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Financial connectedness in the digital age: The impact of regional FinTech development☆,☆☆

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ABSTRACT

This study investigates how FinTech development affects financial institutions' network connectedness and systemic risk in China's rapidly digitalizing financial sector. While existing research examines FinTech's impact on financial stability, these approaches inadequately address how FinTech reshapes broader financial network structures. Using data from Chinese listed financial institutions from 2011 to 2021, we measure connectedness through stock-return interconnections and employ panel regression analysis to examine the relationship with regional FinTech development. Our analysis reveals that FinTech development significantly enhances financial institutions' network connectedness, with this impact moderated by industry concentration and internal FinTech innovation. The effects are stronger in digitization and usage depth dimensions and more pronounced in non-state-owned institutions. These findings demonstrate that FinTech creates new systemic risk transmission channels through digital platform effects and technological interdependence. The results provide crucial insights for regulatory frameworks addressing systemic risk in financial digitalization.

1. Introduction

The rapid development of financial technology (FinTech) is fundamentally reshaping the financial industry. These innovations, including digital payments, blockchain, and big data analytics, have transformed traditional financial services (Goldstein et al., 2019). While FinTech has the potential to enhance efficiency and financial inclusion (Gomber et al., 2017), it also raises concerns about its impact on financial stability and systemic risk (Ozili, 2018; Cevik, 2024). A key aspect of systemic risk is the interconnectedness of financial institutions, which serves as critical transmission channels through which localized disturbances can escalate into system-wide crises (Jackson and Pernoud, 2021).

This study explores how FinTech development reshapes financial institutions' connectedness. As financial systems undergo rapid digital transformation, new forms of technological interdependence may fundamentally alter traditional risk transmission pathways and create novel systemic vulnerabilities.

Using data from Chinese listed financial institutions from 2011 to 2021, we measure connectedness through principal component analysis following (Billio et al., 2012). This approach allows us to examine how FinTech development affects both market-wide connectedness and individual institutions' contributions to network interconnectedness. We measure FinTech development using the Digital Financial Inclusion Index (DFII) developed by the Institute of Digital Finance at Peking University in collaboration with Ant Group. Our findings reveal that FinTech development significantly enhances financial institutions' contributions to overall network connectedness.

Our analysis considers two key channels: institutions' internal digital transformation, measured through the frequency of FinTech-related words in annual reports, and market competition, captured by the Herfindahl–Hirschman Index (HHI). The impact is more pronounced for institutions with higher levels of internal innovation and in less competitive markets.

While data limitations prevent us from examining specific technological channels in detail (e.g., blockchain or digital payments), we

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leverage the multidimensional nature of the DFII which includes subindices for coverage breadth (accessibility of digital services), usage depth (intensity of digital service adoption), and digitization level (sophistication of digital financial offerings). Our heterogeneous analysis further shows that the quality and depth of FinTech adoption, rather than its widespread availability, drive increased connectedness. Moreover, private-owned institutions are more responsive to FinTech development compared to state-owned institutions in terms of increased connectedness. These findings offer practical insights for regulators and policymakers managing systemic risks in an increasingly digitized financial ecosystem.

To understand the mechanisms through which FinTech influences financial connectedness, we first establish the conceptual foundation. Research has established interconnectedness as a fundamental contributor to systemic risk (De Nicolo and Kwast, 2002; Haldane and May, 2011). Billio et al. (2012) conceptualize financial connectedness through direct relationships such as interbank lending and similar exposures that create pathways for shock transmission (Wagner, 2010; Elliott et al., 2014). Jackson and Pernoud (2021) extend this framework to include indirect linkages such as portfolio commonalities, price-mediated connections through asset markets, and perception-based associations where similar institutions face correlated investor reactions. Our stock-return based measure captures these multifaceted relationships, reflecting both direct financial exposures and the market's integrated assessment of complex linkages. This provides a comprehensive view of systemic vulnerability that balance sheet measures alone might miss.

