The interpretation of CBDC within an endogenous money framework. Res. Int. Bus. Finance 65, 101970.

Bindseil, U., 2020. Tiered CBDC and the financial system. ECB Working Paper, No. 2351, ISBN 978-92-899-3994-2, European Central Bank (ECB).

Blundell, R., Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. J. Econometrics 87 (1), 115–143.

Boar, C., Wehrli, A., 2021. Ready, steady, go?-results of the third BIS survey on central bank digital currency. BIS Pap..

Castrén, O., Kavonius, I.K., Rancan, M., 2022. Digital currencies in financial networks. J. Financial Stab. 60, 101000.

Chen, H., Siklos, P.L., 2022. Central bank digital currency: A review and some macro-financial implications. J. Financial Stab. 60, 100985.

Chen, H., Siklos, P.L., 2023. Currency substitution in a world of looming retail CBDCs: Suggestive currency substitution-based evidence. J. Int. Financial Markets, Inst. Money 88, 101828.

Choi, K.J., Henry, R., Lehar, A., Reardon, J., Safavi-Naini, R., 2021. A proposal for a Canadian CBDC. Available at SSRN 3786426.

Cornett, M.M., Minnick, K., Schorno, P.J., Tehranian, H., 2020. An examination of bank behavior around federal reserve stress tests. J. Financial Intermediation 41, 100789.

Cullen, J., 2022. "Economically inefficient and legally untenable": constitutional limitations on the introduction of central bank digital currencies in the EU. J. Bank. Regul. 23 (1), 31–41.

Didenko, A.N., Zetzsche, D.A., Arner, D.W., Buckley, R.P., 2020. After libra, digital yuan and COVID-19: Central bank digital currencies and the new world of money and payment systems. SSRN Electron. J. http://dx.doi.org/10.2139/SSRN.3622311.

Dowd, K., 2024. So far, central bank digital currencies have failed. Econ. Aff. 44 (1), 71–94.

Dunbar, K., 2023. CBDC uncertainty: Financial market implications. Int. Rev. Financ. Anal. 87, 102607.

Fabris, N., et al., 2019. Cashless society–the future of money or a utopia. J. Cent. Bank. Theory Pract. 8 (1), 53–66.

Fama, E.F., 1970. Efficient capital markets. J. Finance 25 (2), 383–417.

Fan, S., Wei, Y., Niu, X., Balezentis, T., Agnusdei, L., 2023. Can FinTech development pave the way for a transition towards inclusive growth: Evidence from an emerging economy. Struct. Change Econ. Dyn. 67, 439–458.

Fang, L., Cheng, J., Su, F., 2019. Interconnectedness and systemic risk: A comparative study based on systemically important regions. Pac.-Basin Finance J. 54, 147–158.

Frank, M.W., et al., 2005. Income inequality and economic growth in the US: A panel cointegration approach. Sam Houston State University Working Paper, 05–03.

Giglio, S., Kelly, B., Pruitt, S., 2016. Systemic risk and the macroeconomy: An empirical evaluation. J. Financ. Econ. 119 (3), 457–471.

Gorton, G.B., Zhang, J.Y., 2023. Taming wildcat stablecoins. U. Chi. L. Rev. 90, 909.

Gupta, S., Pandey, D.K., El Ammari, A., Sahu, G.P., 2023. Do perceived risks and benefits impact trust and willingness to adopt cbdcs? Res. Int. Bus. Finance 66, 101993.

Han, K., Choi, J.H., Choi, Y., Lee, G.M., Whinston, A.B., 2023. Security defense against long-term and stealthy cyberattacks. Decis. Support Syst. 166, 113912.

Hassan, M.S., Islam, M.A., Yusof, M.F., Nasir, H., 2023. Users' fintech services acceptance: A cross-sectional study on Malaysian insurance & takaful industry. Heliyon 9 (11).

Helmi, M.H., Çatık, A.N., Akdeniz, C., 2023. The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-var model. Res. Int. Bus. Finance 65, 101968.

Hoang, Y.H., Ngo, V.M., Vu, N.B., 2023. Central bank digital currency: A systematic literature review using text mining approach. Res. Int. Bus. Finance 101889.

Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. J. Econometrics 115 (1), 53–74.

Knight, F.H., 1921. Risk, Uncertainty, and Profit. Houghton Mifflin Company.

