Finance Research Letters 64 (2024) 105424

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

# Heterogeneous dependence of the FinTech Index with Global Systemically Important Banks (G-SIBs)

Hongjun Zeng [a,*], Mohammad Zoynul Abedin [b], Brian Lucey [c]

[a] Department of financial planning and tax, School of Accounting, Information Systems and Supply Chain, RMIT University, Melbourne, Australia
[b] Department of Accounting and Finance, School of Management, Swansea University, Bay Campus, Fabian Way, Swansea SA1 8EN, Wales, United Kingdom
[c] Trinity Business School, Trinity College Dublin, The University of Dublin, Dublin, Ireland

ARTICLE INFO

*Keywords:*
FinTech
Global Systemically Important Banks (G-SIBs)
Granger causality
Quantile relationship
Heterogeneous dependence
Financial stability

ABSTRACT

This paper aims to investigate the Granger causality relationship in quantile between the FinTech Index and globally systemically important banks (G-SIBs). The result was observed that at the median and under conditions of extreme quantiles in the FinTech Index, there was no Granger causality relationship between the FinTech Index and the vast majority of systemically important banks. Our research offered vital insights to regulatory agencies, highlighting the importance of monitoring market conditions at higher or lower quantiles to prevent the impact of financial technology on G-SIBs and to maintain global financial stability.

## 1. Introduction

Since the Fourth Industrial Revolution, progress in science and its innovative applications have been key drivers in the development of financial technology (Pollari, 2016). The global financial technology (FinTech) industry is currently experiencing rapid growth, leveraging technology to enhance financial activities. Influenced by market demand, traditional providers of financial services have found it increasingly challenging to meet the growing demands for digitized and intelligent financial services. Consequently, the financial industry has significantly increased its investment in technology (Chen et al., 2021). Simultaneously, the substantial growth potential of FinTech has gained recognition from investors, leading to a strong preference for FinTech investment and financing in the capital market (Lee and Shin, 2018).

For existing banks, FinTech disruption has posed challenges (Anagnostopoulos, 2018; Anand and Mantrala, 2019). On one hand, due to continuous regulatory upgrades, banks were compelled to lower risk degrees, boost capital adequacy, and maintain the steadiness of their operations and assets (Rapih et al., 2023). Meanwhile, banks benefited from technological developments, as financial technology aided them in venturing into new markets and launching innovative products at competitive costs (Stulz, 2019). It should be noted that FinTech disruption compelled banks to respond through transformation (Gomber et al., 2018). Furthermore, relevant research findings indicated that FinTech disruption had a negative impact on banks' profit formation (Temelkov, 2018). It's worth noting that excessive investment in financial innovation may deteriorate a bank's performance (Fostel and Geanakoplos, 2016). However, according to the theory of disruptive innovation, when new market entrants confront existing competitors with superior products or services, existing players accelerate innovation to defend their businesses (Christensen et al., 2011). Therefore, banks must

* Corresponding author.
*E-mail address:* hongjun.zeng@student.rmit.edu.au (H. Zeng).

https://doi.org/10.1016/j.frl.2024.105424
Received 15 February 2024; Received in revised form 8 April 2024; Accepted 14 April 2024
Available online 15 April 2024

adapt and respond judiciously to the evolving environment regarding the development of FinTech. Overall, the integration of FinTech technology into banks contributes to enhancing their performance, efficiency, and stability (Zhao et al., 2022). Numerous developing technologies in FinTech have a direct influence on the provision of retail banking products. Considering the evolution of consumer and commercial banking practices, these reforms should be regarded as crucial aspects of strategic planning assessments.

On the practical level, the convergence across banks and FinTech is shown to be a widely discussed theme. Previous literature mentioned that existing banks in the Middle East and North Africa considered collaborating with FinTech firms as their preferred strategy in the global digitized context (Zalan and Toufaily, 2017). Additionally, existing literature confirmed that promoting FinTech could enhance financial stability for emerging market banks, while producing the opposite impact in developed countries (Fung et al., 2020). Other literature suggests that the connection between bank stock returns and FinTech financing could serve as complementary indirect proof (Allen et al., 2021).

