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Does digital transformation matter for operational risk exposure?

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A B S T R A C T

Basel Committee recommends banks maintain a capital buffer for operational risk exposure based on business volumes, assuming aggressive actions for quicker business growth could increase risk exposures. We argue that technological innovations expose banks to more operational risk because technology helps increase business volume, but system failure, problems with internal processes, and disruptions from external and internal security threats are inherent to technology. Based on 10 years of data for 264 banks from 43 countries, we find that digitalized banking operation is an underlying driver of operational risk that comes with increased business volume. Banks proactively take more operational risks by increasing cyber spending to tackle FinTech competition in the digitalized economy. Digitalization could generally matter for operational risk exposure, but the natural experiment does not find cybersecurity threats per se could increase operational risks even though cybersecurity appears to be a serious threat to digital banking. The study creates new avenues for future research.

1. Introduction

The global financial industry has been transformed significantly over the years with the help of disruptive innovations of digital or cyber technologies,[1] big data analytics, machine learning, and artificial intelligence.[2] As banks' operational landscape is shifting rapidly with disruptive innovations, increased spending on digital technology is inevitable for enhancing efficiency, service quality, and performance (Roth and Jackson-III, 1995). This digital transformation in the banking industry was unavoidable as technology adoption has silently occurred and transformed the entire socio-economic ecosystem leading to the 4th and 5th industrial revolutions (Dąbrowska et al., 2022). Hence, banks as financial intermediaries must improve efficiency and remain competitive by adopting the latest financial technology (FinTech), but the marginal cost-benefit analysis of digital infrastructure use is often ignored (Kauffman et al., 2015). The recent evidence shows that bank stability suffers when cyber technology spending exceeds the threshold level (Uddin et al., 2020b). Therefore, the question is whether excess digitalization[3] could lead a bank to the danger zone where operational hazards are high.[4]

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[1] We used 'cyber' and 'digital' terminologies interchangeably as writing context demands. Generally, the digital word is used in a broader perspective to indicate the system of receiving and sending information in digital format (series of numbers zero and one), and cyber word commonly refers to remote connectivity through an internet system that allows digital technologies (devices and software) to function and process data. Hence, digital and cyber technologies are intertwined and commonly defined or known as digitalization

[2] A disruptive innovation gives rise to new business opportunities and value chains by displacing the established firms and products from the market (Christensen et al., 2015).

[3] Digitalization refers to the extensive use of computer systems (hardware and software) for most (if not all) banking operations, fintech solutions (own and third-party) application for online or remote banking services delivery, intra and interbank monetary transaction systems, and security intelligence setup

[4] The Basel Committee attempts to assess operational risks exposure from inadequate or failed internal processes, people, and systems or external events (BCBS, 2004a, 2004b). But there is no proven method available to assess the actual operational risks exposure due to the fact that operational risks are quite diverse by their nature and are highly unpredictable in assessing its overall financial impact. The regulatory regimes view operational risk management as a developing discipline and suggest banks maintain a capital buffer for their potential operational risk exposure. The latest recommendation by the Basel Committee includes a business indicator to determine operational risk exposure (BCBS, 2017).

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This question is important because operations become quicker, and business grows faster with digitalization. At the same time, the likelihood of disruptions in operations also increases, which has direct and indirect costs for banks, customers, and the economy. The reason because no technology is free from loopholes (always leaving a door open to cybercriminals), and software glitches or bugs are inevitable in digital operations (Uddin et al., 2020a), even though advanced systems with artificial intelligence (AI) might help detect and self-correct potential hazards. Still, a single incidence of risk event could be a disaster.

The recent cyber incident with Credit Swisse could be a good example of how digitalization contributes to information asymmetry and, thereby, more operational risks. Credit Suisse recently experienced massive data leaks for about 18,000 bank accounts, exposing 80 billion of hidden wealth despite data confidentiality being their top priority and that the top-level system and processes work for security control. Credit Suisse denies its offense, but cyber experts believe the internal operational control on staff working with technology has the advantage of inside knowledge to exploit loopholes in digital systems. While the operational control risk always existed when technologies were not advanced, the data leakage hazards amplified when operations are automated, as perpetrators (insiders or outsiders) often go undetected; and risk accountability is hard to ascertain. Thereby, people with strong tech knowledge can take advantage. This argument is consistent with the classical asymmetric information theory (Akerlof, 1970; Bergh et al., 2019). Hence, the digitalization of operations contributes to an asymmetric information environment, leading to more operational risks. Overall, risk events in digital operations are unpredictable, and direct and indirect losses are hard to estimate (Gordon and Loeb, 2002a; Gordon and Loeb, 2002b; Low, 2017; Uddin et al., 2020a). Hence, operational risk has been challenging for banks worldwide as technological innovations are on the verge of taking over human roles in the modern banking system.

Operational risk always exists in the banking industry, but the finance literature traditionally focused on credit and market risks, although a few researchers studied some issues of operational risks and internal losses (Aldasoro et al., 2020a; Jarrow, 2008; Mitra et al., 2015; Cummins et al., 2006). Likewise, the Basel I capital framework concentrated on banks' credit risk management. However, the Basel Committee on Bank Supervision (BCBS) later recognized the consequences of banks' operational failures in the Basel II and III capital guidelines. Therefore, BCBS asks banks to maintain a minimum capital buffer to offset losses from unexpected operational risk events – in addition to credit and market risks (BCBS, 2004a, 2004b, 2011, 2014). Although managers and regulators recognize risks associated with unexpected business disruptions, a prudential measure for operational risks is yet to be developed – because the sources of operational hazards are very diverse, and literature in this area is still growing (Cummins et al., 2006; Jarrow, 2008).

Due to the absence of established academic literature on operational risk, the Basel Committee applies gross income and business indicator as measures for operational risk exposure for banks (BCBS, 2014). However, the Basel III capital framework recommends the business indicator to benchmark operational risk exposure. The business indicator tracks all primary income-generating activities in determining operating risk capitals – assuming that operational risk increases with the bank's total business volume (BCBS, 2017). Academic literature examines banks' operational risk from various perspectives, such as litigation expenses (McNulty and Akhigbe, 2017), governance complexity (Chernobai et al., 2011), financial crisis (Cope and Carrivick, 2013), supervisory regulations (Barakat and Hussainey, 2013), and reputation losses (Gillet et al., 2010), among others. The existing studies investigate whether operational risk caused any of the above problems, such as litigation expenses, governance complexity, financial crisis, supervisory regulations, reputation losses, etc. However, none of these studies answer the following questions: Why and how does operational risk arise? Why does the Basel Committee ask financial institutions to maintain an adequate operational risk capital buffer?

As the literature exploring the underlying causes of operational risks is limited, we review extant research around different disciplinary areas and find that operation speed or scale helps banks increase their business volume (He et al., 2017; Caputo et al., 2021). At the same time, it gives rise to their operational risk exposure (Jarrow, 2008). It means that as banks become more aggressive to increase business volume and achieve quicker growth, their exposure to operational risk also increases. Hence, the underlying assumption of the Basel recommendation for measuring operational risk exposure based on a bank's business volumes is consistent with the understanding of academic literature. With this view, we argue that technological innovations and digital transformations helped financial institutions globally accelerate business volume and growth much faster than before. At the same time, managers, analysts, and researchers witness that the global financial system has become more vulnerable to various technology hazards, including security breaches (Uddin et al., 2020a). Thus, we hypothesize that banks are exposed to more operational risks with the more digitalized operations.

We implement an empirical study using 10 years' data from 2008 to 2017 for a global sample of 264 banks from 43 countries from different regions. Following Basel II and III, we apply gross income and business indicator as the proxies of operational risk. We also apply two digitalization proxies (e.g. log of total spending on digital technology and the total spending on digital technology relative to bank size) in the study. The results show that both digitalization proxies affect operational risk positively, confirming that faster business expansion with extensive usage of digital technology exposes banks to more operational risks. The results remain robust across different estimation procedures and alternatives proxies. Thus, the study documents digitalized banking operation as an underlying driver of operational risk exposure, and banks proactively take this risk for faster business expansion and growth.

Subsample tests identify that digitalization's impact changes with technology regimes across countries. The effect is significant in counties that are yet to reach the plateau stage of technological advancement and in countries that have made substantial progress with more intelligent technological innovations. The study finds that cyber legislation worldwide contributes to creating digital ecosystems, paving the way for quicker business expansion, which comes with more operational risk exposure. Still, for strategic necessity, banks actively take more risks to achieve faster business growth with product diversifications and to compete with FinTech firms. We run a natural experiment using two groups of matched observations and the results indicate that cybersecurity per se does not expose a bank to more operational risks – contrary to the perception that cybersecurity is a big concern for the financial industry. Finally, we find banks incur more costs for every dollar of revenue by stressing capacity to speed up operations for more business volume. This might happen as banks absorb losses from letdowns coming with expediting operations and stressing their ability. Thereby, our study proves Basel's recommendation for using the business indicator measure as a prudent operational risk exposure proxy.

We make several original contributions to the literature. First, this is the first study to document that digitalized banking is the primary driver of operational risk exposure in the Basel regulatory framework. As economic sectors and the financial industry have evolved worldwide with digital innovations, this study contributes to knowing how banks could characterize operational risk exposure from technological transformation. Jarrow (2008) suggested that the risk of losses could arise due to a firm's operating technology and agency costs. Hence, our study provides insights supporting Jarrow's view of technology as a source of operational risk, as operational technology or system causes the failure of internal processes and transactions, resulting in economic value losses (Cummins et al., 2006). Also, Uddin et al. (2020b) document that bank stability is affected negatively by cyber technology spending if it crosses the threshold level. This study provides new insight into the discussion by showing that operational hazards from more digitalization could be a potential channel of bank instability. Second, with the advancement of more intelligent digital technologies, banks take more operational risk proactively by drifting from core business to more complex hybrid services and structured products in the wake of FinTech competition. Thereby, this study substantiates the argument that business complexity increases operational risk (Chernobai et al., 2021). Third, our findings shed a different light on the view that information technology improves transparency; we find that it could be the opposite, as sources of digital hazards are diverse and unknown, and a fair estimation of economic impact is challenging for banks. Accordingly, operational risk could increase market information asymmetry with more digital operations. Thus, our study supports Barakat et al. (2014), who found that market information asymmetry increases after announcing operational risk events.

We arrange the rest of the paper in different sections. Section 2 provides the literature review and hypothesis development. Section 3 elaborates test variables and empirical test models. Section 4 describes study samples and data. Section 5 presents results and provides a discussion. Finally, we identify the key takeaways in the conclusion section.

2. Literature and hypotheses

Operational risk is a broad concept that implies a chance of loss from unpredictable events like process failure, errors, frauds, lawsuits, data breaches, etc. – that adversely affect business operations (Moosa, 2007). Earlier researchers tried to define operational risk from various perspectives but failed to distinguish between a quantifiable risk and a typical uncertainty in daily business operations (Crouhy et al., 2001). Therefore, researchers, financial institutions, and regulatory bodies for the financial sector generally classify the operational as the residual risk, covering everything other than credit or market risks (Rao and Dev, 2006). However, measuring the residual risks as a proxy for operational risk is challenging because there is no established framework for assessing operational risk parameters. An appropriate measure of operational risk is to capture both direct and indirect losses from inadequate or failed internal processes, people and system errors, and external events (BCBS, 2004a, 2004b). Hence, the Basel II Accord required banks globally to maintain adequate capital to buffer against operational risks in addition to common financial risks (BCBS, 2011).

Banks would track their loss data across different categories of loss events[5] and scale them on the risk exposure level using the basic indicator approach[6] that relies on the bank's gross income as an appropriate indicator for operational risk exposure. However, the Basel III Accord adopts a revised standardized approach to estimate operational risk exposure based on the business indicator as a more comprehensive indicator for operational risk exposure by tracking the bank's business volume from its financial statements (BCBS, 2017). Based on the Basel Committee's guidance, we argue that operational risk exposure is fundamentally linked to the banks' business expansion activities. As banks escalate their operations for faster business expansion in the competitive market, the chance of errors, mistakes, and unwanted events would also increase.

