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Article

Research on Emerging Risk Identification and Mitigation Mechanisms in the Digital Transformation of Financial Institutions

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Abstract: Digitalisation of banking has introduced new risks, such as cybersecurity, data protection, algorithmic accountability and third-party dependence, which are not covered by the traditional risk indicators. This paper builds a text-based system to identify these exposures and studies their mitigation by analyzing the annual reports of the 20 listed Chinese commercial banks from 2017 to 2023. Dictionary-based indices for the four risk categories are constructed from disclosure narratives, their validity is assessed by distinctness from conventional credit risk and alignment with regulatory milestones, and they are related to a lagged transformation index in two-way fixed-effects panel models supported by wild cluster bootstrap inference. Disclosed exposure more than doubled in the window, driven primarily by data-related risks that surged around new privacy laws, and the composition of these risks varied among institutions. Transformation intensity, however, carries no within-bank association with emerging risk exposure, a null robust to alternative index constructions and an alternative risk measure, and governance moderation through board independence finds no support under admittedly thin identifying variation. The evidence points out that the new risks are industry-wide phenomena, supports a multi-level mitigation system emphasising supervisory coordination and segment-specific technical standards, and leaves governance reform as a question for longer panels.

Keywords: digital transformation; emerging risk; text mining; commercial banks; risk mitigation

1. Introduction

Digitalisation of banks has moved from plan to daily operation, and as a result, the risk characteristics of these banks have also changed. In addition to the general problems of credit and liquidity, digital banks are now also subject to data privacy obligations and all-around cybersecurity risks [1]. Assessments of the fintech-bank nexus consistently identify cyber incidents, data misuse and technology dependence as hazards that are not well covered by traditional risk frameworks [2], and the accumulation of these exposures is no longer a firm-level problem; cyber events can spread through payment and settlement networks to cause system-wide damage [3]. Supervisory bodies have responded in kind, and the financial stability implications of artificial intelligence are now on the agenda of global standard-setters [4], with dedicated regimes for digital operational resilience taking statutory form [5].

Scholarship on how transformation changes bank risk has not yet reached a consensus. Panel data of Chinese listed banks show that digitalisation enhances risk management and reduces risk-taking [6]; this is consistent with other studies that have linked the digital revolution to improved operating efficiency and stability [7], as well as findings that fintech adoption increases the risk-bearing capacity of commercial banks [8]. Other work makes it worse. Fintech participation has been shown to promote risk-taking through liquidity-creating channels [9], digital transformation interacts with competition in a way that can increase systemic risk [10], and the direction of the effect is sensitive to regulatory conditions, as supervisory tightening has reduced the amount of risk appetite in fintech exposure [11]. Quantile evidence also shows that the relationship changes sign across the conditional risk distribution and is not uniform [12]. Reading through this literature, two deficiencies have emerged. The dependent variables are almost always traditional, non-performing loans, Z-scores and their variations, so the new hazards

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specific to digitalisation are largely unmeasured, and the mitigation side of the problem is generally addressed through normative recommendations rather than empirical tests.

Both deficiencies are addressed using the annual reports of the 20 listed Chinese commercial banks from 2017 to 2023. It has established a text-based measurement system for the four types of emerging risks, covering cybersecurity, data, algorithms and third-party dependencies; validated the resulting indices against regulatory milestones and traditional risk indicators; and recorded how disclosed exposure has changed over time and across institutions. Then it examines whether the speed of digitalisation is associated with new risk exposure in banks and, at the same time, empirically investigates whether governance structures, such as board independence, moderate this relationship. The contribution has three parts. The measurement system adds risk quantification for hazard categories that the current bank-level indices have not included. Panel data provide a careful test of the transformation-risk relationship, with inference adjusted for a small number of clusters. The governance assessment puts a widely recommended mitigation lever to an empirical test to determine whether the data support such a claim, and offers a multi-level view of mitigation by assigning different roles to supervisory, technical and governance instruments according to the strength of the supporting evidence.

The rest of this paper presents the sample, measurement and econometric strategy, reports the descriptive statistics and estimation results, discusses the implications of the findings for the governance of digital risk, and finally lists the limitations and future research directions.