Following a series of studies, we conducted a quantile-level analysis of the Granger causality relationship between the financial technology index and systemically important banks in specific segments, as described in Troster (2018)'s research on quantile testing. This method is crucial for examining the causal connection between the financial technology index and systemically important banks in subdivisions. Firstly, this causal relationship can reveal the interconnected mechanisms of returns in both markets. Secondly, by assessing the dependency structures at various quantile levels, we were able to accurately infer the asymmetry of the influencing mechanisms and the complex relationships that exist at different quantile levels (Uddin et al., 2023; Zeng et al., 2024). The limited extant literature predominantly focused on the role of systemically important banks in financial stability (e.g., Batten et al., 2023; Kim et al., 2020; Daly et al., 2019). However, a paucity of literature existed that addressed the substantive impact of Fintech assets on systemically important banks. Furthermore, the novelty of quantile regression, which enabled the observation of heterogeneous effects under different market conditions, was rarely explored in existing banking-themed studies. Therefore, the present study addresses these issues.

Our contribution to academic literature and public policy discourse is manifold. Firstly, this study is the first deliberate investigation of the quantile causality between FinTech assets and globally systemically important banks, concurrently assessing both the median and tails of the distribution. This allows us to observe the predictability of FinTech assets on globally systemically important banks under different market conditions. Secondly, the study specifically focuses on globally systemically important banks, and thus, the policy implications derived from the empirical analysis of these banks will constitute a sufficiently valuable sample size for effectively leveraging the impact of FinTech assets on banks. Specifically, this type of investigation is crucial, as these banks have a significant impact and contribution to global financial stability (Batten et al., 2023). Therefore, it is within the context of these banks that the connection between FinTech and global financial institutions can be best understood and evaluated. Finally, there had been no empirical research concerning the sensitivity of specified G-SIBs to the impact of FinTech. Consequently, this paper represented the first empirical effort to answer how these specified G-SIBs were differentially affected by the FinTech index. It enables the identification of institutions that may require specific attention or measures due to their unique sensitivities to financial technology. Furthermore, based on the heterogeneous responses to the impact of the FinTech Index, banks can better prepare for potential disruptions or capitalize on opportunities arising from technological advancements.

## 2. Theoretical alignment

In theoretical terms, FinTech is associated with the following potential channels of connection to G-SIBs,

1. FinTech, by offering innovative technological solutions, assisted G-SIBs in enhancing service efficiency and risk management capabilities (Pramanik et al., 2019).

2. FinTech enabled G-SIBs to provide more personalized and convenient customer services through digital channels, thereby aiding banks in customer attraction and retention. This encompassed mobile banking applications, online payment systems, and digital asset management tools in practical terms.

3. With the increasing stringency of financial regulations and supervision, as well as the constant evolution of criminal tactics with technological advancements, FinTech can aid G-SIBs in developing tools and systems compliant with financial regulations and effective in combating financial crimes, particularly in Anti-Money Laundering (AML) and Know Your Customer (KYC) aspects.

Through the construction of advanced data analytics and predictive models, FinTech contributes to G-SIBs' enhanced ability to forecast and manage various financial risks, including credit risk and operational risk (Xie et al., 2023).

## 3. Methodology and data

This paper chose to utilize the Granger non-causality test in quantiles, as it offers valuable insights into the causal relationships within the various quantiles. This approach is particularly valuable since quantiles can effectively characterize a distribution.

If we designate $Q_\tau^{Y,X}(\cdot\,|I_t^Y, I_t^X)$ and $Q_\tau^Y(\cdot|I_t^Y)$ as the τ-quantiles of $F_Y(\cdot|I_t^Y, I_t^X)$ and $F_Y(\cdot|I_t^Y)$, respectively, the null hypothesis of Granger non-causality in quantiles can be extended as follows:

$$H_0^{X\Rightarrow Y} : Q_\tau^{Y,X}\left(Y_t|I_t^Y, I_t^X\right) = Q_\tau^Y\left(Y_t|I_t^Y\right), \textit{for all}\, \tau \in \mathrm{T} \tag{1}$$

In accordance with Troster (2018), we formulate the null hypothesis in Equation (5) as bellows:

$$H_0^{X\Rightarrow Y} : E[1(T_t)] \le m\left(I_t^Y, \theta_0(\tau)\right)|\left(I_t^Y, I_t^X\right) = \tau, \textit{for all}\, \tau \tag{2}$$

Where $1(\cdot)$ represents an indicator framework, and $m(I_t^Y, \theta_0(\tau))$ accurately denotes the true conditional quantile $Q_\tau^Y(\cdot|I_t^Y)$.