We can link this argument to the body of literature on social sciences and economics. In social psychology and behavioral theory, the accuracy of human judgment of a situation at the current time depends on the individual's cognition ability (Tversky and Kahneman, 1983), perception process (Funder, 1987), thinking speed (Kauffman et al., 2015), and information quality and availability (Keller and Staelin, 1987). It means more errors and mistakes in the decision process are inevitable, particularly as people exceed the threshold to absorb mental stress. Also, based on the classical theory of diminishing returns in economics, we can deduce that increased errors and mistakes in managers' operational decisions could reduce the marginal gains – contributing to the operational risk exposure and internal operational loss. Therefore, researchers make efforts to estimate operational risk and the chance of losses based on the extreme value theory, as the economic effects of unexpected events from errors or mistakes are uncertain and they may be disastrous for the institution (Zhu et al., 2019; Abbate et al., 2009).

Overall, the Basel Committee's guidelines and our analysis on theoretical perspectives suggest that the speed and scale of operations matter for business growth, but could also drive up banks' exposure to operational risks. The economic theory and related literature recognize the role of technology in propelling productivity (Ayres, 1953; Nordhaus, 1969) by accelerating the operational process through reengineering (Gunasekaran and Nath, 1977; Attaran, 2004) and business model innovation (Haaker et al., 2021). With the continued innovation and transformation in technology over the last decades, the ecosystem of the global financial industry has been evolving continuously, and digital banking operations have become the norm worldwide. The use of more advanced technology such as data analytics, machine learning, and artificial intelligence can speed up managerial decisions and business operations in a competitive market, helping businesses grow enormously and expanding financial inclusion (Levine, 1993; King and Levine, 1993; Demirgüç-Kunt et al., 2018). However, the extensive literature review by Uddin et al. (2020a) identifies that the global financial system has become more vulnerable to the pervasive effects of widespread application of cyber technology in banking operations, and institutions have become more unstable due to the excessive spending on digital technology (Uddin et al., 2020b).

Extensive use of digital technology could improve the speed of banking operations (Banker et al., 1990), financial services delivery (Barrett et al., 2015), and liquidity due to real-time and seamless integration with local and international financial systems (Casu et al., 2016). However, the faster business expansion and operational functions relying aggressively on cyber technology may increase the likelihood of digital hazards or disastrous events that are difficult to predict (Cherdantseva et al., 2016; Ralston et al., 2007). It is nearly impossible to have foolproof technology against human error, mistakes, technical glitches, system faults, security breaches, etc. (Aseef et al., 2005; Choo, 2011; McConnell et al., 2013). Based on the global risks perception survey, the World Economic Forum assessed 12 emerging technological innovations, including, among others artificial intelligence, robotics, blockchain, and distrusted ledger, and neurotechnology. The assessment revealed that the emerging technologies have high inherent risks[7] behind their potential benefits (World Economic Forum, 2017).

Hence, although the digitalization of operations is essential for productivity increase and business growth, the Basel Committee requires banks globally to create a buffer against potential losses from operational hazards, which we argue to be linked to the extensive use of digital technology in banking operations. Compared to traditional risks like credit and liquidity risks, the assessment of operational risks driven

[5] Banks are to systematically track internal losses for various events across seven broad categories of risk events: (i) internal fraud, (ii) external fraud, (iii) employment practices and workplace safety, (iv) clients, products, and business practices, (v) damage to physical assets, (vi) business disruption and system failures, and (vii) execution, delivery, and process management (BCBS, 2004a, 2004b).

[6] In the Basel II Accord, the basis indicator is the common approach that allows banks to set aside a fixed percentage of their average gross income over the past three years as a regulatory capital charge. Banks could also apply a standardized approach to assess the scale of operational risk exposure across different business lines. Subject to supervisory approval, a bank could alternatively apply an advanced management approach if it has its own risk management framework.

[7] While the risks of these emerging technologies are hidden and multidimensional, the report documents the concerns about decisions taken by machines when there is a question of ethics involved. This is a serious matter in using widespread hybrid technology: an artificial brain cannot replace the human mind in making ethical judgments.

by the extensive digital banking operations would be more complex and pervasive due to the unpredictable nature of the risk events and potential direct and indirect losses (Gordon and Loeb, 2002a; Gordon and Loeb, 2002b). In a nutshell, the above conceptual analysis, theoretical insights, and Basel Committee's guidelines suggest that speeding up banks' operational functions to increase business volume and achieve faster growth relying on the extensive use of digital technology would contribute to increasing operational hazards for banks. Accordingly, we construct the following as a primary hypothesis of this study.

H.A. Banks are exposed to more operational risks with more digitalized operations.

This hypothesis connects to the classical theory of information asymmetry (Akerlof, 1970; Bergh et al., 2019). As it is proven that no digital technology (including AI) is free from loopholes, which can give rise to information asymmetry in favor of the insiders and outsiders who are experts in operating the advanced digital system. If these people with strong tech knowledge can take advantage, it is difficult to ascertain their responsibility and make them accountable, thus creating a moral hazard problem (Mirrlees, 1999), for digitalization.

3. Variables and test models

3.1. Dependent variables

This study examines if the scale of digitalization affects a bank's operational risk exposure. We adopt the operational risk (*OPR*) exposure proxies under the Basel II and III risk capital estimation frameworks[8] (BCBS, 2004a, 2004b, 2017) as the dependent variables in our test models. Basel II first applies gross income, but Basel III later develops a comprehensive business indicator measure as the better proxy for banks' operational risk exposure. Both the proxies are financial-statement-based indicators for a bank's operational risks. We define them as below:

$$OPR1_{it} = \mathrm{Ln}(Net\ Interest\ Income_{it} - Net\ Non-Interest\ Income_{it}) \quad (1)$$

where $OPR1_{it}$ is operational risk exposure proxy 1, which follows the Basel II approach, and represents the gross income for bank i in year t, *Net Interest Income* is the total interest income less the total interest expense of a bank, and *Net Non-Interest Income* includes the net of service fees & commissions received and paid, net of investment returns, net of the gain and loss from the foreign exchange transactions, and other incomes reported in the income statement.

$$OPR2_{it} = \mathrm{Ln}(Interest\ Element_{it} + Service\ Element_{it} + Financial\ Elements_{it}) \quad (2)$$

$OPR2_{it}$ is operational risk exposure proxy 2, which follows the Basel III approach, representing the Business Indicator for bank i in year t. The *Interest Element* consists of the absolute value of the interest margin (interest income minus interest expenses). This element also includes the bank's net lease income and dividend income (if any). The *Service Element* consists of the sum of (i) fee income, (ii) fee expenses, (iii) other operating income, and (iv) other operating expenses. Finally, the *Financial Element* consists of the absolute profit or loss value from trading and banking books.

3.2. Independent variable

We apply two proxies that represent the scale of bank digitalization. The first proxy (*Digitalization-1*) is the natural log of the total digital technology-related expense of the bank. Uddin et al. (2020b) first applied this variable to test the effect of the growth in cyber technology spending on banks' stability. It includes expenses for computer hardware depreciation, software (procurement and development) amortizations, payments for data processing support, third-party cybersecurity services, delivery of products and services through FinTech agents, staff training on information technology, and server maintenance online-based operational systems and apps. These are hand-collected data from the annual reports of sample banks after screening the financial statement items and corresponding notes. Overall, the proxy would reflect the scale of the digital operation of a bank that we need to test the hypothesis empirically. We also apply *Digitalization-2*, the total digital technology-related expense to bank size (total asset), which determines the scale of the digital operation of a bank relative to its size.

3.3. Bank-level controls

Following the extant literature, we take (i) *total asset*, (ii) *liquidity ratio*, (iii) *deposit to asset*, (iv) *loan to asset*, (v) *loan loss provision*, (vi) *liability to assets*, and (vii) *interest margin* as the bank-level controls. *Total asset* is a common control across all models as the volumes of business operations and risk-taking (Gropp et al., 2014) increase with bank size. With an increased *liquidity ratio*, banks can aggressively increase business and other interbank banking services, contributing to network risk (Denbee et al., 2021). Both *deposit to assets* and *loan to asset* reflect the scale of bank financing and customer lending – contributing to banks' risk exposure (Ibrahim and Rizvi, 2018). However, a high *loan loss provision* indicates inefficient loan management, resulting in more litigation due to operational lapses (McNulty and Akhigbe, 2017). An increased *liability to assets* implies extensive fund mobilization and offering more services to large customer groups in competitive markets, such as interbank payments, among others, contributing to operational hazards. Finally, banks may need a higher *interest margin* to cover a higher operating cost.

3.4. County-level controls

As the study sample includes multi-country data, we add (i) financial freedom, (ii) cyber index, (iii) inflation, and (iv) gross domestic product (GDP) of the country as a control to capture variations in banks' operational risk exposure due to relevant country-level common factors. *Financial freedom* in the country allows banks to be more productive and expand banking services faster because of the government policy support (Chortareas et al., 2013). *Cyber index* of a country could influence banks' choice of security systems due to regulatory requirements, affecting the level of operational risk exposure (Crisanto and Prenio, 2017). *Inflation* level in the economy affects money supply, savings, credit demand, and financial market performance in the country (Boyd et al., 2001), affecting banks' business growth and risk. *GDP* level of a country could matter as evidence shows banks incur more operational losses in an adverse economic environment (Abdymomunov et al., 2020).

3.5. Test model and estimation

We specify the following generic base model for our empirical analysis.

[8] We rely on Basel proxies because there is no established literature on how to estimate operational risk exposure. A few researchers used risk events and loss data and analyzed them using the value at risk (VaR) framework to assess operational risk (Eling and Wirfs, 2019; Biener et al., 2015). However, challenges and pitfalls exist in measuring operational risk from loss data (Cope et al., 2009), because there is no standardized accounting approach or established record-keeping system to uniformly track losses from operational breakdowns across banks globally. Also, banks do not normally disclose such loss data. Overall, Basel proxies are broader and more based on the audited financial statements that reflect the volume of business and operational activities of a bank, which drive the likelihood of operational risk – in line with theoretical insights discussed.

$$OPR_{it} = \alpha + \beta_i Digitalization_{it} + \sum_{i=1}^{N} \gamma_i Controls_{it} + \varepsilon_i \tag{3}$$

where, OPR_{it} is the proxy ($OPR1_{it}$ and $OPR2_{it}$) for operational risk exposure taken from the Basel capital regulatory framework for global banks – as defined earlier. $Digitalization_{it}$ is a proxy measuring the scale of bank digitalization. We test two proxies: *Digitalization-1* measures total spending by a bank on digital technology, and *Digitalization-2* measures total spending by a bank on digital technology relative to its size. As discussed earlier, *Controls* include several bank and country variables and country and year interaction to capture unknown effects across countries and time.[9] Appendix 1 provides more details about the model variables. We estimate the base model based on ordinary least square (OLS), fixed-effect (FE), and two-step dynamic system generalized method of moments (GMM) estimation procedure to draw an inference on our hypothesis that is consistent across test methods.

4. Sample and data

We apply a systematic process to identify the sample banks. First, we generate a long list of banks from various sources, including the Bankers Almanac directory, then shortlist countries to represent different regions worldwide (both developed and emerging economies) to create a global sample. Second, after searching the Bloomberg database, we remove banks not listed on the exchange, or where relevant data for operational risk exposure variable (*OPR*) are missing after 2008.[10] The next challenge was collecting banks' spending on digital technology. There was no mandatory regulation for such disclosure, so a database was unavailable. Thus, a search of annual reports manually was the only option to construct independent variables (*Digitalization-1* and *Digitalization-2*). Accordingly, we download 10 years' annual reports from websites after the Bloomberg search. We drop banks when the annual reports are unavailable for seven of the 10 years. Also, at the final screening, we exclude countries with fewer than three banks. Overall, the clean sample consists of 264 banks from 43 countries disclosing digital technology expenses over 10 years from 2008 to 2017. Countries represent North America, Europe, Asia, Asia Pacific, Latin America, the Middle East, and North Africa (MENA).

We find 264 banks report spending information related to digital technology usage, which we collect by carefully checking all expenses items in the audited financial statements of sample banks.[11] After checking 10 years' annual reports, we get 2165 observations for the panel data set. Table 1 shows a maximum of 292 observations from the US market, about 13.49 % of the sample. The observations vary from 21 (1 %) to 101 (4.6 %) for the remaining countries. Overall, study observations are fairly distributed across 43 countries from different regions to provide a global outlook of the sample.