2. Data and Methods

2.1. Samples and Data Sources

A panel of 20 listed Chinese commercial banks from 2017 to 2023 was selected for the analysis, including six state-owned banks, nine national joint-stock commercial banks and five leading city commercial banks. Together, these institutions hold most of the banking-sector assets in China and constitute the part where digitalisation has been most evident and far-reaching. The window opened in 2017, one year before the 2018-2023 regression sample; therefore, the lag structure employed below does not truncate the panel and covers a period of increased supervisory attention to fintech, data governance and algorithmic accountability.

Two sources are combined. Annual reports were obtained from the CNINFO disclosure platform, filtered to keep only complete Chinese-language main documents, and converted into machine-readable text; after excluding a small number of unavailable or non-extractable filings, 132 usable reports were obtained. Financial and governance variables were obtained from the public financial data service and verified with the reports. The resulting panel is slightly unbalanced, and the two banks that listed their A-shares after 2017 do not pose a problem for the fixed-effects estimators in this study.

2.2. Text-Based Measurement of Digital Transformation

The intensity of digitalisation is reflected in the narrative content of the annual report, and a text-based method is used for this study [13]. The assumption is that the proportion of digital vocabulary in a bank's main disclosure document reflects the strategic importance given to its digital plan, and indices constructed in this way have been shown to track digital investment and subsequent performance outcomes reasonably well [14].

A dictionary of digital keywords was built, and all areas of change were covered by four groups. Strategic dimensions are high-level commitment indicators, such as the strategy for digitalisation and open banking. The technology dimension refers to the basic capabilities of artificial intelligence, cloud computing, big data and blockchain. The business dimension covers customer-facing applications such as mobile banking, intelligent risk control and digital currency services. Organisational enablers for the Management component include fintech subsidiaries, technology staff and data governance structures. Keyword occurrences in each dimension are counted by exact string matching and scaled by document length to obtain occurrences per ten thousand characters; thus, the steady increase in the volume of annual reports over the sample period does not distort the indices.

The four dimension scores are combined into a composite index called DTI by entropy weighting, and more weight is given to dimensions with a larger cross-sectional dispersion to avoid giving equal weight to different facets [15]. The index follows the expected path, increasing steadily from 2017 to a peak around 2022, and there has been considerable and continuous cross-bank heterogeneity in the sample period.

2.3. Identification of Emerging Risks from Risk Disclosures

Emerging risk exposure is quantified from the same disclosure documents, and it is known that textual risk disclosures contain economically significant information about the risks faced by firms [16]. Risk indices based on disclosure narratives have been shown to predict distress in fintech-intensive enterprises [17], and systematic mining of disclosure text has demonstrated the ability to separate individual risk drivers aggregated by traditional financial ratios [18].

The four categories of emerging risks are defined here, and these are closely related to digitalised banking. Cybersecurity risk includes references to network attacks, information security incidents and system vulnerabilities, and a lexicon that has been validated for disclosure-based measurement in capital-market settings [19]. Data risk covers data security, data compliance and personal information protection. Algorithm and model risk records references to model validation, model failure and algorithmic accountability. Third-party dependency risk refers to outsourcing, vendor concentration and business continuity. Category frequencies are scaled per ten thousand characters, and a term in the data category is counted only when it appears within a narrow window containing an explicit risk-related qualifier to exclude promotional uses of data vocabulary. The four category scores are averaged with equal weights to obtain a composite exposure index, ERI, as the categories share a common metric and no single dimension should be dominant by construction. Because disclosure practices differ across institutions in ways not related to underlying exposure [20], the analysis later checks that the results are insensitive to alternative index constructions.

Validity is checked in two ways. The composite index has a weak negative correlation with the non-performing loan ratio, and this association disappears after removing the common-year effect; thus, ERI does not reflect a restatement of conventional credit risk but rather a type of risk that is distinct from it. The category trajectories are close to the regulatory milestones. Data risk disclosure rose sharply between 2020 and 2022, around the implementation of the Data Security Law and the Personal Information Protection Law; after the introduction of rules for generative artificial intelligence in 2023, algorithm risk disclosure recorded its largest single-year rise. This response to identifiable regulatory events supports the content validity of the measurement.