Let $\Psi$ be the matrix $T \times n$ with factors $\psi_{i,j} = \Psi_{\tau_j}\{Y_i - m(I_i^Y, \theta_T(\tau_j))\}$. Subsequently, the test statistic $S_T$, as proposed by Troster (2018):

$$S_T = \frac{1}{T_n} \sum_{j=1}^{n} |\psi'_{.j} W \psi_{.j}| \tag{3}$$

Where $W$ represents the matrix $T \times T$ with elements $w_{t,s} = \exp[-0.5(I_t - I_s)^2]$, and d'$\psi_{.j}$ signifies the column $j^{\text{th}}$ of $\Psi$.

Following the approach outlined by Troster et al. (2018), this paper employed the following specification of QAR models $m(\cdot)$ for all instances $\tau$ in order to conduct the $S_T$ test as described:

$$\text{QAR} : m^1\left(I_t^Y, \theta(\tau)\right) = \mu_0(\tau) + \mu_1(\tau) Y_{t-1} + \sigma \Phi_u^{-1}(\tau) \tag{4}$$

Where $\Phi_u^{-1}(\tau)$ denotes the inverse of the standard normal probability framework.

This study examined whether the performance of the Financial Technology Index had an impact on globally systemically important banks under different market conditions. For the financial technology variable, we followed the research of Tiwari et al. (2023) and used the KBW Nasdaq Financial Technology (KFTX) to track the performance of publicly listed financial technology companies in the United States. It is worth noting that on a global scale, the status of the United States as a hub for financial technology is hard to challenge, as it holds a leading position in both the technology and finance sectors worldwide. Therefore, we utilized the KBW Nasdaq Financial Technology Index as the financial technology variable.

Subsequently, we selected 30 globally significant banks based on the Financial Stability Board's 2022 List of Global Systemically Important Banks (G-SIBs). These systemically important banks were categorized into Buckets 4, 3, 2, and 1, according to their level of significance, as outlined in Table 1.

Since the latest 2022 version of the G-SIBs report was released in November 2022,[1] the data utilized in our study spans from January 1, 2017, to July 1, 2022. All data was sourced from Datastream.

## 4. Empirical findings

Table 2 presents the descriptive statistics of the variables under analysis. Our particular emphasis was on the Unit Root tests, where we observed that the findings of the ERS test confirmed the stationarity of the return series for all variables.

According to the quartile granger results in Table 3, we initially observed that at the overall quantile (All), except for NTIX, GLE, and STAN, there was a Granger causality relationship between the price movements of KFTX for all other systemically important banks. It is interesting and noteworthy that the results in Table 3 indicated that the return change of KFTX at median distribution ($q = 0.5$) did not lead to a Granger effect on the majority of systemically important banks, except for ACGBF, BK, and WFC.

Next, we examined the quantile Granger causality relationship between KFTX and the subset of systemically important banks. Firstly, focusing on JPM in Bucket 4, the results in Table 3 clearly demonstrate a significant Granger causality relationship between KFTX and the price of JPM across all quantile distributions, except at the median ($q = 0.5$) and the extreme upper tail ($q = 0.95$).

Furthermore, for the three banks in Bucket 3 (BAC, HSBC, and CITI), the research findings indicate that, except for the median distribution, at a 5 % significance level, KFTX Granger caused changes in their prices. This was particularly evident for HSBC and BAC. As for the banks in Bucket 2, the study results show that for BACHY, KFTX only exhibited feedback causality at higher quantile levels ($q = 0.75$ and 0.9). Additionally, at a 5 % significance level, the results indicate that at higher ($q = 0.75$ and 0.9) and/or lower ($q = 0.1$ and 0.25) quantile levels, KFTX had a Granger causality relationship with the other banks in Bucket 2.

Lastly, but not insignificantly, in line with the earlier findings, there is substantial evidence indicating that the returns of KFTX could predict changes in the returns of most banks in Bucket 3 at higher ($q = 0.75$ and 0.9) and/or lower ($q = 0.1$ and 0.25) quantile distributions. This suggests that when KFTX performed either poorly or well in the market, they were the primary drivers of integration between banks and financial technology.