Table 2 shows the descriptive statistics for test variables after winsorization at the 1st and 99th percentiles. The operational risk exposure proxy *OPR1* (natural log of gross income) ranges from 1.264 to 4.833 with a mean of 2.883 and standard deviation of 0.777, while OPR2 (natural log of business indicator) varies from 1.502 to 5.073 with an average value of 3.136 and standard deviation of 0.796. Both *OPR1* and *OPR2* are fairly symmetrical with skewness of 0.274 and 2.607, respectively, for both proxies. Also, they are slightly platykurtic with kurtosis of 2.607 and 2.529 respectively for *OPR1* and *OPR2*. For the main independent variables, *Digitalization-1* is relatively symmetric with skewness of −0.318 and kurtosis of 2.984. However, *Digitalization-2* is skewed to the right with skewness of 2.884 and has a leptokurtic peak with a kurtosis of 12.534. The bank-level controls have both positive and negative skewness but are mostly leptokurtic except *total assets* and *loan-to-asset*. The country-level control variables generally show negative skewness and leptokurtic peak. Overall, the dependent variables and *Digitalization-1* are fairly symmetrical, but other variables have less symmetric distributions. Hence, we estimate models based on the winsorized data and assess the significance of coefficients based on the robust *t-values* using the standard errors clustered across country and year dimensions.

Table 1
Sample distribution.

No.	Country	Banks	Observations
1	Argentina	4	35
2	Australia	6	48
3	Bangladesh	14	101
4	Belgium	4	40
5	Brazil	6	51
6	Canada	4	31
7	Chile	3	28
8	China	8	76
9	Denmark	4	27
10	Egypt	7	39
11	Finland	3	22
12	France	8	61
13	Germany	5	44
14	Greece	5	50
15	India	8	51
16	Indonesia	5	44
17	Israel	4	21
18	Italy	6	60
19	Japan	3	30
20	Jordan	8	71
21	Malaysia	9	87
22	Mexico	3	27
23	Netherland	3	23
24	New Zealand	4	34
25	Norway	9	69
26	Oman	5	37
27	Pakistan	7	66
28	Poland	9	77
29	Qatar	4	28
30	Russia	4	31
31	Saudi Arabia	7	44
32	Singapore	3	22
33	South Africa	4	40
34	South Korea	4	25
35	Spain	4	37
36	Sweden	4	33
37	Switzerland	9	56
38	Thailand	4	24
39	Tunisia	5	26
40	Turkey	9	77
41	UAE	3	30
42	UK	6	50
43	USA	30	292
Total		264	2165

This is a clean sample after implementing a screening process. These banks report their annual spending on digital technology in their audited financial statements.

[9] As the study uses a panel data set from multiple countries over10 years, by following Beck et al. (2013), we apply *country* and *year* interaction control to capture any unobserved effect from unknown sources across countries and yearly periods. We use this control in Ordinary Least Square (OLS) estimation.

[10] We apply 2008 as the starting time because digitalization in the financial sector received global momentum after the financial crisis period, witnessing a FinTech revolution to affect the earnings and market share of traditional banks (Vives, 2019; Buchak et al., 2018).

[11] We consider an expense or cost item as digital technology spending if associated with a word/term like technology, IT, ICT, software, hardware, data process, system, server, IT training, etc. We checked the depreciation and amortizations for intangibles to find any sub-item linked to software and data processing.

Table 2
Descriptive statistics.

Variables		Obs	Mean	Std.Dev.	Min	Max	Skew.	Kurt.
Dependent variables	*OPR1*	3292	2.883	0.777	1.264	4.833	0.274	2.607
	OPR2	3298	3.136	0.796	1.502	5.073	0.259	2.529
Main independent variables	*Digitalization1*	2164	3.042	2.179	−2.989	7.476	−0.318	2.984
	Digitalization2	2124	0.165	0.219	0.001	1.242	2.884	12.534
Bank-level variables	*Total Asset*	3341	9.843	1.922	5.749	14.484	0.337	2.609
	Liquidity ratio	3063	4.521	15.672	0.002	136.656	7.02	56.058
	Deposit to asset	3341	0.401	0.069	0.000	0.43	−5.283	30.647
	Loan to asset	3188	0.493	0.472	0.000	0.985	−0.078	1.02
	Loan loss provision	3078	1.121	1.581	−0.269	9.621	3.032	14.17
	Liability to asset	3328	0.899	0.051	0.621	0.974	−2.531	13.074
	Interest margin	3105	3.685	3.039	0.595	20.269	3.132	15.29
Country-level variables	*Financial freedom*	3540	58.175	18.047	20.00	90.00	−0.294	2.22
	Cyber index	3540	0.592	0.184	0.176	0.919	−0.397	2.31
	Inflation	3540	4.113	5.593	−15.713	23.949	0.934	7.123
	GDP	3540	4.166	0.576	2.861	4.955	−0.676	2.38

Please refer to the appendix for variable definitions and measurements. The minimum values of *Digitalization1* and loan loss provisions (measured as a natural log) are negative numbers in this table. This is possible because we extract annual report data in millions, which becomes negative when the figure is less than a million, and log of a fraction is a negative value.

Table 3
Banks' operational risk exposure and digitalization scale.

Variables	OLS Estimate		Fixed Effect Estimate		GMM Estimate	
	OPR1	*OPR2*	*OPR1*	*OPR2*	*OPR1*	*OPR2*
Lag OPR1$_{t-1}$					0.606***	
					(7.66)	
Lag OPR2$_{t-1}$						0.538***
						(5.962)
Digitalization-1	0.013***	0.020***	0.018***	0.024***	0.042**	0.056**
	(4.457)	(5.929)	(4.802)	(5.194)	(2.12)	(2.474)
Total asset	0.419***	0.419***	0.307***	0.319***	0.132***	0.155***
	(136.858)	(114.495)	(33.310)	(28.378)	(3.771)	(3.520)
Liquidity ratio	0.000***	0.001***	−0.000	−0.000	0.002	0.003
	(2.694)	(3.576)	(−1.409)	(−0.761)	(1.601)	(1.240)
Deposit to asset	1.493***	1.849***	0.487***	0.778***	0.116	0.752
	(8.050)	(5.136)	(3.514)	(4.620)	(0.017)	(0.860)
Loan to asset	−0.021	−0.017	0.773***	0.544***	0.039	0.117
	(−1.518)	(−1.026)	(7.151)	(4.098)	(0.551)	(1.164)
Loan loss provision	0.019***	0.031***	0.007***	0.012***	−0.010	−0.002
	(4.385)	(5.874)	(3.176)	(4.635)	(−1.280)	(−0.180)
Liability to asset	−1.503***	−1.503***	−0.358***	−0.466***	0.115	−0.462
	(−10.082)	(−8.445)	(−2.834)	(−3.004)	(0.290)	(−0.854)
Interest margin	0.053***	0.044***	0.040***	0.022***	0.018***	0.020***
	(10.295)	(8.273)	(17.417)	(8.027)	(2.443)	(2.875)
Financial freedom	0.000	0.001***	−0.001*	−0.001	−0.001	0.004
	(1.102)	(3.768)	(−1.839)	(−1.302)	(−0.470)	(1.548)
Cyber index	0.019	0.080***	−0.071***	−0.004	−0.215***	−0.246***
	(0.966)	(3.209)	(−2.901)	(−0.137)	(−3.220)	(−2.975)
Inflation	0.005***	0.006***	−0.001***	−0.002***	0.002	0.002
	(6.237)	(6.062)	(−3.084)	(−2.641)	(1.041)	(1.082)
GDP	−0.063***	−0.075***	0.334***	0.364***	0.017	−0.086
	(−6.752)	(−6.024)	(5.185)	(4.609)	(0.240)	(−0.873)
Constant	−0.547***	−0.509**	−1.848***	−1.775***	−0.481	−0.146
	(−3.077)	(−2.481)	(−6.386)	(−4.994)	(−0.890)	(−0.214)
Country and year control	*Yes*	*Yes*			*Yes*	*Yes*
Observations	1775	1778	1775	1778	1573	1571
R-squared	0.973	0.959	0.625	0.545		
F value/Wald-chi	5452.37	3961.17	210.29	151.75	466,847.24	290,279.68
AR 1					0.000	0.018
AR 2					0.433	0.346
Hansen test					0.187	0.290

Baseline model: $OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}$.
The dependent variable is OPR1 or OPR2 – proxies for the operational risk exposure considered for estimating a bank's risk capital under Basel frameworks. The main independent variable is *Digitalization-1*, the natural log of the bank's total spending on digital technology. *Control* vectors include both bank- and country-level control variables. See the appendix for more details about the variables. Values in the parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

5. Results and discussion

5.1. Baseline models

Table 3 shows the estimations of the baseline model based on OLS, Fixed-Effect, and GMM, providing consistent results to confirm that the scale of digitalization significantly increases the level of banks' operational risk exposures proxied by *OPR1* and *OPR2*. All coefficients of the *Digitalization-1* variable are significant at less than the 1 % level across the three alternative estimations methods. However, *OPR2* results are more substantial than *OPR1* – as the magnitude of coefficients and the corresponding *t-values* are higher for *OPR2*. This finding is in line with the Basel Committee's recommendation to apply the business indicator measure (*OPR2*) as a superior proxy – relative to gross income (*OPR1*) – to capture the maximum exposure of operational risk in determining a bank's risk capital (BCBS, 2014). The coefficient estimate of *Digitalization-1* indicates that a 1 % increase in spending on digital technology leads to a 2 % to 5.6 % upsurge in operational risk exposure based on *OPR2* – subject to estimation method. The surge in risk exposure could be around 6 % to 15 % if the coefficient is standardized[12] to the variances of dependent and independent variables.

This means the scale of digitalization in banking operations is the critical driver escalating banks' operational risk exposure (Williams, 1995; Buchelt and Unteregger, 2003). We find this reflection on the R^2 values – above 90 % for OLS models and over 50 % for fixed-effect models. The *Digitalization-1* variable alone explains nearly 58 % of the variations in *OPR2* in the univariate test. We reexamine the base model for *Digitalization-2*, the natural log of a bank's total spending on digital technology divided by its total assets. This measures the scale of digitalization relative to bank size. In Table 4, the results for this relative digitalization measure are more robust. The coefficients of *Digitalization-2* for *OPR1* and *OPR2* are much larger than those of *Digitalization-1* in Table 3. All coefficients are significant at the less than 1 % level and consistent across OLS, Fixed-Effect, and GMM estimations. The escalation in risk exposure (*OPR2*) could be around 6 % for a 1 % increase in the relative digitalization (*Digitalization-2*) – after standardization of the coefficients. Overall, results in Tables 3 and 4 provide strong evidence supporting our hypothesis: a bank's exposure to operational risk increases with the scale of digitalization.

Overall, baseline results reflect the technology power for faster business growth, relying on cyber technology innovations that contribute to the operational hazards alongside business growth. Therefore, ceteris paribus, institutions with more digital operations are vulnerable to unknown dangers from the likelihood of risk events (Aldasoro et al., 2020a; Aldasoro et al., 2020b; Uddin et al., 2020b; Boot et al., 2021), even though digitalization contributes to business expansion and revenue growth (Aldasoro et al., 2020b). Also, banks have challenges in keeping pace with the speed of technological innovations. Thus, service-providing FinTech agents take over bank servers and customer communications (Boot et al., 2021), which means banks increasingly lose operational controls with faster digitalization.

5.2. Technological regime and operational risks

The state policies and strategic priorities for the digital economy influence institutions, particularly banks, to embark on a digitalization journey and increase spending on technology (Hanna, 2018; Uddin et al., 2020b). Therefore, we presume that technological development in a country determines bank digitalization's scale and operational risk exposure. Countries strongly committed to technological transformation are likely to influence their organizations toward digital changes (Crisanto and Prenio, 2017). Therefore, we classify banks into three groups based on the country's technological development following the International Telecommunication Union (ITU).[13] The early-level countries are those with a score below the 33rd percentile, the maturing-level countries are those with a score between the 33rd and 67th percentiles, and the advanced-level countries are those with a score above the 67th percentile.

Table 5 shows that digitalization significantly impacts on banks' operational risk exposures in countries in the early and advanced stages of technological advancement – as the coefficient estimates for these sample groups are significant at less than the 1 % level for all tests. We confirm this based on the alternative proxies of dependent (*OPR1* and *OPR2*) and independent (*Digitalization-1* and *Digitalization-2*) variables. Digitalization's effect on operational risk exposure is not significantly noticeable in countries in the maturing phase of technological development. These findings suggest technological regime changes due to the economic law of diminishing returns (Uddin et al., 2020b). Technical efficiency and productivity increase dramatically in the early stages when institutions shift from non-digital to digital operations. The marginal productivity from the same technology applications wanes as the country's economic sectors unfold with digital transformations – reaching a technological plateau. The countries and institutions then emerge from the technological plateau and increase their marginal productivity by replacing it with more advanced and new-generation technologies like AI, blockchain, nanotechnology, etc. Hence, our findings suggest that operational risk exposure in banks globally shifts with changes in technological regimes.