Building on this understanding of interconnectedness, FinTech development could influence financial interconnectedness through multiple channels. First, digital platforms, such as P2P lending, enable customers to easily observe others' decisions and herd (Zhang and Liu, 2012). Second, intelligent algorithms enable the automatic acquisition of information, processing of data, and, finally, the generation of tailored investment advice (Jung et al., 2018), potentially increasing return correlations. Third, as institutions integrate with similar FinTech platforms and infrastructure, new forms of technological interdependence emerge, creating common vulnerabilities to technological disruptions (Haldane and May, 2011).

The relationship between FinTech and financial connectedness is likely mediated by two channels. Market concentration shapes how FinTech affects interconnectedness, as dominant institutions in concentrated markets often establish technological standards that others follow Frost et al. (2019), potentially increasing homogeneity in risk exposures. Additionally, an institution's internal digital transformation capabilities determine its responsiveness to external FinTech developments (Vives, 2019), with digitally advanced institutions more likely to integrate with external platforms and adopt similar risk management approaches, potentially amplifying network effects.

Recent studies have examined FinTech's implications for financial stability, with contrasting perspectives. While Daud et al. (2022) suggest that FinTech promotes stability through advanced technologies and Yu (2024) demonstrate that FinTech can play a countercyclical role in risk reduction by helping banks balance their asset allocation structure and achieve optimal leverage ratios that minimize commercial bank risks, others find that greater FinTech presence increases financial institutions' risk-taking (Elekdag et al., 2025; Wang et al., 2021).

Some researchers have begun to explore systemic dimensions, with Cevik (2024) examining FinTech's impact on financial stability using distance-to-default measures, and Chen and Shen (2024) investigating digital transformation's effect on bank systemic risk. Parallel developments in systemic risk methodology have focused on extreme risk transmission, where Baumöhl et al. (2022) propose a cross-quantilogram network approach to measure systemic risk in global banking, identifying significant transmitters and receivers of extreme downside risk through network topological properties. Similarly, Addi and Bouoiyour (2023) examine simultaneous transmission of extreme risk, revealing tight connectivity and asymmetric spillover effects that increase significantly during periods of instability.

The broader literature on macroprudential policies provides crucial context for understanding how external shocks affect financial stability. Bratsiotis and Gloria (2025) demonstrate that countercyclical loan-to-value rules can enhance social welfare during pandemic shocks, while Benbouzid et al. (2022) show that counter-cyclical capital buffer tightening effectively reduces bank credit risk by strengthening capital ratios. These findings underscore the pivotal role of macroprudential instruments in mitigating systemic disruptions during periods of heightened uncertainty.

However, these approaches still inadequately address how FinTech reshapes broader financial network structures and the complex interactions between external FinTech ecosystems and internal institutional transformation processes.

Our study makes three distinct contributions to this literature. First, we employ network analysis to examine how FinTech reshapes systemic risk transmission pathways, moving beyond traditional individual institution risk assessments. Second, unlike Chen and Shen (2024)'s bank-focused study using approximated exposure networks, we analyse the entire financial ecosystem using market-based connectedness measures that capture both direct and indirect linkages. Third, we develop a framework exploring the interaction between external FinTech ecosystems and institutions' internal digital transformation, extending Caragea et al. (2024)'s finding that competitive innovation pressures drive incumbents' technology adoption.

The remainder of this paper is organized as follows: Section 2 introduces the data and variables used in our analysis. Section 3 presents our empirical models and results, demonstrating how FinTech affects connectedness and examining its specific mechanisms. Finally, Section 4 concludes our study and discusses policy implications.

2. Data and variables

2.1. Data

Our study utilizes an unbalanced panel dataset comprising up to 116 financial institutions listed on Chinese stock exchanges from 2011 to 2021. To measure connectedness and contributions to connectedness, we use monthly stock return data obtained from the CSMAR database.

The key independent variable, FinTech development, is measured using the DFII published by the Institute of Digital Finance at Peking University. This comprehensive index captures various aspects of FinTech development across China. We also incorporate data on moderating and control variables that may influence connectedness, including internal FinTech transformation, market competition (HHI), and institution characteristics. The data were obtained from various sources, primarily CSMAR and RESSET.

2.2. Financial institutions connectedness

Following the methodology proposed by Billio et al. (2012), we measure the connectedness of financial markets by analysing stock return interconnections. The methodology proceeds in several steps:

First, we gather monthly return data for all financial institutions in our sample over the study period. Assuming the time length is T and the number of financial institutions is N, we can obtain a $T \times N$ return matrix. After standardizing each column of returns, we can calculate the $N \times N$ (assuming $T > N$) variance–covariance matrix of the entire return matrix.