## 5. Discussion of findings

This section of the study discusses the implications of the results presented in Table 3. Overall, the current research findings suggest that during periods of market stability ($q = 0.5$), KFTX did not have a significant impact on the majority of systemically important banks. Furthermore, under extreme tail conditions in the market ($q = 0.05$ or 0.95), KFTX did not exert a significant influence on the majority of systemically important banks. In contrast, when the market experienced rises or falls, rather than extreme rises or falls ($q =$ 0.1/0.25 or 0.75/0.9), KFTX exhibited a Granger causality relationship with the vast majority of systemically important banks that we observed. Implicit in this is the inference that the impact of KFTX on systemically important banks is not uniformly determined, but rather, it displays heterogeneity across different quantile distributions and specific banks. Therefore, the empirical findings of this study support the viewpoint that during FinTech market rises or falls, rather than extreme fluctuations, there is a greater need for financial technology to mitigate potential risks for banks. This is because in periods of extreme market fluctuations and stable market

[1] https://www.fsb.org/wp-content/uploads/P211122.pdf

**Table 1**
2022 List of Global Systemically Important Banks (G-SIBs).

**Bucket 4** (2.5%): JP Morgan Chase (JPM; US)
**Bucket 3** (2.0%): Citigroup (Citi; US), Bank of America (BAC; US), HSBC (HSBC; UK)
**Bucket 2** (1.5%): BNP Paribas (BNPQY; France), Bank of China (BACHY; China), Barclays (BCS; UK), Goldman Sachs (GS; US), Mitsubishi UFJ FG (MUFG; Japan), Deutsche Bank (DB; German), Industrial and Commercial Bank of China (IDCBY; China)
**Bucket 1** (1.0%): Bank of New York Mellon (BK; US), Mizuho FG (MFG; Japan), Credit Suisse (CS; Switzerland), China Construction Bank (CICHY; China), Agricultural Bank of China (ACGBF; China), Group BPCE (NTIX; France), Group Crédit Agricole (ACA; France), ING Bank (ING; Netherlands), Santander (SAN; France), Société Générale (GLE; France), State Street (STT; US), Toronto Dominion (TD; Canada), UBS (UBS; Switzerland), UniCredit (UCG; Italy), Wells Fargo (WFC; US), Sumitomo Mitsui FG (SMFG; Japan), Standard Chartered (STAN; UK), Morgan Stanley (MS; US), Royal Bank of Canada (RY; Canada)

***Notes:*** Table 1 presented the 2022 List of Global Systemically Important Banks (G-SIBs). The banks were categorized into four buckets, labelled Bucket 1 to Bucket 4, which indicated the level of systemic importance of each bank to the global financial system. Bucket 1 represented the most systemically important banks, while Bucket 4 represented the least systemically important banks, with the importance decreasing from Bucket 1 to Bucket 4 in descending order. In parentheses are the abbreviations used in this article and where they are headquartered.