5.3. Cyber legislation and operational risks

As cybercrime has emerged as a global concern for the digital transformation of society, particularly in the economic and financial sectors, we notice a worldwide momentum in enacting cyber legislation. According to the United Nations Conference on Trade and Development (UNCTAD), nearly 80 % of countries worldwide have legislation that covers at least one of the four focus areas: (i) consumer protection, (ii) privacy and data protection, (iii) electronic transactions, and (iv) cybercrime control. We assume that cyber legislation across countries would influence social awareness of digitalization, firms' behavior in offering secure digital services, and adopting digital operations. Hence, banks' operational risk exposure would vary with the digital ecosystem developed with cyber legislation. We classify banks into two groups. The countries in Group 1 have a developed digital ecosystem, as they have legislation in the four areas mentioned above. Group 2 countries have a less-developed digital environment as their legislation does not cover all four focus areas.

Table 6 shows that operational risk is a concern for the banks working in a developed digital ecosystem. Panel A shows that coefficients of *Digitalization-1* and *Digitalization-2* are highly significant at less than the 1 % level for both proxies of operational risk exposure (*OPR1* and *OPR2*). However, in Panel B, none of the coefficients for *Digitalization-1* and *Digitalization-2* are significant. These findings suggest two things. First, comprehensive cyber legislation creates a positive environment facilitating more digital transactions – as customers and banks as service providers have legal protection against cybercrimes and unlawful online activities. Second, more online transactions and digital internal operations give rise to unknown digital hazards with increased business volume.

[12] $\textit{Standardized coefficient for Digitalization} - 1 = \frac{\sigma_{Digitilization-1}}{\sigma_{OPR2}} \times \textit{Digitalization} - 1\ \textit{coeffient}$

[13] The ITU scores the countries worldwide by determining the degree of advancement in informational and communications technology (ICT). Based on some established criteria, the ITU assess each country based on its ICT policies, cyber infrastructure, ICT initiative programs, capacity building, and cooperation with local and international agencies.

Table 4
Banks' operational risk exposure and digitalization relative to their size.

Variables	OLS estimate		Fixed effect estimate		GMM estimate	
	OPR1	*OPR2*	*OPR1*	*OPR2*	*OPR1*	*OPR2*
Lag OPR1$_{t-1}$					0.392***	
					(3.220)	
Lag OPR2$_{t-1}$						0.557***
						(6.174)
Digitalization-2	0.117***	0.176***	0.124***	0.169***	0.146*	0.236***
	(4.873)	(7.016)	(5.702)	(6.345)	(1.741)	(2.741)
Total asset	0.434***	0.441***	0.330***	0.350***	0.268***	0.204***
	(219.301)	(191.854)	(37.055)	(32.307)	(5.240)	(5.025)
Liquidity ratio	0.001***	0.001***	−0.000	−0.000	0.002	0.002
	(3.069)	(4.091)	(−1.362)	(−0.708)	(1.431)	(1.288)
Deposit to asset	1.577***	1.972***	0.504***	0.800***	−0.437	0.558
	(8.367)	(5.320)	(3.649)	(4.775)	(−0.532)	(0.721)
Loan to asset	−0.009	0.000	0.763***	0.531***	−0.061	−0.008
	(−0.641)	(0.010)	(7.081)	(4.019)	(−1.071)	(−0.128)
Loan loss provision	0.018***	0.028***	0.007***	0.012***	−0.005	−0.014*
	(3.968)	(5.461)	(3.076)	(4.533)	(−0.482)	(−1.667)
Liability to asset	−1.524***	−1.534***	−0.362***	−0.470***	0.171	−0.784
	(−10.317)	(−8.747)	(−2.874)	(−3.041)	(0.031)	(−1.549)
Interest margin	0.051***	0.042***	0.039***	0.022***	0.023*	0.021***
	(9.880)	(7.919)	(17.357)	(7.939)	(1.773)	(3.058)
Financial freedom	0.000	0.001***	−0.001	−0.001	0.001	0.006***
	(1.492)	(4.354)	(−1.504)	(−0.931)	(0.008)	(2.703)
Cyber index	0.014	0.074***	−0.072***	−0.004	−0.164**	−0.189***
	(0.736)	(2.956)	(−2.919)	(−0.143)	(−2.760)	(−2.807)
Inflation	0.005***	0.006***	−0.001***	−0.001**	0.001	0.003*
	(6.325)	(6.084)	(−2.989)	(−2.528)	(0.930)	(1.730)
GDP	−0.066***	−0.078***	0.333***	0.362***	0.013	−0.113
	(−6.893)	(−6.164)	(5.186)	(4.606)	(0.172)	(−1.580)
Constant	−0.687***	−0.720***	−2.053***	−2.050***	−0.786	−0.004
	(−4.265)	(−3.816)	(−7.136)	(−5.810)	(−1.402)	(−0.009)
Country and year control	*Yes*	*Yes*			*Yes*	*Yes*
Observations	1775	1778	1775	1778	1573	1571
R-squared	0.9743	0.9607	0.627	0.549		
F value/Wald-chi	5475.64	3987.67	212.36	154.15	296,930	326,301
AR 1					0.000	0.018
AR 2					0.471	0.236
Hansen test					0.577	0.118

Baseline model: $OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}$.
The dependent variable is OPR1 or OPR2 – proxies for the operational risk exposure considered for estimating a bank's risk capital under Basel frameworks. The main independent variable is *Digitalization-2*, the natural log of the bank's total spending on digital technology divided by the total assets. *Control* vectors include both bank- and country-level control variables. See the appendix for more details about the variables. Values in the parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

5.4. Digitalization lagged effect

The above results confirm that more digitalization is responsible for increasing operational risk exposure for banks – set aside exceptions. Hence, we explore whether managers proactively take more risks arising from digitalization. We need to know this because the global society is on the edge of a digital revolution that has profoundly changed the human living environment. With an exponential increase in technology power, banks have no better choice but to go with strategic investment in digital operations and risk-taking for business growth by remaining at the forefront of digital banking operations and market competition (Gordon and Loeb, 2002a; Gordon and Loeb, 2002b; Uddin et al., 2020b).

Table 7 shows that previous digitalization spending has a persistent effect on the current period's operational risk exposure. The coefficients of both *Digitalization-1$_{t-1}$* and *Digitalization-2$_{t-1}$* are significant at less than the 1 % level for proxies of operational risk exposures (*OPR1* and *OPR2*). The magnitude of digitalization's lagged effect coefficients in Table 7 is consistent with the level-effect coefficients in Tables 3 and 4. Based on the *Digitalization-1$_{t-1}$* coefficient, a 1 % increase in gross digitalization spending last year has a 1.5 % to 1.6 % persistent effect on the current year's risk exposure. Based on the *Digitalization-2$_{t-1}$* coefficient estimate, a 1 % increase in gross digitalization spending last year scaled by bank size has an 8.1 % to 9.3 % risk exposure in the following year; but, standardized coefficients suggest the effect could be between 2.23 % and 2.60 %. The model R^2 is higher than 70 % for all tests, suggesting that digitalization's lagged impact on operational risk exposure is substantial.

5.5. Across countries and regions

We can glean more insights into the findings from the results for different regions and countries. Table 8 reports the base model results for 43 sample countries and seven regions individually, showing that the effect of digitalization on banks' business volume, and thereby operational risk, varies across the countries and regions. The effect is significantly positive for 11 countries based on all alternative proxies of operational risk exposure and digitalization. The countries are: the USA, Belgium, Poland, Sweden, Switzerland, Bangladesh, South Korea, Argentina, the UAE, and Russia. In another 12 countries, the effect is significantly positive based on at least one or more proxies each for operational risk exposure and digitalization. For the rest, results are mixed and insignificant – except for Italy and Malaysia, where more digitalization has a significantly negative effect on the operational risk exposure. From a regional perspective, the effect is significantly positive for all regions worldwide, except Latin America.

Table 5
Digitalization and operational risk exposure for banks – technological regimes.

Variables	Early level				Maturing level				Advance level			
	OPR1	*OPR1*	*OPR2*	*OPR2*	*OPR1*	*OPR1*	*OPR2*	*OPR2*	*OPR1*	*OPR1*	*OPR2*	*OPR2*
Digitalization-1	0.022***		0.022***		0.005		0.009*		0.014***		0.030***	
	(3.649)		(2.937)		(1.043)		(1.692)		(3.408)		(6.216)	
Digitalization-2		0.174***		0.198***		0.012		0.039		0.121***		0.219***
		(4.254)		(3.959)		(0.254)		(0.776)		(6.167)		(9.642)
Total asset	0.408***	0.430***	0.410***	0.434***	0.424***	0.429***	0.427***	0.436***	0.425***	0.441***	0.414***	0.447***
Liquidity ratio	0.002***	0.002***	0.002***	0.002***	0.000	0.000	0.001**	0.001***	0.000	0.000	0.000	0.000
Deposit to asset	1.630*	2.062**	3.563**	3.962***	1.761***	1.784***	2.114***	2.148***	−0.987	−0.874	−1.105	−0.739
Loan to asset	−0.000	0.014	−0.059	−0.043	0.022	0.021	0.089**	0.090**	−0.009	0.002	0.014	0.037*
Loan loss provision	0.002	0.004	0.009	0.011	0.021**	0.021**	0.039***	0.039***	0.032***	0.032***	0.041***	0.040***
Liability to asset	−1.428***	−1.456***	−1.831***	−1.846***	−2.042***	−2.043***	−2.060***	−2.056***	−0.496	−0.639**	−0.305	−0.597*
Interest margin	0.051***	0.048***	0.053***	0.049***	0.047***	0.048***	0.035***	0.035***	0.103***	0.102***	0.089***	0.088***
Financial freedom	−0.000	0.000	0.001*	0.001**	0.002***	0.002***	0.004***	0.004***	−0.001*	−0.001	−0.000	−0.000
Cyber index	0.170***	0.135***	0.307***	0.260***	−0.199	−0.191	−0.102	−0.098	0.212*	0.199*	0.226	0.219
Inflation	0.006***	0.006***	0.007***	0.007***	0.005***	0.005***	0.006***	0.005***	0.001	0.001	0.000	0.000
GDP	−0.025	−0.030	−0.000	−0.008	−0.124***	−0.123***	−0.153***	−0.153***	−0.044	−0.042	−0.040	−0.034
Constant	−0.762	−1.095**	−1.176*	−1.505**	0.076	0.027	0.061	−0.030	−0.784***	−0.855***	−0.673**	−0.891***
Country*year	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	570	570	572	572	603	603	604	604	602	602	602	602
R-squared	0.971	0.972	0.953	0.955	0.970	0.970	0.957	0.957	0.986	0.987	0.979	0.980
F value	3219.12	3346.91	2411.47	2442.01	1251.23	1225.95	931.95	916.38	4346.50	4521.72	2556.85	2578.86

We classify banks into three groups based on the technological development of the country as scored by the International Telecommunication Union (ITU). The early-level countries are those with a score below the 33th percentile, the maturing-level countries are those with a score between the 33th and 67th percentiles, and the advanced level are those with a score above the 67th percentile. Finally, we estimate our base model: $OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}$ for the three groups separately with alternative proxies for the dependent and main independent variables. The appendix provides the details of the variables. Values in the parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels. For control variables, we only report the level of significant to save space (*t-stats* available upon request).

Table 6
Cyber legislation worldwide and operational risk exposure for banks.
Based on the United Nations Conference on Trade and Development (UNCTAD) mapping of global cyber laws across countries, we reexamine our base model for the countries with cyber laws in all four crucial areas of digitalization vs. the countries yet to legislate in all areas.
Base model: $OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}$
UNCTAD tracks cyber laws across countries that provide an overview of legislation around (i) consumer protection, (ii) privacy and data protection, (iii) electronic transactions, and (iv) cybercrime control. We identify a country belonging to Regulation Group 1 if it legislates in all four areas of digitalization. Otherwise, we assign the country into Regulation Group 2. We estimate the baseline results across the two groups to check if sweeping digital legislation across countries adversely affects banks' operational risks.
UNCTAD mapping of the global cyber laws:
https://unctad.org/topic/ecommerce-and-digital-economy/ecommerce-law-reform/summary-adoption-e-commerce-legislation-worldwide.