Kuehnlenz, S., Orsi, B., Kaltenbrunner, A., 2023. Central bank digital currencies and the international payment system: The demise of the US dollar? Res. Int. Bus. Finance 64, 101834.

Lai, K.P., Langley, P., 2023. Playful finance: Gamification and intermediation in FinTech economies. Geoforum 103848.

Landry, P., 2021. A behavioral economic theory of cue-induced attention-and task-switching with implications for neurodiversity. J. Econ. Psychol. 86, 102423.

Li, Z., Yang, C., Huang, Z., 2022. How does the fintech sector react to signals from central bank digital currencies? Finance Res. Lett. 50, 103308.

Lu, Y., Wang, Y., 2023. Bank liquidity hoarding and bank systemic risk: The moderating effect of economic policy uncertainty. Pac.-Basin Finance J. 82, 102189.

Luo, P., Wu, B., Law, R., Xu, Y., 2023. Herding behavior in peer-to-peer trading economy: The moderating role of reviewer photo and name. Tour. Manag. Perspect. 45, 101050.

Luu, H.N., Nguyen, C.P., Nasir, M.A., 2023. Implications of central bank digital currency for financial stability: Evidence from the global banking sector. J. Int. Financial Markets Inst. Money 89, 101864.

Mangee, N., 2024. Stock price swings and fundamentals: The role of Knightian uncertainty. Int. Rev. Financ. Anal. 91, 102987.

McLemore, P., Mihov, A., Sanz, L., 2022. Global banks and systemic risk: The dark side of country financial connectedness. J. Int. Money Finance 129, 102734.

Minesso, M.F., Mehl, A., Stracca, L., 2022. Central bank digital currency in an open economy. J. Monetary Econ. 127, 54–68.

Morales-Resendiz, R., Ponce, J., Picardo, P., Velasco, A., Chen, B., Sanz, L., Guiborg, G., Segendorff, B., Vasquez, J.L., Arroyo, J., et al., 2021. Implementing a retail CBDC: Lessons learned and key insights. Lat. Am. J. Cent. Bank. 2 (1), 100022.

Murray, J., 2019. Central Banks and the Future of Money. CD Howe Institute Commentary, 540.

Mzoughi, H., Benkraiem, R., Guesmi, K., 2022. The bitcoin market reaction to the launch of central bank digital currencies. Res. Int. Bus. Finance 63, 101800.

Ong, M.H.A., Yusri, M.Y., Ibrahim, N.S., 2023. Use and behavioural intention using digital payment systems among rural residents: Extending the UTAUT-2 model. Technol. Soc. 102305.

Persakis, A., Iatridis, G.E., 2023. How economic uncertainty influences the performance of investor perceptions and behavior. J. Int. Account. Audit. Tax. 100541.

Pesaran, M.H., 1997. The role of economic theory in modelling the long run. Econ. J. 107 (440), 178–191.

Pesaran, M.H., Shin, Y., Smith, R.P., 1997. Estimating Long-run Relationships in Dynamic Heterogeneous Panels, DAE Working Papers Amalgamated Series 9721. University of Cambridge, England.

Pesaran, M.H., Shin, Y., Smith, R.P., 1999. Pooled mean group estimation of dynamic heterogeneous panels. J. Am. Stat. Assoc. 94 (446), 621–634.

Pesaran, M.H., Shin, Y., et al., 1995. An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, vol. 9514, Department of Applied Economics, University of Cambridge Cambridge, UK.

Pesaran, M.H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogeneous panels. J. Econometrics 68 (1), 79–113.

Poletykin, A., Promyslov, V., 2013. Digitally controlled assets subjected to cyberattacks: Definitions and "cyberproof" criteria based on the analysis of explicit and hidden functions. IFAC Proc. Vol. 46 (9), 1038–1042.

Pritsker, M., 2013. Knightian uncertainty and interbank lending. J. Financial Intermediation 22 (1), 85–105.

Rizwan, M.S., 2021. Macroprudential regulations and systemic risk: Does the one-size-fits-all approach work? J. Int. Financial Markets, Inst. Money 74, 101409.

Rizwan, M.S., Ahmad, G., Ashraf, D., 2020. Systemic risk: The impact of COVID-19. Finance Res. Lett. 36, 101682.