Second, we apply principal component analysis and decompose variance–covariance matrix Σ to obtain the corresponding eigenvectors and eigenvalues. The eigenvectors represents the directions of the principal components and eigenvalues indicate the variances at the corresponding directions.

The proportion of variance explained by the first m principal components in the total variance is: $\sum_{i=1}^{m} \lambda_i / \sum_{i=1}^{N} \lambda_i$, where λ_i is the ith largest eigenvalue. A high proportion of variance explained by the first few principal components indicates a high degree of connectedness in the financial system.

The economic intuition underlying this approach is straightforward. When financial institutions are highly interconnected, their stock returns tend to move together in response to common shocks or through direct or indirect linkages. Principal component analysis identifies these common patterns of variation across institutions. If the first few principal components explain a large proportion of total variance, it suggests that institutions' returns are driven by common factors rather than idiosyncratic movements, indicating high systemic interconnectedness. Conversely, when institutions operate more independently, their returns would be driven primarily by institution-specific factors, resulting in lower explanatory power for the initial principal components.

Third, we measure each institution's contribution to connectedness when the connectedness is represented by the proportion of variance explained by the first m principal components in the total variance. The formula is as follows:

$$\text{ConnectPC}_{m,i} = \sum_{k=1}^{m} \frac{\sigma_i}{\sigma_s} L_{ik}^2 \lambda_k, \tag{1}$$

where $\text{ConnectPC}_{m,i}$ represents the contribution of institution i to the overall connectedness based on the first m principal components. σ_i is the return variance of institution i, σ_s is the return variance of the whole market, L_{ik} is the kth factor loading for institution i, and λ_k is the kth eigenvalue. Specifically,

$$\sigma_s = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k.$$

Following Billio et al. (2012), we select the appropriate number of principal components based on the fraction of total risk explained. Specifically, we calculate for each period the fraction of total risk explained by the first principal component, and identify the threshold as the mean of the lowest 20% (lowest quintile) of these values. In our sample, this threshold is 47%, which is substantially higher than the 27% threshold reported in Billio et al. (2012). The average cumulative variance explained by the first 3 principal components in our sample is 71%, which we use for our baseline analysis. For robustness, we also consider specifications using the first principal component (explaining 55% of variance on average) and the first five principal components (explaining 77% of variance on average). This approach captures the most significant common factors driving returns across financial institutions while ensuring consistency with established methodological approaches in the literature.

To capture connectedness changes over time, we follow (Billio et al., 2012) by calculating monthly measures using a 36-month rolling window of data. Since our FinTech development index (DFII) is only available annually, we convert our monthly connectedness values to yearly averages for each institution. This approach allows us to examine how FinTech development affects financial institution connectedness over time.[1]

Fig. 1 illustrates the dynamic relationship between financial institution connectedness (the proportion of variance explained by the first three principal components) and market volatility in China's financial system from 2012 to 2024. Market volatility is estimated using a GARCH(1,1) model on the monthly returns of the CSI 300 Index, which tracks the 300 largest and most liquid A-share stocks traded on China's two main exchanges and serves as a key benchmark for China's stock market performance. In the figure, the thick smooth lines represent the fitted trends with a LOESS (locally weighted regression) smoother, while the lighter background lines show the actual monthly observations of both indicators.

Although not perfectly synchronized, these two indicators demonstrate notable co-movement patterns, particularly during periods of market stress. This relationship is especially pronounced in the two highlighted periods (grey shaded areas): the 2015 market turbulence period, when China's stock market experienced significant volatility, and the 2020–2021 period, when COVID-19 pandemic disrupted market stability. During these stress periods, the elevated levels of both connectedness and market volatility suggest that enhanced interconnectedness among financial institutions tends to coincide with increased market turbulence. This pattern implies that the connectedness measure could serve as a meaningful indicator to monitor systemic risk in China's financial markets, as it demonstrates a strong association with periods of market-wide stress and turbulence.