Variables	*OPR1*	*OPR1*	*OPR2*	*OPR2*
Panel A: countries with a developed digital ecosystem (Group 1)				
Digitalization-1	0.018***		0.022***	
	(4.225)		(4.665)	
Digitalization-2		0.119***		0.153***
		(5.259)		(6.043)
Bank controls	yes	yes	yes	yes
Country controls	Yes	Yes	Yes	Yes
Constant	−1.914***	−2.087***	−1.796***	−2.013***
	(−6.364)	(−6.990)	(−5.321)	(−6.019)
Observations	1548	1548	1548	1548
R-squared	0.768	0.778	0.798	0.809
F value	188.13	190.32	153.74	156.64
Panel B: countries with a less-developed digital ecosystem (Group 2)				
Digitalization-1	0.009		0.007	
	(1.000)		(0.544)	
Digitalization-2		0.067		0.070
		(0.884)		(0.611)
Bank controls	yes	yes	yes	yes
Country controls	Yes	Yes	Yes	Yes
Constant	−3.572***	−3.944***	−6.772***	−7.144***
	(−2.979)	(−3.196)	(−3.867)	(−3.934)
Observations	227	227	230	230
R-squared	0.681	0.681	0.655	0.655
F value	32.45	32.39	29.31	29.33

Values in parentheses are robust *t-statistics* with clustered standard error at both the country and year levels. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels, respectively.

Overall, the cross-country results imply that a country's socio-economic conditions and regulatory environment could also matter for the digitalization impact on the banks' business growth and consequent operational risks. For example, banks can expand their service network with digital technology and reach out to wider customers if they are sufficiently, IT literate, obtain internet access, and have the ability to afford more expensive electronic gadgets to benefit from the latest technology (French and McKillop, 2016).

5.6. Robustness analysis

Previous tests used multiple proxies for test variables and alternative estimation methods to provide some degree of robust results. In this section, we undertake three further analyses to substantiate the argument and disposition of our study. First, we estimate 2SLS using an external instrument to address potential endogeneity bias in the results. Second, we apply Heckman's two-step procedure to address potential sample section bias. Third, we examine a third proxy (*OPR3*) that captures operational risk exposure from the internal loss perspective.

5.6.1. Endogeneity – 2SLS results

The fixed effect and two-step system GMM estimations alongside OLS estimates of our base model have resolved the main econometric issues with empirical analysis. The fixed-effect estimation lessens the potential omitted variable bias from the unknown, time-invariant characteristics of banks (Vallascas et al., 2017). The two-step GMM estimation procedure has also addressed endogeneity bias from various sources (Wintoki et al., 2012). Our earlier baseline results for operational risk proxies (*OPR1 and OPR2*) with digitalization proxies are consistent across OLS, Fixed-Effect, and GMM methods. Hence, the estimates are reliable. Still, we provide more robust baseline results based on the two-stage regression (2SLS) using an external instrumental variable for the digitalization proxy. The main advantage is: an external instrument has a direct and significant effect on the regressor (cause) but not on the dependent variable (effect); thereby, 2SLS estimates are free from reverse causality.

We identify the percentage of government expenditure on primary education as the valid instrument for digitalization proxy. Primary education provides a literacy foundation and literate people like more online transactions that come with digital transformation in the economy and society. Therefore, banks also need to spend more on digitalization in countries where governments commit to a knowledge-based society by spending more on primary education. Using the external instrument for digitalization proxy, we find 2SLS estimates in Table 9 are statistically significant at less than the 1 % level for *OPR1* and *OPR2* but

Table 7
Digitalization lagged effect.

Variables	$OPR1_t$	$OPR1_t$	$OPR2_t$	$OPR2_t$
$Digitalization\text{-}1_{t-1}$	0.016***		0.015***	
	(4.140)		(3.138)	
$Digitalization\text{-}2_{t-1}$		0.081***		0.093***
		(3.722)		(3.365)
Total asset	0.294***	0.309***	0.286***	0.301***
	(30.794)	(33.386)	(23.594)	(25.752)
Liquidity ratio	−0.000	−0.000	−0.000	−0.000
	(−1.508)	(−1.514)	(−0.318)	(−0.313)
Deposit to asset	0.242**	0.241**	0.361***	0.359***
	(2.349)	(2.338)	(2.762)	(2.751)
Loan to asset	0.713***	0.686***	0.467***	0.442***
	(6.753)	(6.505)	(3.472)	(3.301)
Loan loss provision	0.007***	0.007***	0.012***	0.012***
	(3.348)	(3.353)	(4.555)	(4.562)
Liability to asset	−0.364***	−0.401***	−0.286*	−0.323**
	(−2.879)	(−3.178)	(−1.775)	(−2.013)
Interest margin	0.040***	0.039***	0.022***	0.022***
	(16.989)	(16.665)	(7.484)	(7.239)
Financial freedom	−0.001*	−0.001	−0.000	−0.000
	(−1.711)	(−1.271)	(−0.780)	(−0.419)
Cyber index	−0.076***	−0.076***	0.005	0.004
	(−3.241)	(−3.261)	(0.184)	(0.140)
Inflation	−0.002***	−0.002***	−0.001*	−0.001*
	(−3.282)	(−3.370)	(−1.708)	(−1.775)
GDP	0.394***	0.416***	0.443***	0.463***
	(5.862)	(6.222)	(5.188)	(5.450)
Constant	−1.818***	−1.996***	−1.702***	−1.877***
	(−6.143)	(−6.789)	(−4.510)	(−5.017)
Country and year control	Yes	Yes	Yes	Yes
Observations	1574	1573	1577	1576
R-squared	0.734	0.739	0.758	0.757
F value	167.47	166.67	95.97	96.13

$$OPR_{it} = \alpha_i + \beta_i Digitalization_{it-1} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}.$$

The dependent variable is *OPR1* or *OPR2* – proxies for the operational risk exposure considered for estimating a bank's risk capital under Basel frameworks. $Digitalization_{it-1}$ is one year lag of *Digitalization-1* or *Digitalization-2*. *Control* vectors include both bank- and country-level control variables. See the appendix for more details about the variables. Values in the parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

Table 8
Results across countries and regions.

Country & region	*Digitalization-1*		*Digitalization-2*		Country & region	*Digitalization-1*		*Digitalization-2*	
	OPR1	*OPR2*	*OPR1*	*OPR2*		*OPR1*	*OPR2*	*OPR1*	*OPR2*
USA	0.019***	0.045***	0.080***	0.162***	*Singapore*	−0.004	0.012	−0.751	−0.758
Canada	−0.003	0–0.050	0.153	0–0.365	*South Korea*	0.054***	0.064***	1.434***	1.689***
North America	**0.015*****	**0.038*****	**0.077*****	**0.163*****	*Thailand*	0.012	0.014	−0.047	0.011
Belgium	0.315***	0.417***	18.650***	26.040***	***Asia***	**0.001**	**0.001**	**0.089*****	**0.116*****
Denmark	0.572***	0.571***	−2.038***	−2.043***	*New Zealand*	0.238**	0.283**	−7.825	−8.422
Norway	0.001	0.005	0.045	0.193*	*Australia*	0.030*	0.014	0.192	0.100
Finland	0.805***	0.806***	−5.680***	−5.690***	***Asia Pacific***	**0.011**	**0.008**	**0.175****	**0.138***
France	0.005***	0.005***	0.057	0.054	*Argentina*	0.233***	0.249***	4.348***	4.722***
Germany	0.058	0.074	−0.008	0.360	*Brazil*	−0.038	−0.036	−0.071	−0.088
Greece	−0.021	−0.043	−0.631	−1.345	*Chile*	0.027	0.034	0.019	0.004
Italy	−0.037**	−0.035**	−0.997**	−0.811*	*Mexico*	0.557***	0.583***	−0.579***	−0.600***
Netherland	−0.071	−0.065**	−1.193	−1.089**	***Latin America***	**−0.003**	**−0.008**	**−0.002**	**−0.017**
Poland	0.326***	0.333***	0.076	0.112**	*Israel*	0.528***	0.582***	−2.763	−3.308
Spain	0.119	0.095	0.905**	0.811**	*Jordan*	0.002	−0.000	−0.014	−0.026
Sweden	0.125***	0.197***	19.743***	35.092***	*Oman*	0.485***	0.508***	−23.087	−25.354
Switzerland	0.028**	0.069**	1.860**	4.691***	*Qatar*	−0.115	−0.106	−4.223	−4.158
UK	0.033	0.039	−0.023	0.004	*Egypt*	0.010	0.020**	0.069	0.105*
Europe	**0.010*****	**0.018*****	**0.088****	**0.121****	*Saudi Arabia*	0.002	0.005	0.026	0.068
Bangladesh	0.028***	0.039***	0.103***	0.126***	*UAE*	0.042***	0.048***	7.543***	8.186***
China	0.023	0.016	−0.056	−0.137	*Turkey*	−0.002	−0.008	−0.111***	−0.299***
India	0.011	0.025	0.128	0.372	*Tunisia*	0.076	−0.004	−0.408	−1.139**
Indonesia	−0.001	0.001	−0.058*	−0.051	***MENA***	**0.006****	**0.012****	**0.044**	**0.081***
Japan	0.163	0.033	1.222	0.670	*Russia*	0.082***	0.113***	0.191***	0.251***
Malaysia	−0.011	−0.025*	−0.140**	−0.257***	*South Africa*	0.041**	0.035	−0.329	−0.513
Pakistan	0.005	−0.001	0.346	0.542	***Others***	**0.006**	**−0.001**	**0.201*****	**0.299*****

We estimate our base model: $OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}$ for each country and region separately. The dependent variable is OPR1 or OPR2. Digitalization is Digitalization-1 or Digitalization-2. Controls include all bank-level controls plus year dummies. We do not report t-values due to limited space; instead, we indicate the significance level of the coefficients estimates for Digitalization-1 and Digitalization-2 variables with asterisks. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

10 % significant for *OPR3*. Hence, 2SLS results unequivocally established that the scale of digitalization is a crucial driver for banks' operational risk exposure, as envisaged in the Basel risk capital framework.

5.6.2. Sample selection - Heckman estimation

Sample selection might be an issue as random sample selection was not possible in the context of this study. We address potential sample selection bias by employing Heckman's two-stage method in the study. First, we employ a probit estimation to determine the probability of a bank likely to spend more on bank digitalization. Uddin et al. (2020b) document that if cyber spending crosses the threshold for a bank, it affects bank stability negatively. We rely on this finding and construct a digitalization dummy = 1 if a bank's technology spending is more than the median level within the dataset. Then we use log of *z-score* (stability proxy) as the exogenous regressor with other controls in the probit estimation. Following the probit, we generate inverse Mills ratio (IMR) and include its lag in the 2nd stage OLS model as an additional regressor to control self-selection bias. As expected, the results in Table 10 show that the z-score log is significantly (negatively) related to the digitalization dummy, indicating the validity of the exogenous variable. Following Mollah et al. (2021), we control for self-selection bias through the IMR and find that our primary results align with the baseline estimations (see Tables 3 and 4). Thus, we argue that the results are less likely to be driven by self-selection bias.

5.6.3. The operational risk – the internal loss perspective

The Basel risk capital framework suggests that a bank's internal loss experience from various risk events would scale its operational risk exposure from the volume of business operations (gross income or business indicator). In this perspective, research suggests that institutions could assess actual risk within their operational risk management framework, focusing on the failure that occurred in the process design, management, and human aspects (Xu et al., 2017; Lewis, 2003; Chapelle et al., 2008). We agree that using internal loss information from various risk events could help assess the operational risk rather than exposure (Chernobai et al., 2011). However, estimating risk events based on probability theories is challenging because of the highly extreme nature of such events, and the overall financial impact could differ from the recorded loss (Chavez-Demoulin et al., 2006). Also, identifying loss events is subjective due to the variations in ad-hoc risk management frameworks applied by different banks across countries. Importantly, the International Accounting Standards Board (IASB) has no explicit guidelines for recognizing and reporting losses from operational failures.[14] Banks may not track the risk events linked to operational failures precisely as the Basel Committee recommended, but the financial statements would somehow reflect the losses determined by the bank because losses from operational failures (if any) have to be factored into operational costs for accounting purposes. This implies that banks' operational costs would increase for every dollar of income, ceteris paribus, if the operational risk occurs with business growth.