**Table 2**
Summary statistics.

| | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera | ERS |
|---|---|---|---|---|---|---|---|---|
| KFTX | 0.000412 | 0.111636 | -0.135678 | 0.014821 | -0.845305 | 16.12783 | 9781.893*** | -4.664*** |
| MFG | -0.00034 | 0.089746 | -0.126752 | 0.014257 | -0.470498 | 10.75499 | 3407.251*** | -4.474*** |
| MS | 0.000431 | 0.180403 | -0.169603 | 0.021627 | 0.07162 | 16.18489 | 9707.281*** | -8.848*** |
| MUFG | -0.000103 | 0.111377 | -0.121439 | 0.016118 | -0.350368 | 9.949876 | 2724.209*** | -4.328*** |
| NTIX | 4.55E-06 | 0.269756 | -0.235829 | 0.026593 | -0.309341 | 27.00353 | 32,190.82*** | -14.401*** |
| C | -0.000192 | 0.165381 | -0.214414 | 0.023334 | -0.634514 | 17.72937 | 12,203.2*** | -8.972*** |
| CICHY | -8.67E-05 | 0.083764 | -0.08305 | 0.015218 | 0.043142 | 6.371491 | 635.0704*** | -14.879*** |
| CS | -0.000735 | 0.151387 | -0.201624 | 0.022371 | -0.925295 | 14.36634 | 7404.525*** | -3.030*** |
| DB | -0.000581 | 0.129544 | -0.163152 | 0.026898 | -0.138014 | 7.083129 | 935.1043*** | -2.817*** |
| GLE | -0.000634 | 0.168981 | -0.194243 | 0.025925 | -0.692363 | 12.39455 | 5034.776*** | -11.662*** |
| GS | 0.00016 | 0.161951 | -0.135881 | 0.020221 | -0.152188 | 12.99633 | 5584.403*** | -13.027*** |
| HSBC | -0.000167 | 0.09865 | -0.108101 | 0.016896 | -0.158477 | 8.539305 | 1718.793*** | -9.650*** |
| IDCBY | -6.24E-05 | 0.090481 | -0.070941 | 0.015238 | 0.212619 | 6.771144 | 804.1314*** | -11.700*** |
| ING | -0.000278 | 0.17093 | -0.227217 | 0.024836 | -0.773637 | 15.49215 | 8846.669*** | -9.800*** |
| JPM | 0.0002 | 0.16562 | -0.162106 | 0.019382 | -0.103548 | 17.03153 | 10,995.08*** | -14.510*** |
| ACA | -0.000224 | 0.128102 | -0.18469 | 0.02145 | -0.783733 | 14.09869 | 7014.778*** | -12.493*** |
| ACGBF | 0.001196 | 0.173272 | -0.108214 | 0.038803 | 0.029207 | 2.96557 | 0.256702*** | -9.824*** |
| BAC | 0.000252 | 0.163786 | -0.167205 | 0.021571 | -0.058941 | 14.31902 | 7154.158*** | -6.834*** |
| BACHY | -8.56E-05 | 0.064888 | -0.073949 | 0.012929 | -0.232147 | 6.428025 | 668.1534*** | -12.715*** |
| BCS | -0.000301 | 0.172486 | -0.246564 | 0.024975 | -0.603716 | 15.91734 | 9397.612*** | -7.261*** |
| BK | -9.16E-05 | 0.145109 | -0.156693 | 0.019117 | -0.556895 | 14.55444 | 7523.292*** | -6.759*** |
| BNPQY | -0.00022 | 0.165722 | -0.236071 | 0.0235 | -0.674864 | 15.41144 | 8702.496*** | -5.259*** |
| RY | 0.000267 | 0.127567 | -0.111272 | 0.013664 | -0.32117 | 25.94386 | 29,414.85*** | -3.645*** |
| SAN | -0.000472 | 0.155485 | -0.208491 | 0.023956 | -0.729197 | 12.06354 | 4705.338*** | -11.831*** |
| SMFG | -0.000189 | 0.116577 | -0.120953 | 0.015425 | -0.293545 | 10.68718 | 3318.592*** | -6.201*** |
| STAN | -7.50E-05 | 0.152662 | -0.129909 | 0.021354 | 0.017525 | 9.987794 | 2726.37*** | -11.870*** |
| STT | -0.000167 | 0.201464 | -0.209811 | 0.023091 | -0.37376 | 15.32623 | 8514.283*** | -3.624*** |
| TD | 0.000213 | 0.148982 | -0.149889 | 0.015238 | -0.215746 | 27.69953 | 34,072.47*** | -4.396*** |
| UBS | -9.65E-06 | 0.125907 | -0.170267 | 0.019341 | -0.547056 | 13.60491 | 6346.087*** | -3.631*** |
| UCG | -0.000327 | 0.128597 | -0.189466 | 0.026086 | -0.510273 | 9.34806 | 2308.115*** | -14.105*** |
| WFC | -0.000253 | 0.135707 | -0.172779 | 0.02301 | -0.485393 | 12.19459 | 4772.793*** | -15.930*** |

***Notes*:** The Jarque–Bera test is used to determine whether a sample of data follows a normal distribution. Elliott, Rothenberg and Stock (ERS) is a time series Unit Root test.

conditions, banks may be less inclined to engage with FinTech firms due to concerns about assuming additional risks (Varma et al., 2022).

Furthermore, it is worth noting that KFTX showed no significant correlation with STAN, GLE, and NVIX overall, and had low correlations with CS and DB. This suggests that using KFTX may not be effective in predicting the market performance of the most systemically important banks located in Europe. This seems to reflect the fact that the proportion of FinTech investment in the banking sector in Europe is relatively low compared to total technology capital expenditure (Mirza et al., 2023).

## 6. Results and policy insights

In this study, we employed the quantile Granger causality method to analyze the impact of the financial technology index on 30 globally systemic banks at different quantile distribution levels.

The research findings indicate that at the median ($q = 0.5$), the financial technology index did not exert a Granger effect on the majority of systemically important banks. Additionally, under extreme quantile conditions ($q = 0.05$ or 0.95), the financial technology