Rizwan, M.S., Ahmad, G., Ashraf, D., 2022. Systemic risk, islamic banks, and the COVID-19 pandemic: An empirical investigation. Emerg. Mark. Rev 51, 100890.

Rizwan, M.S., Qureshi, A., Sahibzada, I.U., 2023. Macro-prudential regulations and systemic risk: the role of country-level governance indicators. J. Bank. Regul. 1–21.

Roodman, D., 2009. How to do xtabond2: An introduction to difference and system GMM in stata. Stata J. 9 (1), 86–136.

Saengchote, K., 2023. Decentralized lending and its users: Insights from compound. J. Int. Financial Markets Inst. Money 87, 101807.

Samargandi, N., Fidrmuc, J., Ghosh, S., 2015. Is the relationship between financial development and economic growth monotonic? Evidence from a sample of middle-income countries. World Dev. 68, 66–81.

Savitha, B., Hawaldar, I.T., Kumar, N., 2022. Continuance intentions to use FinTech peer-to-peer payments apps in India. Heliyon 8 (11).

Scharnowski, S., 2022. Central bank speeches and digital currency competition. Finance Res. Lett. 49, 103072.

Schwarcz, S.L., 2022. Regulating global stablecoins: A model-law strategy. Vand. L. Rev. 75, 1729.

Shabbir, A., Shabir, M., Javed, A.R., Chakraborty, C., Rizwan, M., 2022. Suspicious transaction detection in banking cyber–physical systems. Comput. Electr. Eng. 97, 107596.

Shabir, M., Jiang, P., Shahab, Y., Wang, P., 2023. Geopolitical, economic uncertainty and bank risk: Do CEO power and board strength matter? Int. Rev. Financ. Anal. 87, 102603.

Soderberg, G., Bechara, M.M., Bossu, W., Che, M.N.X., Davidovic, S., Kiff, M.J., Lukonga, M.I., Griffoli, M.T.M., Sun, T., Yoshinaga, A., 2022. Behind the Scenes of Central Bank Digital Currency: Emerging Trends, Insights, and Policy Lessons. International Monetary Fund.

Sohag, K., Nabilah, A.B., Begum, R.A., 2015. Dynamic impact of financial development on economic growth: heterogeneous panel data analysis of island economies. Int. J. Econ. Policy Emerg. Econ. 8 (1), 77–95.

Son, J., Ryu, D., Webb, R.I., 2023. Central bank digital currency: Payment choices and commercial bank profitability. Int. Rev. Financ. Anal. 90, 102874.

Temperini, J., D'Ippoliti, C., Gobbi, L., 2024. Is the time ripe for helicopter money? Growth impact and financial stability risks of outright monetary transfers. Struct. Change Econ. Dyn. 69, 24–36.

Tian, S., Zhao, B., Olivares, R.O., 2023. Cybersecurity risks and central banks' sentiment on central bank digital currency: Evidence from global cyberattacks. Finance Res. Lett. 53, 103609.

Tomuleasa, I.-I., 2015. Central bank communication and its role in ensuring financial stability. Procedia Econ. Finance 20, 637–644.

Tronnier, F., Harborth, D., Hamm, P., 2022. Investigating privacy concerns and trust in the digital euro in Germany. Electron. Commer. Res. Appl. 53, 101158.

Wang, Y., Lucey, B.M., Vigne, S.A., Yarovaya, L., 2022. The effects of central bank digital currencies news on financial markets. Technol. Forecast. Soc. Change 180, 121715.

Xu, Y., Bao, H., 2023. FinTech regulation: Evolutionary game model, numerical simulation, and recommendations. Expert Syst. Appl. 211, 118327.

Yousaf, I., Goodell, J.W., 2023. Linkages between CBDC and cryptocurrency uncertainties, and digital payment stocks. Finance Res. Lett. 54, 103765.

Yuan, K., Li, W., Zhang, W., 2023. Your next bank is not necessarily a bank: FinTech expansion and bank branch closures. Econom. Lett. 222, 110948.

Zarrouk, H., El Ghak, T., Bakhouche, A., 2021. Exploring economic and technological determinants of FinTech startups' success and growth in the United Arab Emirates. J. Open Innov.: Technol. Market Complex. 7 (1), 50.

Zhou, G., Zhu, J., Luo, S., 2022. The impact of fintech innovation on green growth in China: Mediating effect of green finance. Ecol. Econom. 193, 107308.