With the above argument in line with the Basel Committee's view on internal losses and the literature body, we examine the costs-to-income ratio as a proxy (*OPR3*) for *ex-post* operational risk from the internal losses. The findings in Table 11 are consistent with those business volume-based proxies of the operational risk exposure: *OPR1* and *OPR2*. The coefficients of *Digitalization-1* and *Digitalization-2* are significant at

[14] The IASB has international accounting standards (IAS) # 9, 36, and 38 for credit risk, assets impairments, and intangible assets that do not essentially capture operational failure issues. The Basel Committee, however, provides guidelines on tracking of internal risk losses by banks, but they have no obligation to report them in the financial statements under IAS. Hence, internal risk loss data are publicly unavailable for analysis. Therefore, the Basel capital framework permits calculation of the operational risk capital requirement based solely on the business indicator component if banks cannot provide high-quality loss data to the regulator.

Table 9
Endogeneity - 2SLS estimation.

Variables	First stage	Second stage		First stage	Second stage	
	Digitalization-1	*OPR1*	*OPR2*	*Digitalization-2*	*OPR1*	*OPR2*
Primary education	0.010***			0.001***		
	(5.00)			(5.882)		
Digitalization-1		0.081***	0.140***			
		(3.453)	(4.119)			
Digitalization-2					0.443***	0.766***
					(3.755)	(4.649)
Total asset	0.871***	0.361***	0.316***	−0.022***	0.441***	0.455***
	(45.25)	(17.670)	(10.635)	(−7.501)	(128.94)	(95.203)
Liquidity ratio	−0.003	0.001**	0.001***	−0.001***	0.001***	0.002***
	(−1.36)	(2.412)	(3.010)	(−3.122)	(3.297)	(4.222)
Deposit to asset	9.769***	0.856***	0.748*	0.447*	1.447***	1.750***
	(6.39)	(2.948)	(1.804)	(1.891)	(8.371)	(7.381)
Loan to asset	0.028	−0.026*	−0.022	−0.091***	0.017	0.051**
	(0.22)	(−1.700)	(−1.011)	(−4.553)	(1.004)	(2.185)
Loan loss provision	0.111***	0.016***	0.023***	0.032***	0.010**	0.014**
	(3.96)	(3.814)	(3.891)	(7.405)	(2.181)	(2.104)
Liability to asset	−3.024**	−1.383***	−1.248***	−0.182	−1.547***	−1.527***
	(−2.95)	(−10.295)	(−6.440)	(−1.154)	(−13.980)	(−9.911)
Interest margin	0.124***	0.042***	0.026***	0.026***	0.040***	0.023***
	(6.02)	(10.857)	(4.696)	(8.377)	(10.172)	(4.219)
Financial freedom	0.014***	−0.001*	−0.001	0.001	−0.000	0.001
	(5.21)	(−1.824)	(−1.392)	(1.381)	(−0.124)	(1.171)
Cybersecurity	1.071***	−0.047	−0.053	0.145***	−0.025	−0.014
	(5.11)	(−1.370)	(−1.069)	(4.489)	(−0.895)	(−0.376)
Inflation	−0.016**	0.006***	0.008***	−0.001	0.006***	0.007***
	(−2.33)	(6.881)	(6.055)	(−1.513)	(7.216)	(6.337)
GDP	0.176*	−0.074***	−0.089***	0.049***	−0.082***	−0.102***
	(1.70)	(−5.850)	(−4.860)	(3.114)	(−6.612)	(−5.942)
Constant	−9.637***	0.169	0.698*	0.072	−0.641***	−0.701***
	(−8.45)	(0.633)	(1.803)	(0.415)	(−5.226)	(−4.104)
Country x year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1732	1732	1735	1732	1732	1735
R-squared	0.637	0.961	0.922	0.228	0.967	0.938
Wald-chi	231.87	43,247.84	21,355.06	51,151.51	51,151.51	27,204.01
Wu-Housman F-stat		12.72***	25.29***		10.168***	24.92***
Anderson-Rubin Wald Chi^2	25.03***			34.531***		

The instrument for digitalization is primary education, which is the percentage of government expenditure on primary education. Other variables are used in the earlier tables, and details are available in the appendix. We run second-stage regression for OPR3, and results are consistent. Wu-Housman F-stat tests the existence of endogeneity and Anderson-Rubin Wald Chi^2 tests for weak instrument. The values within parentheses are robust *t-stats* adjusted for heteroscedasticity. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels

less than the 1 % level of OLS and Fixed-Effect tests and less than the 5 % level for the GMM test. The *OPR3* results indicate that a bank could become a less cost-efficient entity with increased operational costs due to potential internal losses from operational risk events. This supports the argument that faster business expansion and internal operations relying aggressively on cyber technology may increase the likelihood of unknown digital hazards or disastrous events that are difficult to predict (Cherdantseva et al., 2016) (Ralston et al., 2007). Therefore, extensive application of digital technology does not guarantee more cost-efficiency, particularly beyond the threshold (Uddin et al., 2020b). Overall, the finding of this section provides insights into how digitalization could influence actual risk, apart from risk exposure.

5.7. Additional analysis

This section provides some results that give additional insight into operational risk exposure for banks. First, we will experiment if the operational risk links to cybersecurity events. Second, we try to understand the underlying premise of operational risk exposure as viewed in the Basel risk capital framework.

5.7.1. Cybersecurity breach and operational risk perspective – a natural experiment

There is a perception that operational risks for the banks and financial institutions operating in virtual environments escalate due to growing cybersecurity breaches (Uddin et al., 2020a). Cybersecurity becomes an operational risk issue as online criminal activities and frauds could disrupt operations and inflict losses (Aseef et al., 2005; Choo, 2011; Choo et al., 2007; Javaid, 2013), and cybersecurity incidents account for a significant operational value-at-risk (Aldasoro et al., 2020a) and cybersecurity breaches provide a negative shock to the firm reputation (Tosun, 2021). However, in the Basel regulatory framework, the operational risk appears as the residual risk element (beyond credit and market risk) that arises due to the chance of direct and indirect losses from inadequate or failed internal processes, people and system errors, and external events, etc. (BCBS, 2004a, 2004b). Therefore, it is unclear whether a cybersecurity event per se is a concern should we look at operational risk from a broader perspective as in the Basel framework for banks' risk capital. Hence, we implement a natural experiment based on selected observations for two types of banks. The first type experienced at least one cyberattack in the year *t*, and the second did not experience any attack. We matched two kinds of observations based on

Table 10
Sample selection - Heckman two-stage estimation.

Stage 1: Probit regression		Stage 2: OLS regression				
Variables	Coefficient	Variables	*OPR1*	*OPR2*	*OPR1*	*OPR2*
Log of Z-score	−0.007**					
	(−2.101)					
Total asset	0.530***	*Digitalization-1*	0.019***	0.027***		
	(24.741)		(4.541)	(5.119)		
Liquidity ratio	−0.001	*Digitalization-2*			0.104***	0.159***
	(−0.680)				(4.846)	(6.849)
Deposit to asset	4.643***	*Total asset*	0.389***	0.380***	0.401***	0.397***
	(3.422)		(29.069)	(26.055)	(31.743)	(28.748)
Loan to asset	−0.005	*Liquidity ratio*	0.001***	0.001***	0.001***	0.001***
	(−0.005)		(4.145)	(3.756)	(4.461)	(4.223)
Loan loss provision	0.046*	*Deposit to asset*	1.344***	1.360**	1.346***	1.353**
	(1.891)		(3.505)	(2.318)	(3.244)	(2.177)
Liability to asset	−1.392	*Loan to asset*	−0.055***	−0.052**	−0.051***	−0.044*
	(−1.542)		(−3.367)	(−2.248)	(−3.149)	(−1.925)
Interest margin	0.026	*Loan loss provision*	0.026***	0.034***	0.026***	0.034***
	(1.560)		(4.839)	(4.455)	(4.731)	(4.326)
Financial freedom	0.007***	*Liability to asset*	−1.483***	−1.241***	−1.544***	−1.336***
	(2.850)		(−6.372)	(−4.550)	(−6.489)	(−4.808)
Cyber index	1.338***	*Interest margin*	0.053***	0.047***	0.051***	0.043***
	(7.121)		(8.866)	(7.246)	(8.313)	(6.494)
Inflation	−0.018***	*Financial freedom*	0.001**	0.002***	0.001***	0.002***
	(−2.721)		(2.354)	(3.529)	(2.660)	(3.887)
GDP	−0.192**	*Cyber index*	−0.111***	−0.079*	−0.128***	−0.107**
	(−2.051)		(−3.076)	(−1.822)	(−3.440)	(−2.407)
Constant	−6.791***	*Inflation*	0.006***	0.008***	0.006***	0.007***
	(−6.845)		(4.980)	(4.952)	(4.844)	(4.773)
		GDP	−0.109***	−0.114***	−0.108***	−0.113***
			(−7.464)	(−6.444)	(−7.434)	(−6.441)
		IMR_{t-1}	−0.096**	−0.110**	−0.123***	−0.153***
			(−2.221)	(−2.346)	(−2.812)	(−3.278)
		Constant	0.144	0.198	0.152	0.225
			(0.484)	(0.538)	(0.503)	(0.605)
Observations	1719	*Observations*	865	866	865	866
Country & Year FE	Yes	*Country & Year FE*	Yes	Yes	Yes	Yes
Adj R-square	0.3224	*Adj R-square*	0.974	0.958	0.974	0.958

In the first stage model, we apply 'digitalization dummy' as the dependent variable and estimate probit regression with Z-score as the exogenous regressor. We create the digitalization dummy = 1 if a bank's technology spending is more than the median level within the dataset. In the 2nd stage, we add IMRt-1 (Lag Inverse Mills Ratio) from the 1st stage - then we run the regression of digitalization proxy and other controls on operational risk proxies. The variables are the same as those in the baseline models. Asterisks ***, **, and * denote significance at the less than or equal to one, five, and ten percent levels, respectively.

propensity score matching.[15]

Table 12 reports two main findings. First, digitalization matters for banks' operational risk based on at least two risk proxies. Second, cybersecurity breaches have no impact on operational risk exposure. The coefficient of the *Cyberattack* dummy was insignificant for all proxies of the operational risk exposure. Also, the digitalization and cyberattack interaction is insignificant for all tests. Hence, this natural experiment with a propensity-score-matched sample of 72 observations from banks with cyberattack experience and another 72 without such experience indicates that cybersecurity breach per se does not matter significantly for banks' operation on a digital platform. Also, the cyberattack does not considerably mediate the digitalization effect on operational risk. Perhaps enormous cybersecurity concerns in digitalization impacted the banks globally to invest heavily in risk protection and security system. Therefore, cybersecurity possibly did not materialize as we thought, as more intelligent security systems could tackle external attacks and hacking. Thus, our experiment provides a different insight, contradicting the current view about cybersecurity as a major source of operational risk.

5.7.2. *Business indicator as an operational risk proxy*

Our operational risk exposure proxies originate from the Basel regulatory risk capital framework. The *OPR1* variable represents the gross income prescribed in Basel II, while *OPR2* is the business indicator measure suggested in the Basel III framework. Both determine business volume differently, although according to the Basel committee, *OPR2* is a superior operational risk proxy because it is a comprehensive estimate of the total business volume based on the audited financial statements. If a bank can track its risk events and record all losses, then the loss amount is utilized as a scaling element in the calculation (subject to supervisory validation). The business indicator is also superior, as it systematically tracks the total business influencing risk exposure (BCBS, 2016) - because errors, mistakes, and unwanted events increase with faster growth in operations and business activities. Theoretically, operational risk is a residual element that captures all losses other than those arising from credit and market risks (Rao and Dev, 2006). However, an appropriate measurement is still in its infancy (BCBS, 2016). Therefore, we checked whether the business volume could reflect operational risk exposure as suggested by Basel regulatory framework.

The financial statements would capture the losses should risk incidents increase with the acceleration of operational activities to achieve high business volume. Then, ceteris paribus, the operating cost for every

[15] First, we extensively explore the Google search engine to identify publicly available information about cyberattack events that occurred during the 2008 and 2017 period for the sample banks of this study. Second, we identify a total of 72 cyberattacks involving several banks in our sample. Next, all cyberattack events are tracked by their event-year and bank name, then a '*Cyberattack*' dummy is created – where *Cyberattack* equals 1 if a bank's data observation belongs to the year in which the bank's cybersecurity system was breached by the attack. Finally, using the '*Cyberattack*' dummy, we apply a propensity-score-matching technique to identify another set of 72 observations from the years in which the sample bank has no experience of cyberattack. Hence, our total observations for this experiment consists of 144 bank-year observations.