**Table 3**
Quantile Granger causality outcomes of KFTX to global systemically important banks (G-SIBs).

| | From KFTX *To* | | | | | |
|---|---|---|---|---|---|---|
| *q* | *JPM (Bucket 4)* | *Citi (Bucket 3)* | *HSBC (Bucket 3)* | *BAC (Bucket 3)* | *BNPQY (Bucket 2)* | *BACHY (Bucket 2)* |
| All | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.078*** |
| 0.05 | **0.014**** | **0.051*** | 0.267 | **0.031**** | **0.082*** | 0.826 |
| 0.10 | **0.001***** | **0.001***** | **0.072*** | **0.001***** | **0.001***** | 0.259 |
| 0.25 | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.001***** | 0.242 |
| 0.50 | 0.840 | 0.155 | 0.181 | 0.272 | 0.164 | 0.883 |
| 0.75 | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.001***** |
| 0.90 | **0.001***** | **0.016**** | **0.001***** | **0.001***** | **0.001***** | **0.069*** |
| 0.95 | 0.216 | **0.001***** | 0.120 | **0.067*** | 0.253 | 0.526 |
| | From KFTX *To* | | | | | |
| *q* | *BCS (Bucket 2)* | *DB (Bucket 2)* | *GS (Bucket 2)* | *IDCBY (Bucket 2)* | *MUFG (Bucket 2)* | *CICHY (Bucket 1)* |
| All | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.030**** | **0.001***** |
| 0.05 | **0.095*** | 0.365 | 0.462 | 0.290 | 0.342 | 0.236 |
| 0.10 | **0.001***** | 0.121 | **0.019**** | **0.039**** | **0.057*** | **0.011**** |
| 0.25 | **0.001***** | **0.001***** | **0.001***** | **0.015**** | **0.023*** | **0.001***** |
| 0.50 | 0.490 | 0.438 | 0.734 | 0.454 | 0.430 | 0.491 |
| 0.75 | **0.001***** | **0.027**** | **0.001***** | **0.001***** | **0.060*** | **0.001***** |
| 0.90 | **0.001***** | **0.035**** | **0.047**** | 0.193 | **0.014**** | **0.001***** |
| 0.95 | 0.125 | 0.542 | 0.355 | 0.406 | 0.126 | **0.001***** |
| | From KFTX *To* | | | | | |
| *q* | *ACGBF (Bucket 1)* | *BK (Bucket 1)* | *CS (Bucket 1)* | *NTIX (Bucket 1)* | *ACA (Bucket 1)* | *ING (Bucket 1)* |
| All | **0.001***** | **0.001***** | **0.012**** | 0.113 | **0.001***** | **0.001***** |
| 0.05 | 0.306 | 0.198 | 0.119 | 0.317 | **0.031**** | 0.152 |
| 0.10 | **0.002***** | **0.001***** | **0.047**** | **0.002***** | **0.001***** | **0.001***** |
| 0.25 | **0.001***** | **0.001***** | **0.001***** | **0.002***** | **0.001***** | **0.001***** |
| 0.50 | **0.001***** | **0.013**** | 0.375 | **0.076*** | 0.0130 | 0.371 |
| 0.75 | **0.001***** | **0.001***** | 0.116 | 0.112 | **0.001***** | **0.001***** |
| 0.90 | **0.025**** | **0.001***** | **0.001***** | 0.368 | **0.052*** | **0.001***** |
| 0.95 | 0.375 | **0.044**** | 0.176 | 0.545 | 0.294 | 0.188 |
| | From KFTX *To* | | | | | |
| *q* | *MFG (Bucket 1)* | *MS (Bucket 1)* | *RY (Bucket 1)* | *SAN (Bucket 1)* | *GLE (Bucket 1)* | *STT (Bucket 1)* |
| All | **0.030**** | **0.001***** | **0.001***** | **0.072*** | 0.406 | **0.001***** |
| 0.05 | 0.364 | **0.002***** | **0.065*** | 0.180 | **0.001***** | 0.167 |
| 0.10 | **0.054*** | **0.001***** | **0.001***** | 0.150 | **0.001***** | **0.020**** |
| 0.25 | 0.234 | **0.001***** | **0.001***** | **0.023**** | **0.001***** | **0.001***** |
| 0.50 | 0.883 | 0.820 | 0.179 | 0.216 | **0.002***** | 0.146 |
| 0.75 | **0.001***** | **0.001***** | **0.001***** | **0.038**** | **0.001***** | **0.001***** |
| 0.90 | **0.027**** | **0.001***** | **0.001***** | 0.228 | 0.219 | **0.014**** |
| 0.95 | **0.038**** | **0.074*** | **0.001***** | 0.474 | 0.338 | **0.015**** |
| | From KFTX *To* | | | | | |
| *q* | *SMFG (Bucket 1)* | *TD (Bucket 1)* | *UBS (Bucket 1)* | *UCG (Bucket 1)* | *WFC (Bucket 1)* | *STAN (Bucket 1)* |
| All | **0.001***** | **0.001***** | **0.001***** | **0.038**** | **0.001***** | 0.140 |
| 0.05 | 0.103 | **0.013**** | **0.072*** | 0.391 | **0.010***** | 0.384 |
| 0.10 | **0.001***** | **0.001***** | **0.001***** | **0.001***** | **0.001***** | 0.514 |
| 0.25 | **0.001***** | **0.001***** | **0.001***** | **0.068*** | **0.001***** | 0.183 |
| 0.50 | 0.845 | 0.148 | 0.555 | 0.832 | **0.064*** | **0.047**** |
| 0.75 | **0.001***** | **0.001***** | **0.001***** | **0.022**** | **0.001***** | 0.112 |
| 0.90 | **0.031**** | **0.001***** | **0.001***** | 0.304 | **0.065*** | 0.311 |
| 0.95 | 0.481 | **0.019**** | **0.050**** | 0.559 | 0.0174 | 0.438 |