2.3. FinTech development

To measure FinTech development, we utilize the DFII developed by the Institute of Digital Finance at Peking University in collaboration with Ant Group. The DFII covers 31 provinces and 337 prefecture-level cities from 2011 to 2021, capturing three key dimensions of digital financial inclusion:

Coverage breadth: This sub-index measures the extent of digital financial services coverage. It includes indicators such as the number of Alipay accounts per 10,000 people, reflecting the penetration of digital payment platforms.

Usage depth: This component gauges the intensity of digital financial service usage. It incorporates metrics like the number of users with Internet loans for consumption per 10,000 adult Alipay users, providing insights into the adoption of digital lending services.

Digitization level: This sub-index assesses the degree of digitization in financial services. It includes indicators such as the average loan interest rate for small and micro businesses, reflecting how digital technologies are impacting traditional financial metrics.

To merge regional DFII data with our institution-level data, we adopt a headquarters-based approach. Specifically, we use the province-level DFII to represent the FinTech development faced by a financial institution whose headquarters is located in that province. This approach is based on the assumption that listed financial institutions are primarily influenced by the FinTech environment in their home province, where key strategic decisions are typically made. However, we acknowledge that this method may not fully capture the FinTech exposure of institutions with significant operations in multiple provinces.[2]

For robustness, we also employ an alternative measure using the city-level DFII. This allows us to capture potential variations in FinTech development at a more granular level, acknowledging that some institutions may be more sensitive to local FinTech ecosystems.

[1] Our study is limited by the annual frequency of FinTech development data, which necessitates averaging of higher-frequency connectedness measures. Future research with higher-frequency FinTech indicators could provide more granular insights into the dynamic relationship between FinTech innovation and financial connectedness.

[2] A more comprehensive approach would be to construct institution-specific FinTech exposure measures by weighting each province's DFII according to the institution's branch distribution across provinces. Unfortunately, detailed branch distribution data are only available for a subset of banks and are not available for other financial institutions in our sample, which would significantly reduce our sample size and introduce selection bias if implemented.

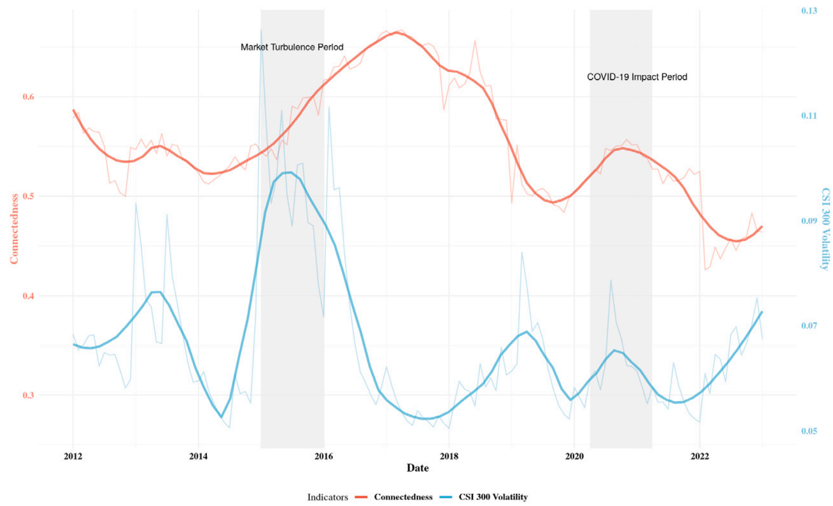

Fig. 1. Comparison of financial connectedness and CSI 300 volatility.

2.4. Moderator and control variables

Our study incorporates several channel and control variables to account for institution-specific characteristics that may influence the relationship between FinTech development and financial institution connectedness.

We measure the internal transformation to FinTech development by analysing the frequency of FinTech-related words, such as "artificial intelligence", "cloud computing", "blockchain" and "big data", in each institution's annual reports. The data source is CASMAR database. To account for the time lag in implementing FinTech strategies and to smooth out short-term fluctuations, we calculate a 3-year moving average of this word frequency. This approach allows us to capture the sustained commitment to FinTech innovation rather than temporary fluctuations in reporting language.