Table 11
Operational risk – internal loss perspective.

Variables	OLS estimate		Fixed effect estimate		GMM estimate	
	OPR3	*OPR3*	*OPR3*	*OPR3*	*OPR3*	*OPR3*
Lag of $OPR3_{t-1}$					0.378***	0.373***
					(7.020)	(6.471)
Digitalization-1	0.031***		0.014***		0.031***	
	(11.452)		(2.922)		(3.621)	
Digitalization-2		0.243***		0.123***		0.159***
		(13.549)		(4.497)		(3.320)
Total asset	−4.535***	−1.296***	−1.384	0.552	−3.747***	−0.718*
	(−14.131)	(−6.054)	(−1.208)	(0.500)	(−4.151)	(−1.810)
Liquidity ratio	0.100**	0.117***	0.072***	0.073***	0.269***	0.226***
	(2.424)	(2.906)	(3.073)	(3.119)	(3.72)	(2.850)
Deposit to asset	−37.266*	−18.074	21.808	22.629	−16.128	−26.419
	(−1.655)	(−1.002)	(1.265)	(1.318)	(−0.190)	(−0.300)
Loan to asset	6.953***	9.346***	−82.356***	−82.937***	−0.216	−1.241
	(4.893)	(6.670)	(−5.971)	(−6.039)	(−0.071)	(−0.390)
Loan loss provision	2.720***	2.374***	0.853***	0.828***	2.288***	1.710***
	(6.060)	(5.526)	(3.190)	(3.110)	(4.762)	(3.530)
Liability to asset	126.774***	122.140***	48.925***	48.833***	−38.345	−13.507
	(9.942)	(9.796)	(3.112)	(3.122)	(−0.930)	(−0.301)
Interest margin	−1.479***	−1.762***	−3.827***	−3.846***	−1.974***	−1.764***
	(−4.929)	(−6.480)	(−12.821)	(−12.935)	(−4.320)	(−4.061)
Financial freedom	0.205***	0.229***	0.083	0.097*	0.045	−0.082
	(5.992)	(7.306)	(1.448)	(1.697)	(0.411)	(−0.780)
Cyber index	3.985*	3.478	−2.143	−2.235	0.464	1.467
	(1.848)	(1.634)	(−0.693)	(−0.726)	(0.081)	(0.230)
Inflation	0.322***	0.303***	0.095	0.102*	0.219	0.220
	(3.848)	(3.641)	(1.615)	(1.745)	(1.480)	(1.421)
GDP	0.277	−0.144	−18.788**	−19.093**	2.617	5.919
	(0.248)	(−0.133)	(−2.331)	(−2.379)	(0.630)	(1.401)
Constant	−33.752**	−66.131***	138.368***	121.273***	92.849***	44.537
	(−2.285)	(−4.968)	(3.803)	(3.355)	(3.190)	(1.542)
Country and year control	*Yes*	*Yes*			*Yes*	*Yes*
Observations	1774	1774	1774	1774	1568	1568
R-squared	0.297	0.325	0.140	0.146		
F value/Wald-chi	58.48	67.75	20.57	21.70	11,055	12,141
AR 1					0.001	0.000
AR 2					0.866	0.963
Hansen test					0.130	0.212

$OPR3_{it} = \alpha_i + \beta_i Digitalization_{it} + \sum_{i=1}^{n} YControl_{it} + \varepsilon_{it}.$

Where *OPR3* is the cost to income ratio used as an alternative ex-post proxy for the operational risk exposure based on the assumption that incurred losses from operational failures (internal loss in Basel framework) have been factored into the bank's operational costs. Other variables are the same as those in previous tables. Values in parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

dollar of revenue would rise due to the absorption of various risk losses into the operational costs. Therefore, this implies that a bank might be cost-inefficient when overstressing its capacity. Hence, we test the following model.

$$Costs_{it} = \alpha + \beta Operational\ speed_{it} + \sum_{i=1}^{N} Controls + e_{it} \tag{4}$$

The *cost* is total operating costs to total revenue, which we examined earlier as an alternative ex-post proxy for operational risk (*OPR3*). The *operational speed* is the total business volume estimated by the business indicator measure (*OPR2*) divided by the bank's total assets. A higher business volume to total assets indicates that the bank stresses its capacity to speed up operations for more business. Table 13 shows that the coefficient of *operational speed* is positive and highly significant for OLS, Fixed-Effect, and GMM estimates – proving the underlying assumption of the operational risk exposure in the Basel framework.

Therefore, we draw inferences from our hypothesis using a valid proxy of operational risk exposure for banks. Advances in technology and human adaptation to innovations and changes (Helpman and Rangel, 1999) have allowed banks to accelerate operations and business growth faster than ever before due to quick process reengineering, product diversifications, services customizations, and convenient remote banking with digital technology (Bartel et al., 2007; Barrett et al., 2015; Chen et al., 2013). However, we provide credible evidence showing that banks are exposing themselves to more operational risks with more digitalized operations.

5.8. Analysis and reflection

Innovations unfolding with digital transformations over the last several decades paved the way for banks and financial institutions to accelerate business volume and growth faster. At the same time, managers, analysts, and researchers find that the financial system globally is more vulnerable due to unavoidable and unknown hazards inherent in technology and widespread digitalization. Hence, there is a question of whether banks are exposed to more operational risk with faster digitalization. We examine this question because the Basel regulatory risk capital framework contemplates banks' operational risk exposure linked to the business volume (business indicator). Following extant literature,

Table 12
Natural experiment with banks experiencing a cyberattack.

Variables	OPR1	OPR2	OPR3	OPR1	OPR2	OPR3
Digitalization1	0.017*	0.020	0.038***			
	(1.648)	(1.194)	(3.123)			
Cyberattack	0.044	−0.002	0.067			
	(0.741)	(−0.015)	(1.197)			
*Digitalization1*Cyberattack*	−0.010	−0.004	−0.013			
	(−0.718)	(−0.171)	(−1.196)			
Digitalization2				0.191**	0.590***	0.126
				(2.271)	(4.448)	(0.697)
Cyberattack				0.014	0.027	0.002
				(0.488)	(0.521)	(0.056)
*Digitalization2*Cyberattack*				−0.077	−0.288	0.106
				(−0.498)	(−1.067)	(0.568)
Total asset	0.420***	0.397***	−0.055***	0.439***	0.422***	−0.028**
	(41.350)	(21.988)	(−4.413)	(55.195)	(36.624)	(−2.565)
Liquidity ratio	−0.007***	−0.016**	−0.005	−0.006**	−0.017**	−0.006*
	(−2.634)	(−2.263)	(−1.536)	(−2.461)	(−2.503)	(−1.717)
Deposit to asset	0.077	8.762***	1.685	−0.036	9.034***	1.634
	(0.037)	(2.946)	(0.964)	(−0.017)	(2.995)	(0.839)
Loan to asset	0.060	0.029	0.057	0.052	0.093	0.072
	(1.092)	(0.315)	(0.754)	(0.978)	(1.258)	(0.916)
Loan loss provision	−0.006	0.054***	0.030**	−0.005	0.030**	0.029**
	(−0.523)	(2.733)	(2.557)	(−0.422)	(2.143)	(2.381)
Liability to asset	−2.276***	−1.780**	2.511***	−2.395***	−1.372**	2.925***
	(−7.232)	(−2.448)	(3.468)	(−7.877)	(−2.007)	(4.014)
Interest margin	0.082***	0.035**	−0.025	0.074***	0.034***	−0.021
	(5.390)	(2.154)	(−1.528)	(4.926)	(3.344)	(−1.166)
Financial freedom	0.002**	0.004***	0.000	0.003***	0.003**	0.001
	(2.498)	(2.630)	(0.000)	(2.898)	(2.254)	(0.150)
Cyber index	−0.155**	0.088	0.015	−0.165**	−0.018	0.039
	(−2.179)	(0.658)	(0.206)	(−2.414)	(−0.163)	(0.519)
Inflation	0.006**	0.008**	0.007**	0.005*	0.007**	0.006
	(2.156)	(2.139)	(2.264)	(1.867)	(2.254)	(1.652)
GDP	−0.078**	−0.189***	0.026	−0.107***	−0.176***	0.024
	(−2.104)	(−2.914)	(0.478)	(−3.147)	(−3.389)	(0.435)
Constant	0.654	−2.607**	−2.230**	0.781	−3.382***	−2.805***
	(0.822)	(−2.022)	(−2.372)	(0.939)	(−2.724)	(−2.999)
Country and year control	Yes	Yes	Yes	yes	Yes	Yes
Observations	102	104	108	102	104	108
R-squared	0.983	0.950	0.477	0.983	0.957	0.447
F value	803.91	197.30	8.85	858.47	224.07	6.29

$$OPR_{it} = \alpha_i + \beta_i Digitalization_{it} + \theta_i Cyberattack_{it} + \vartheta_i Digitalization^{*}Cyberattack_{it} + \sum\nolimits_{i=1}^{n} \Upsilon Control_{it} + \varepsilon_{it}.$$

The dependent variable is the operational risk proxy: *OPR1*, *OPR2*, or *OPR3*. The independent variable is either *Digitalization1* or *Digitalization-2*. *Cyberattack* = 1 if an observation belongs to a bank that experienced at least one cyberattack in the year. Otherwise, the value is 0. *Digitalization*Cyberattack* tests if cyberattacks have a role in the relation between digitalization and operational risk. *Controls* are the same as those in earlier tests. Based on an extensive Google search, we get 72 cyberattacks involving our sample banks. Then, we find similar 72 observations from banks with no cyberattack experience. So, a total of 144 observations. Values in parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels

we argue that digitalization has a critical role in increasing banks' operational risk due to faster business expansion with extensive usage of digital technology. We prove it based on a global sample from 43 countries applying different estimation procedures, using alternative proxies, and addressing potential endogeneity biases.

The subsample identifies that the digitalization effect varies with the changes in technology regimes globally. The impact is significant until countries reach the technological plateau and again when they emerge with more intelligent technology innovations – suggesting that national priorities for technology innovations matter regarding how digitalization would influence operational risk. Also, cyber legislation worldwide fosters an environment for faster digitalization, thus contributing to increasing operational risks via exponential growth in business volume. The study further finds that managers proactively take more operational risk as the digitalized banking operation is not a matter of choice; rather, it is necessary to cope with the market changes. The natural experiment identifies that cybersecurity breaches per se do not expose banks to more operational risks, providing an insight against common perceptions about cybersecurity concerns.

This means that digitalization has broader risk impacts – as technology is inherently susceptible to system failure and disruption due to unknown causes or failures in the internal processes due to system and human errors. There are economic losses from diverse types of visible and invisible risk events that are hard to estimate exactly, but we find banks at least incur more operational costs, possibly due to absorption of the risk losses, for every dollar of revenue. This occurs when banks stress their capacity to rapidly increase business volume by using digital technology. Thus, the study supports the recommendation in Basel II to apply the business indicator proxy while assessing the degree of operational risk exposure in a bank.

Overall, our study contributes to academic debates around operational risk characterization. By documenting that digitalized banking gives rise to operational risk exposure in Basel III regulatory framework, our study corroborates Jarrow (2008), who showed that a firm's

Table 13
Does the speed of business expansion affect efficiency?