***Notes***: Table 3 displays the *p*-values for the Granger causality test of KFTX to GSIBs. *q* denotes the quantile distribution. Bold figures denote instances where the initial hypothesis was rejected, at least at the 10 % significance level.

index also did not significantly impact most systemically important banks. Conversely, during periods of market rises or falls, as opposed to extreme fluctuations ($q = 0.1/0.25$ or $0.75/0.9$), the financial technology index exhibited a Granger causality relationship with almost all systemically important banks. These findings also provide insights into tail dependencies, which contribute to practices in FinTech financing and risk management.

### *6.1. Theoretical contributions*

Our theoretical contribution resides in providing an in-depth and nuanced analysis of the relationship between financial technology and G-SIBs, areas potentially underexplored in the existing literature. Based on the previous literature, we filled the research gap on the impact of the fintech index on the market performance of global systemically important banks and considered the heterogeneous effects of different market conditions on this impact. These contributions significantly aid in filling the knowledge gap regarding the influence of financial technology on key financial institutions under diverse market conditions.

Firstly, we extensively explored the quantile causality relationship between the FinTech index and G-SIBs. While existing literature may primarily focus on the general relationship between financial technology and the banking sector, there is a notable lack of comprehensive analysis of these relationships under varying market conditions, especially at different quantile levels. Our study, by assessing the quantile causality, meticulously observed and analysed the impact of the FinTech index on G-SIBs under diverse market conditions, particularly in extreme market scenarios, thus addressing a notable lacuna in existing research. The results of our study are instrumental in understanding the heterogeneous effects of financial technology on segmentally significant banks during periods of market volatility and stability.

Secondly, previous research on financial technology may not have given due consideration to the critically important category of globally systemically important banks (G-SIBs). These banks have a profound impact on global financial stability; therefore, specialised research on these institutions is crucial for a better understanding of the role and influence of financial technology within the global financial framework. This is key for regulatory bodies and policymakers in comprehending and addressing the impact of rapidly evolving financial technology on the banking sector and the broader financial industry.

### *6.2. Policy implications*

Our findings suggest that under extreme market conditions, the impact of the FinTech index on systemically important banks is minimal. However, as market unstable intensifies, particularly under conditions processing towards extremity, the relationship between the FinTech index and these banks becomes more pronounced. Therefore, in developing regulatory frameworks, policymakers should adopt targeted, flexible policies that vary according to different market situations, with a special focus on periods when the market shifts from stability to turbulence.

## Ethics approval and consent to participate

Not applicable.

## Consent for publication

All authors are very positive to publish this manuscript on this journal.

## CRediT authorship contribution statement

**Hongjun Zeng:** Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Investigation. **Brian Lucey:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Investigation.

## Declaration of competing interest

There is no competing interest among the authors.

## Data availability

Data will be made available on request.

### *Funding*

There is no funding for this research. However, authors will use personal fund for the associated costs of publications in this journal.

### *Acknowledgements*

We will be grateful to the anonymous reviewers who will comment on this manuscript

## References

Allen, F., Gu, X., Jagtiani, J., 2021. A survey of fintech research and policy discussion. Rev. Corp. Finance 1, 259–339.
Anagnostopoulos, I., 2018. Fintech and regtech: impact on regulators and banks. J. Econ. Bus. 100, 7–25.