2.4. Model Specification

The baseline relationship between digitalisation and new-age risk exposure is estimated by a two-way fixed-effects panel model of the form

$$ERI_{it} = \alpha + \beta_1 DTI_{i,t-1} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where ERI_{it} is the standardized exposure index of bank i in year t, $DTI_{i,t-1}$ is the standardized transformation index lagged one year to mitigate simultaneity, X_{it} collects bank-level controls, and μ_i and λ_t denote bank and year effects. The controls comprise bank size measured as the natural logarithm of total assets, the capital adequacy ratio, return on assets, the non-performing loan ratio, the cost-to-income ratio, and the loan-to-deposit ratio. Table 1 reports full variable definitions. Standard errors are clustered at the bank level, and because the panel contains only 20 clusters, inference on the key coefficients is supplemented with wild cluster bootstrap p-values. Estimates are additionally examined within bank-type subsamples, although the small group sizes limit the weight these splits can bear.

Table 1. Variable Definitions

Category	Variable	Symbol	Definition
Dependent	Emerging risk exposure index	ERI	Sum of four category-specific keyword frequencies per 10,000 characters; equal-weighted average; standardized in regressions
Sub-indices	Cybersecurity risk exposure	ERI_cyber	Cybersecurity keyword frequency per 10,000 characters
	Data risk exposure	ERI_data	Data-related keyword frequency within risk context windows, per 10,000 characters
	Algorithm and model risk exposure	ERI_algo	Algorithm and model keyword frequency per 10,000 characters
	Third-party dependency risk exposure	ERI_third	Third-party keyword frequency per 10,000 characters
Independent	Digital transformation index (lagged)	DTI(t-1)	Entropy-weighted composite of four min-max normalized dimension scores, one-year lag; standardized in regressions
Moderator	Board independence	INDEP	Independent directors / total board members; gaps filled from nearest adjacent year
Supplementary moderator	Fintech subsidiary	FINSUB	1 from the year a dedicated fintech subsidiary is first disclosed onward, 0 otherwise
Controls	Bank size	SIZE	Natural logarithm of total assets
	Capital adequacy	CAR	Capital adequacy ratio (%)
	Profitability	ROA	Net income / total assets (%)
	Credit risk	NPL	Non-performing loans / gross loans (%)
	Cost efficiency	CIR	Cost-to-income ratio (%)
	Loan-to-deposit ratio	LDR	Gross loans / total deposits (%)
Grouping	Bank type	TYPE	State-owned, joint-stock, or city commercial bank (heterogeneity analysis only)
Fixed effects	Bank and year	μi, λt	Two-way fixed effects

The mitigation side of the research question is handled by governance moderation. Board independence is a type of governance that has been shown to affect a bank's risk-taking decisions under various institutional circumstances [21], and generally speaking, internal governance structures have been associated with risk behaviour in both developed and developing countries [22]. Interaction designs of this type are the standard means for testing whether governance conditions affect risk outcomes [23]. The moderation model adds the following terms to the baseline

$$ERI_{it} = \alpha + \beta_1 DTI_{i,t-1} + \beta_2 (DTI_{i,t-1} \times MOD_{it}) + \beta_3 MOD_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where MOD_{it} denotes the independent director ratio in the main test and a fintech subsidiary indicator in a supplementary test, both mean-centered before interaction. The independence ratio is extracted from governance disclosures, with gaps filled from the nearest adjacent year given the stability of board composition, and a robustness check excludes the filled observations. The subsidiary indicator equals one from the year a bank first discloses a dedicated fintech subsidiary onward, a first-disclosure convention that is noted when interpreting results.

3. Results

3.1. Descriptive Statistics

As shown in Table 2, the mean of the composite transformation index is 0.276 and its standard deviation is 0.124; the range between the least digitalised bank-years and the most digitalised is about thirty times, and thus the sample contains institutions at very different levels of digitalisation. The new risk exposure index averages 0.221 per ten thousand characters, and the four components have different

degrees of prominence. Cybersecurity vocabulary is the most common, appearing almost twice as often as third-party terminology, and algorithm and model language are the rarest. The financial controls are within the range of the listed Chinese banking sector, with a mean capital adequacy ratio of 14.4 per cent, a mean non-performing loan ratio of 1.3 per cent, and independent directors accounting for about 38.5 per cent of the board. Transformation intensity rose through the sample period and then eased after 2022, which is consistent with the maturity of the digital programmes introduced in the late 2010s.