Variables	OLS estimate	Fixed effect estimate	GMM estimate
	Costs		
$Costs_{t-1}$			0.667***
			(9.220)
Operational speed	0.968***	0.479***	0.283*
	(11.973)	(5.403)	(1.89)
Liquidity ratio	0.001***	0.001*	0.001
	(0.046)	(1.799)	(1.405)
Deposit to asset	−10.286	0.063	−0.288
	(−0.007)	(0.469)	(−0.900)
Loan to asset	0.063***	−0.340***	−0.099*
	(5.484)	(−4.578)	(−1.753)
Loan loss provision	0.016***	0.004**	0.009
	(4.422)	(2.368)	(1.445)
Liability to asset	1.233***	0.229**	−0.292
	(11.338)	(2.015)	(−0.610)
Interest margin	−0.019***	−0.032***	−0.018***
	(−7.693)	(−14.503)	(−3.920)
Financial freedom	0.002***	0.001	0.001
	(7.622)	(0.625)	(0.567)
Cybersecurity	0.091***	−0.031	0.024
	(5.552)	(−1.193)	(0.400)
Inflation	0.002***	0.001*	0.001
	(3.182)	(1.954)	(0.711)
GDP	−0.013	−0.092	−0.064
	(−1.466)	(−1.404)	(−1.389)
Constant	−0.773***	3.021**	0.914**
	(−6.826)	(2.056)	(1.99)
Country and year control	Yes		Yes
Observations	2688	2688	2297
R-squared	0.2291	0.0973	
F value/Wald-chi	50.88	21.10	26,519
AR 1			0.000
AR 2			0.357
Hansen test			0.396

Baseline model: $Costs_{it} = \alpha + \beta Operational\ speed_{it} + \sum_{i=1}^{N} Controls + e_{it}$.
The dependent variable is *Cost*, which is total operating costs to total revenue – proxy for the cost. The main independent variable is *Operational Speed*, the total volume of a bank's operational activities scaled by the size of the bank. *Control* vectors include both bank- and country-level control variables. See the appendix for more details about the variables. Values in parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

operational technology or system links to the failure of internal processes and transactions, resulting in economic value losses (Cummins et al., 2006). Our results support another study documenting that banks' business complexity increases the operational risk (Chernobai et al., 2021) because banks are increasingly drifting from core businesses to hybrid services with innovations in intelligent digital technology and FinTech competition worldwide. Therefore, our study complements Barakat et al. (2014), who found that operational risk incidents might increase market information asymmetry because sources of digital hazards are diverse and unknown, and economic impact is hard to estimate.

At last, we tried to understand whether banks' digitalization and operational risk relationship persist in different circumstances. Cross-checking of results in Appendix 2 shows that the relationship between the digitalization and operational risks, considered by the Basel regulatory framework, is common across a variety of circumstances like different degrees of economic globalization, regulatory surveillance in the country, level of digital adoption in the society, and bank-level technology adoption. We find an exception: digitalization is safe when banks function in a strong regulatory surveillance regime.

6. Conclusions

The study investigates whether digitalization exposes banks to more operational risks. By employing data for 264 banks from 43 countries for the period of 2008–2017, we identify digitalized banking operation as an underlying driver of operational risk, which originates from increased volume of business. We also find that banks are proactive in taking more operational risks not only through increasing cyber spending but also in tackling FinTech competition. However, we fail to show a significant effect of cybersecurity on banks' operational risks through a natural experiment, even though cybersecurity appears to be a serious threat to digital banking. There are several takeaways from this research.

First, the study shows that digitalized banking operation is an underlying driver of the operational risk exposure that emerges from increased business volume. Second, national technology policies, strategic priorities for developing a digitalized economy, and cyber legislation worldwide drive up digital society and ecosystems with inherent operational hazards. Third, banks proactively take operational risks by investing in digital technology, as they have no choice. Still, caution is essential because there is a possibility that excessive risk-taking could lead to cost inefficiency due to additional risk losses. Fourth, cybersecurity is a growing concern for the financial industry, but results suggest that the impact on operational risk exposure could be insignificant – as intelligent security systems typically tackle most security breaches. This is interesting because security hazards will not deter institutions from digital transformation and will focus on other areas of digital disruption. Fifth, operational risk as a residual risk factor captures all visible and invisible risk events, except the credit and market risks, suggesting that business volume could broadly reflect operational risk exposure. By identifying the underlying driver of business volume and operational risks, this study provides new insights for the banks, regulators, and Basel Committee to review further their recommendations for estimating banks' risk capital. Further research can explore the points drawn from this study more deeply to obtain new insights and guide financial institutions' risk management practices in the future as technological innovations will continue to evolve.

Overall, this study examined if excessive digitalization of banking operations contributes to operational risk exposure under the Basel framework for creating capital provisions to cushion the risk. We document evidence supporting our assertion. However, a bank may digitalize its processes by choosing between buying or outsourcing technology supports, which may be a risk management strategy in the digital business environment as technology selections and investment may not be like a typical corporate finance decision. This idea could be a new research avenue that researchers can explore more.

Finally, it is understandable that high business volume could lead to a linear association. However, the question remains if risk exposure increase linearly, as banks always take measures to contain the probability of risk. We estimate the non-linear (quadratic) parameters of digitalization degrees using our base model, and results (Appendix 3) show that operational risk does not increase linearly with business volume, as the Basel III framework perceived. This finding, perhaps, can guide them to revise the banks' calculation method of operational risk capital in the future. In this line, further research might be needed to understand better what makes a big difference in the kinds of digitalized businesses the banks invest in and what technologies apply to contain their operational risks.

CRediT authorship contribution statement

Md Hamid Uddin: Idea Conceptualization, Literature Review, Theory and Argument Building, Hypothesis, Project Preparation, and Funding Application, Methodology Selection, Variable Selection, Data Analysis and Software, Paper Drafting, Knowledge Contribution, and Presentation

Sabur Mollah: Ideas Conceptualization, Hypothesis Development Project Preparation and Funding Application Methodology Selection, Theory and Argument Building, Analysis and Knowledge Contribution.

Nazrul Islam: Contextualization of literature, hypothesis development, and arguments for technology and innovation perspectives. Analyze study findings providing new insights for digital disruption in the global banking sector, providing critical avenues for new research.

Md Hakim Ali: Literature Review and Hypothesis and Concept Building, Data Extraction from Annual Reports and Bloomberg Database, Data Curating and Validation, Variable Construction, Running Software, Data Analysis, Drafting, and Editing.

Data availability

Data will be made available on request.

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Appendix 1. Definition of variables

Variables	Measurement	Data source	Reference
Dependent variables			
OPR1	Natural log of the Gross Income calculated as net interest income minus net non-interest expense, following Basel II approach.	Authors' calculation based on Bloomberg data	BCBS (2014) BCBS (2016)
OPR2	Natural log of the Business Indicator following Basel III approach. It consists of three elements. The *Interest Element* covers the absolute value of the interest margin plus lease income and dividend income (if any). The *Service Element* is the sum of (i) fee income, (ii) fee expenses, (iii) other operating income, and (iv) other operating expenses. The *Financial Element* covers the absolute value of profit or loss from trading and banking books.	Authors' calculation based on Bloomberg data	BCBS (2014) BCBS (2016) BCBS (2017)
OPR3	The ratio of total operating costs to total revenue of the bank. It indicates the costs incurred for every dollar of revenue.	Bloomberg	Schaeck & Cihák (2014)
Main independent variables			
Digitalization1	Natural log of total spending on digital technology. It includes the costs associated with computer software, hardware, data processing, third-party security services, IT training, depreciation of hardware and amortization of software, etc.	Hand collected data from banks' annual reports	First time in our study
Digitalization2	The ratio of total spending on digital technology to total asset of the bank.	Hand collected data from banks' annual reports	Authors' innovation based on Shi et al. (2022)
Operational speed	The ratio of total business volume to bank size.	Authors' calculation, Bloomberg data	First time in our study
Bank-level controls			
Total asset	The log of total book value of the bank.	Bloomberg	Anginer et al. (2018); Gul & Goodwin (2010)
Liquidity ratio	The cash and cash equivalent to total deposit.	Bloomberg	Chernobai et al. (2011); Berger et al. (2009)
Deposit to asset	Total deposit to total asset of the bank.	Bloomberg	Berger et al. (2009); Sun & Chang (2011)
Loan to asset	The ratio of total loan to total asset of the bank.	Bloomberg	McNulty and Akhigbe (2017)
Loan loss provision	Log of total loan loss provision at end of year.	Bloomberg	Sun & Chang (2011); McNulty and Akhigbe (2017)
Liability to asset ratio	The total liability to the total asset.	Bloomberg	Berger et al. (2009)
Interest margin	Spread between interest received and interest paid.	Bloomberg	Gadzo et al. (2019)
Country-level controls			
Financial freedom	The financial freedom index indicating banking efficiency in the country.	The Heritage Foundation	Chortareas et al. (2013)
Cyber index	It indicates the level of commitment of a country to develop a resilient cybersecurity infrastructure.	International Telecommunication Union	Uddin et al. (2020b)
Inflation	The consumer price index.	World Bank	Edmans et al. (2017); Moosa (2011)
Gross domestic product	The natural log of the real gross domestic product per capita of the country in US$ dollars (constant).	World Bank	Dahen & Dionne (2010); Edmans et al. (2017)
Additional variables			
Primary education	The percentage of total government expenditure on primary education.	World Bank	Our study
Cyberattack	*Cyberattack* = 1 if an observation belongs to a bank that experienced cyberattack in the year. Otherwise, the value is 0.	Google search	Our study

Appendix 2. Cross-checking of baseline results in Table 3 across various dimensions

Variables	Globalization level		Regulatory environment		Digital adoption level		Employee numbers	
	High	Low	Strong	Not strong	High	Low	Medium	Low

(*continued on next page*)

(*continued*)

Variables	Globalization level		Regulatory environment		Digital adoption level		Employee numbers	
	High	Low	Strong	Not strong	High	Low	Medium	Low
Digitalization-1	0.013***	0.012***	0.022***	0.006	0.011***	0.015***	0.015***	0.007***
	(3.235)	(2.844)	(3.777)	(1.555)	(2.604)	(3.947)	(4.739)	(2.595)
Controls (as in Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.974	0.979	0.987	0.975	0.9920	0.9752	0.9754	0.9605
F value	3735.29	3273.03	3864.12	4256.34	2725.96	3169.63	4590.59	1588.37

Globalization: we understand technology plays a critical role for countries to do business globally, and banks in these countries are more internationalized, relying on cyber technology. We used the KOF Globalization Index (https://tinyurl.com/5yb8w9pn) to classify the sample countries above and below the median score. We assumed banks in the countries with globalization scores above the median are more internationalized than those in other countries.
Regulatory environment: the country with strong regulatory surveillance requires banks in this jurisdiction to fulfill stringent technology and data protection regulations in place; hence operational risk also could vary. We used the world governance indicators data (www.govindicators.org) to classify the sample countries above and below the median value.
Digital adoption level: we assumed banks in highly digitalized societies are more prone to technology-driven operational risk than those in other countries. We used the World Bank's digital adoption index (https://tinyurl.com/5n8ucs5m) to classify the sample countries above and below the median index score.
Employee numbers: banks using fewer employees relative to their sizes are likely to be more digitalized than other banks. We classified sample banks above and below all sample banks' median value of the employees-to-asset ratio.
In this table, we report the OLS results involving the first measure of operational risk (OPR-1). The results using the second risk measure (OPR-2) are consistent. We also cross-checked the results using Digitalization-2 as the independent variable, and the results generally persist with some variation in the level of significance. Values in parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels.

Appendix 3. Nonlinear effect on operational risk

	OLS estimate	
	Operational risk 1	Operational risk 2
Digitalization-1	0.014***	0.021***
	(3.825)	(5.131)
Squared Digitalization-1	−0.001	−0.001
	(−0.075)	(−0.262)
Total asset	0.419***	0.420***
	(126.713)	(106.884)
Liquidity ratio	0.000***	0.001***
	(2.696)	(3.582)
Deposit to asset	1.494***	1.853***
	(8.102)	(5.189)
Loan to asset	−0.021	−0.018
	(−1.452)	(−1.015)
Loan loss provision	0.019***	0.031***
	(4.381)	(5.872)
Liability to asset	−1.502***	−1.500***
	(−10.019)	(−8.344)
Interest margin	0.053***	0.044***
	(10.250)	(8.248)
Financial freedom	0.000	0.001***
	(1.102)	(3.767)
Cyber index	0.019	0.081***
	(0.962)	(3.204)
Inflation	0.005***	0.006***
	(6.235)	(6.062)
GDP	−0.063***	−0.075***
	(−6.750)	(−6.022)
Constant	−0.548***	−0.516**
	(−3.060)	(−2.502)
Country and year control	Yes	Yes
Observations	1775	1778
R-squared	0.9739	0.9597
F value	5067.48	3682.33

The dependent variable is OPR1 or OPR2 – proxies for the operational risk exposure considered for estimating a bank's risk capital under Basel frameworks. The main independent variable is *Digitalization-1*, the natural log of the bank's total spending on digital technology, the square of *Digitalization-1* has been considered in this model to explore the nonlinear effect on operational risk. *Control* vectors include both bank- and country-level control variables. See the appendix for more details about the variables. Values in the parentheses are robust *t-stats* based on the adjusted standard errors clustered across country and year. Asterisks ***, **, and * denote significance at the less than 1 %, 5 %, and 10 % levels. We also checked non-linearity with Digitalization-2, and the results are consistent.

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