Anand, D., Mantrala, M., 2019. Responding to disruptive business model innovations: the case of traditional banks facing fintech entrants. J. Bank. Financ. Technol. 3, 19–31.
Batten, J.A., Boubaker, S., Kinateder, H., Choudhury, T., Wagner, N.F., 2023a. Volatility impacts on global banks: insights from the GFC, COVID-19, and the Russia-Ukraine war. J. Econ. Behav. Organ. 215, 325–350.
Batten, J.A., Choudhury, T., Kinateder, H., Wagner, N.F., 2023b. Volatility impacts on the European banking sector: GFC and COVID-19. Ann. Oper. Res. 330 (1), 335–360.
Chen, Y., Kumara, E.K., Sivakumar, V., 2021. Investigation of finance industry on risk awareness model and digital economic growth. Ann Oper Res 1–22.
Christensen, C.M., Horn, M.B., Caldera, L., Soares, L., 2011. Disrupting college: how disruptive innovation can deliver quality and affordability to postsecondary education. Innosight Institute.
Daly, K., Batten, J.A., Mishra, A.V., Choudhury, T., 2019. Contagion risk in global banking sector. J. Int. Financ. Markets Instit. Money 63, 101136.
Fostel, A., Geanakoplos, J., 2016. Financial innovation, collateral, and investment. Am. Econ. J. Macroecon. 8 (1), 242–284.
Fung, D.W., Lee, W.Y., Yeh, J.J., Yuen, F.L., 2020. Friend or foe: the divergent effects of FinTech on financial stability. Emerg. Markets Rev. 45, 100727.
Gomber, P., Kauffman, R.J., Parker, C., Weber, B.W., 2018. On the fintech revolution: interpreting the forces of innovation, disruption, and transformation in financial services. J. Manage. Inform. Syst. 35 (1), 220–265.
Kim, H., Batten, J.A., Ryu, D., 2020. Financial crisis, bank diversification, and financial stability: OECD countries. Int. Rev. Econ.Finance 65, 94–104.
Lee, I., Shin, Y.J., 2018. Fintech: ecosystem, business models, investment decisions, and challenges. Bus. Horiz. 61 (1), 35–46.
Mirza, N., Umar, M., Afzal, A., Firdousi, S.F., 2023. The role of fintech in promoting green finance, and profitability: evidence from the banking sector in the euro zone. Econ. Anal. Policy 78, 33–40.
Pollari, I., 2016. The rise of Fintech opportunities and challenges. Jassa (3), 15–21.
Pramanik, H.S., Kirtania, M., Pani, A.K., 2019. Essence of digital transformation—manifestations at large financial institutions from North America. Fut. Gener. Comp. Syst. 95, 323–343.
Rapih, S., Wahyono, B., Borges, J.T., Phongsounthone, S., 2023. Financial openness and fintech credit. Financ. Res. Lett., 104134
Stulz, R.M., 2019. Fintech, bigtech, and the future of banks. J. Appl. Corp. Finance 31 (4), 86–97.
Temelkov, Z., 2018. Fintech firms opportunity or threat for banks? Int. J. Inform. Bus. Manage. 10 (1), 137–143.
Tiwari, A.K., Abakah, E.J.A., Shao, X., Le, T.L., Gyamfi, M.N., 2023. Financial technology stocks, green financial assets, and energy markets: a quantile causality and dependence analysis. Energy Econ. 118, 106498.
Troster, V., 2018. Testing for Granger-causality in quantiles. Econom. Rev. 37 (8), 850–866.
Uddin, G.S., Hasan, M.B., Phoumin, H., Taghizadeh-Hesary, F., Ahmed, A., Troster, V., 2023. Exploring the critical demand drivers of electricity consumption in Thailand. Energy Econ. 125, 106875.
Varma, P., Nijjer, S., Sood, K., Grima, S., Rupeika-Apoga, R., 2022. Thematic analysis of financial technology (Fintech) influence on the banking industry. Risks 10 (10), 186.
Xie, Q., Lu, C., Li, J., Zheng, X., 2023. The impact of treasury operations and off-balance-sheet credit business on commercial bank credit risk. J. Risk (5), 25.
Zalan, T., Toufaily, E., 2017. The promise of fintech in emerging markets: not as disruptive. Contemp.Econ. 11 (4), 415–430.
Zeng, H., Abedin, M.Z., Zhou, X., Lu, R., 2024. Measuring the extreme linkages and time-frequency co-movements among artificial intelligence and clean energy indices. Int. Rev. Financ. Anal., 103073
Zhao, J., Li, X., Yu, C.H., Chen, S., Lee, C.C., 2022. Riding the FinTech innovation wave: finTech, patents and bank performance. J. Int. Money Finance 122, 102552.