Table 2. Descriptive Statistics

Variable	Mean	SD	Min	Max
DTI (composite index)	0.276	0.124	0.023	0.664
ERI	0.221	0.142	0.011	0.920
ERI_cyber	0.463	0.321	0.000	1.564
ERI_data	0.131	0.233	0.000	1.504
ERI_algo	0.052	0.060	0.000	0.248
ERI_third	0.240	0.151	0.000	0.801
SIZE	29.523	0.951	27.741	31.431
CAR (%)	14.368	1.791	11.490	19.260
ROA (%)	0.845	0.190	0.423	1.437
NPL (%)	1.332	0.303	0.750	2.050
CIR (%)	29.054	6.055	18.930	59.010
LDR (%)	86.548	13.085	53.410	111.223
INDEP	0.385	0.071	0.222	0.625
FINSUB	0.440	0.498	0.000	1.000

Notes: 2018-2023 panel. N ranges from 109 to 116 across variables due to missing values, and INDEP includes 29 imputed observations. DTI is an entropy-weighted composite of min-max normalised dimension scores; ERI and its sub-indices are in raw per-10,000-character units, and standardised versions are used for estimation.

3.2. Emerging Risk Profiles in Banks

As shown in Figure 1, aggregate emerging risk disclosure has more than doubled between 2017 and 2023, rising from 0.143 to 0.304 per ten thousand characters, and this increase is not uniform across categories. The main driver of growth is data risk. It was almost absent from the annual reports before 2020, climbed from 0.049 in that year to 0.156 in 2021 and 0.258 in 2022, and has been increasing ever since, in step with the implementation of the Data Security Law and the Personal Information Protection Law. Algorithm and model risk is still the smallest category in absolute terms, but it has shown the fastest proportional growth, and its sharpest single-year increase in 2023 coincided with the release of dedicated rules for generative artificial intelligence. Cybersecurity disclosures are relatively high at the beginning of the window and rise more gradually; third-party dependency language has roughly doubled over the seven years as outsourcing and cloud arrangements deepen.

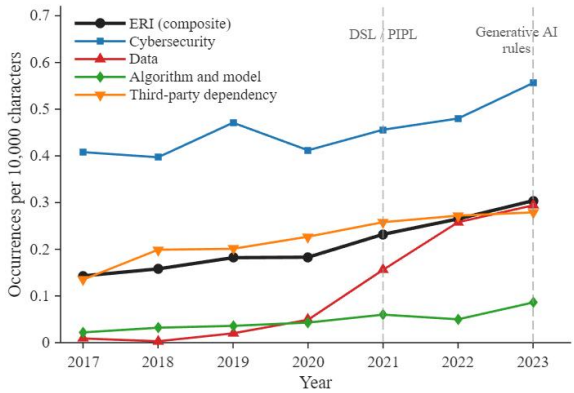


Figure 1. Evolution of Emerging Risk Disclosure by Category, 2017-2023.

As shown in Figure 2, the structure of disclosed risks by banks is not the same. City commercial banks give the most attention to cybersecurity, averaging 0.591 per ten thousand characters against 0.377 for the large state-owned banks, a pattern consistent with thinner in-house security resources. State-owned banks lead by a large margin in data risk, which can be attributed to the compliance requirements

for their extensive customer data, and joint-stock banks sit in the middle across most categories. Therefore, the form of risk disclosure differs by industry; it is not uniform and has been structured based on the cycle of regulation and resource conditions for various institutions.

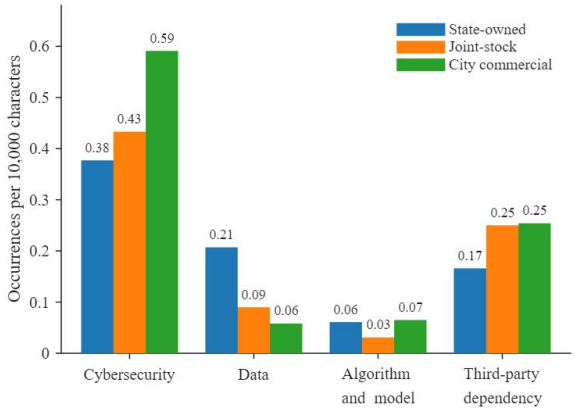


Figure 2. Risk Disclosure Profiles by Bank Type.

3.3. Digital Transformation and New Risk Exposure

As shown in Table 3, the coefficient of the lagged transformation intensity in the baseline specification is small, negative and not statistically significant; the cluster-robust p-value is 0.572 and the wild bootstrap p-value is 0.559. After accounting for bank and year effects, a bank's position in the digital race does not provide additional information on its new risk disclosure. Stable institutional differences account for most of the cross-sectional variation in disclosed exposure, and the pronounced rise documented above is a common movement shared by the entire sector; neither margin leaves room for the idiosyncratic pace of individual transformation to matter. That common movement has been driven by shared forces, and the regulatory milestones recorded earlier are typical examples, along with the sector-wide spread of technology. Splitting the sample by bank type yields the same result in all segments, and the small size of the groups advises against drawing any conclusions from the subsample point estimates. Therefore, this study considers the evidence to show that the new risks in Chinese banking are mainly systemic and cohort-level problems, rather than penalties for faster individual changes; thus, the focus of risk reduction efforts should be adjusted accordingly.

Table 3. Digital Transformation and Emerging Risk Exposure: Baseline, Moderation and Robustness

	M1	**M2**	**M3**	**R1 (NPL)**	**R2 (PCA)**	**R3 (Cyber)**
DTI(t-1)	-0.134	0.066	-0.091	-0.017	-0.090	-0.154
	(0.233)	(0.396)	(0.186)	(0.057)	(0.226)	(0.186)
DTI(t-1) × INDEP		0.479				
		(1.444)				
DTI(t-1) × FINSUB			0.292			
			(0.444)			
INDEP		-0.464				
		(2.521)				
FINSUB			1.129			
			(0.685)			
Bootstrap p (key coef.)	0.559	0.680	0.664	0.869	0.684	0.438
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank & year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	109	80	109	109	109	109
Banks	20	15	20	20	20	20
R^2	0.648	0.650	0.676	0.899	0.650	0.691

Notes: The dependent variable is standardized ERI except in R1 (NPL, with NPL excluded from controls), R2 (first principal component of the four sub-indices), and R3 (standardized cybersecurity sub-index). Cluster-robust standard errors are in parentheses; wild cluster bootstrap p-values based on 4,999 replications refer to the coefficient of interest in each column. The M2 sample is smaller because board independence could not be recovered for five banks; excluding observations with imputed independence ratios (N=61) leaves an insignificant interaction (coef. -2.088, bootstrap p=0.568). None of the coefficients in the table are statistically significant at the 10% level.

3.4. Moderating Effect of Governance Mechanisms

As shown in Table 3, the interaction between lagged transformation and board independence is positive but not statistically significant; the bootstrap p-value is 0.680, and excluding the observations whose independence ratios were filled from adjacent years results in an insignificant coefficient. The supplementary test using the fintech subsidiary indicator points in the same direction; although the indicator dates from first disclosure rather than legal establishment, its positive level coefficient suggests that setting up a separate subsidiary goes together with broader risk disclosure. Two identification constraints qualify these results; they do not support a firm conclusion of irrelevance. Board independence moves little in banks over six years after the regulatory minimums set the level, and subsidiary establishment clusters in a narrow band of years; thus, the within-bank variation available to identify either moderator is small. Therefore, the governance channel for mitigation is still an open problem that the current design can raise but not settle, as noted in the concluding remarks.

3.5. Robustness Tests

The null baseline result is very stable. Replacing the disclosure-based index with the non-performing loan ratio as the dependent variable results in a near-zero coefficient; thus, transformation intensity does not predict either emerging risk disclosure or conventional credit risk. Substituting the first principal component of the four category scores for the equal-weighted composite, and estimating the model on the cybersecurity sub-index alone, gives coefficients with the same sign that remain insignificant, with bootstrap p-values ranging from 0.438 to 0.684. Across all alternative constructions, the lack of a within-bank association remains, and thus it can be concluded that the patterns shown in the risk profiles are driven by sector-level dynamics rather than by individual transformation trajectories.

4. Discussion

Based on the above results, the view of the new risks in digitalised banking needs to change, together with the way they are managed. The disclosure profiles show that attention to cybersecurity, data, algorithms and third-party risks has been spreading rapidly and systematically, but the regression evidence indicates that this expansion is not the result of individual transformation choices. Banks that were more digitally advanced than their peers did not disclose more new risk later on, and the responsibility for explanation fell instead on stable institutional differences and a common sector-wide movement in line with the succession of regulatory milestones. The resulting picture is that risk is spreading along a common sectoral front, and its distribution among banks is determined by long-standing institutional characteristics rather than the speed of any single digital initiative. Such a reading also disciplines the interpretation of what disclosure-based indices measure. The weak correlation between the exposure index and traditional credit risk, as well as the tendency of well-capitalised institutions to disclose more rather than less, suggest that risk disclosure may be a combination of actual exposure and risk management maturity and supervisory responsiveness; thus, narrative-based measurement in banking research should consider multiple signals [24]. Evidence that increased cybersecurity risk leads to measurable changes in bank behaviour [25] indicates that the underlying hazards are real; even so, their textual traces should be interpreted as an institutional response to an evolving threat and compliance environment rather than a direct index of loss potential.

These conclusions point to a mitigation mechanism with three layers at the supervisory, technical and governance levels. If the leading edge of the new risk is a common front, then the most effective place for intervention is supervisory coordination that operates on cohorts rather than outliers, harmonised taxonomies of digital risk, sector-wide incident reporting, and stress tests targeting shared dependencies such as cloud concentration. The profiles of cross-type differences are relatively prominent; therefore, technical expectations should be adjusted according to institutional segments, and city commercial banks have weaker internal cybersecurity resources and the largest state-owned institutions bear a heavier data-compliance burden, so uniform technical mandates will be ineffective at both ends. The governance layer, on the other hand, should be advanced with more modest claims. Moderation analysis could not determine whether board independence or dedicated fintech subsidiaries changed the transformation-risk relationship, and the identification constraints behind this null result were themselves informative; that is, governance arrangements anchored by regulatory minimums varied too little within institutions to reveal any effect over a six-year period. Governance reform is still a possible addition to supervision and technical measures, but the current evidence supports treating it as a hypothesis for longer panels rather than a proven tool.

For practitioners, the results suggest that digital acceleration is not inherently riskier at the institutional level; rather, the data do not support framing it as such, and no institution can avoid hazards that move with the entire sector. Risk officers gain more by comparing their exposure structure with the

cohort trajectory in the risk profiles than by slowing down the speed of transformation. For supervisors, the close link between disclosure surges and new regulations shows that regulatory tools already steer the attention of banks, and the task now is to turn this convening power into actual resilience requirements, especially for third-party dependencies whose disclosure has doubled but remains under-analysed. The combination of a fast-rising common exposure trend and the lack of institutional differentiation defines a policy problem that is narrower than it looks but difficult to delegate; it is a problem for the entire system rather than for a single bank.

5. Conclusion

Based on the annual reports of the 20 listed Chinese commercial banks from 2017 to 2023, this paper identifies new risks that have appeared in the process of digitalisation for financial institutions and explores how they can be managed. A dictionary-based measurement framework for cybersecurity, data, algorithm and third-party dependency risks can monitor this phenomenon at a categorical level, and the resulting profiles show that disclosed exposure has more than doubled in the window, mainly due to data-related concerns that have increased in line with landmark privacy legislation. Fixed-effects estimates then show that this expansion has no within-bank association with the speed of digitalisation, a null result that persists after alternative index construction, an alternative risk measure and small-cluster inference correction. In short, the evidence shows that the new risk is a whole-industry problem driven by regulatory changes and stable institutional differences; therefore, the appropriate response will be strengthened cooperation among regulators and technical standards for different parts of the industry, with internal governance kept as a possible but not yet verified complement.

The limits of the design mark the scope of the above claims. Disclosure-based indices reflect institutional attention rather than actual losses; the panel of 20 institutions limits statistical power, and governance moderators change too little among banks over six years to enable fine-grained identification. Thus, there are natural extensions. Longer panels reaching the mature stage of transformation will sharpen the governance question; loss or incident data can be used to benchmark the disclosure-based measures developed here against realised results, and applying the measurement framework to other banking systems will test whether the regulatory synchronisation documented for China is generalisable to jurisdictions with different supervisory architectures. Generally speaking, this study has found that the risks in digital finance are in a collective form; therefore, managing these risks should be the responsibility of the system rather than the individual members.

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Author Contributions
The author designed the study, collected and analysed the data, and wrote the paper.

Conflict of Interest
The author has no conflict of interest.

Data Availability Statement
The data in this study were obtained from the publicly available annual reports on the CNINFO disclosure platform and from public financial data services.

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