We proxy external competition using the HHI. The HHI is widely used in economic literature as a measure of market concentration, which inversely relates to competition. It is calculated as the sum of squared market shares of each sample institution in terms of total assets within their respective industry sectors. A higher HHI indicates lower market competition and higher market concentration. We choose this measure as it provides a comprehensive view of market structure and competitive dynamics. The definition of each variable is reported in Table 1.

The summary statistics of those variables are reported in Table 2. The mean values of ConnectPC1, ConnectPC3, and ConnectPC5 (representing contributions to connectedness based on the first, first three, and first five principal components, respectively) increase from 20.050 to 39.150. Note that these values have been multiplied by 10^5 for ease of interpretation. The increasing trend indicates higher contributions when more components are considered.

The DFII matched by province (DFII_PROV) shows a larger standard deviation (102.256) compared to the DFII matched by city (DFII_CITY) (71.395), suggesting greater variation in FinTech development at the provincial level in our sample. The mean HHI of 0.133 indicates a moderate level of market concentration. The average FinTechTrans score of 23.148 suggests that, on average, FinTech-related words appear about 23 times in institutions' annual reports.

Among the control variables, STATE_OWN represents the proportion of state-owned shares in each institution's total equity, with values ranging from 0 to 0.908, reflecting the diverse ownership structures in China's financial sector. LEV measures institutional leverage (calculated as total liabilities divided by total assets), with an average of 0.725 indicating that financial institutions in our sample are heavily leveraged, which is typical for the finance industry. ROA (return on assets,

Table 1
Variable measurement.

Variable	Measurement
Dependent variables	
ConnectPC1	The contribution of each institution to the connectedness based on the largest principal component, multiplied by 10^5
ConnectPC3	The contribution of each institution to the connectedness based on the largest three principal components, multiplied by 10^5.
ConnectPC5	The contribution of each institution to the connectedness based on the largest five principal components, multiplied by 10^5.
Independent variable	
DFII_PROV	The provincial-level DFII aggregate index corresponding to the location of each financial institution's headquarters.
DFII_CITY	The city-level DFII aggregate index corresponding to the location of each financial institution's headquarters.
Digitization_PROV	The provincial-level digitization sub-index of DFII, measuring the digitization level of financial inclusion.
Usage_PROV	The provincial-level usage sub-index of DFII, measuring the depth of digital finance adoption.
Coverage_PROV	The provincial-level coverage sub-index of DFII, measuring the breadth of digital finance accessibility.
Moderator variables	
HHI	Calculated as the sum of squared market shares of each institution within their respective industry, based on total assets.
FinTechTrans	Fintech related word frequency in annual reports of sample companies.
Control variables	
STATE_OWN	The proportion of state-owned shares in the institution's total equity, calculated as the number of state-owned shares divided by total share capital.
SIZE	Calculated as the natural logarithm of total assets (in millions).
LEV	Computed as the ratio of total debt to total assets.
ROA	Measured by return on assets, calculated as net income divided by total assets.

Table 2
Summary statistics.

Statistic	Mean	Median	St. Dev.	Min	Max
ConnectPC1	20.050	14.307	18.421	0.027	145.396
ConnectPC3	29.741	19.007	48.295	0.834	873.580
ConnectPC5	39.150	22.309	115.308	0.912	2,888.823
DFII_PROV	286.287	286.370	102.256	20.340	458.970
DFII_CITY	241.384	250.451	71.395	43.740	359.683
Digitization_PROV	333.635	374.540	110.426	7.580	462.228
Usage_PROV	293.229	281.475	112.678	23.600	510.694
Coverage_PROV	268.131	275.401	99.753	7.470	433.423
HHI	0.133	0.103	0.124	0.000	0.998
FinTechTrans	23.148	14.000	25.334	1.000	158.667
STATE_OWN	0.043	0.000	0.121	0.000	0.908
SIZE	11.826	11.738	2.742	6.137	17.615
LEV	0.725	0.770	0.225	0.020	2.377
ROA	0.016	0.012	0.074	−1.309	0.386

calculated as net income divided by total assets) shows considerable variation, ranging from −1.309 to 0.386, suggesting diverse levels of profitability across the sample.

3. Empirical analysis and results

This section presents our empirical strategy and findings on the relationship between FinTech development and the connectedness of financial institutions in China. We begin by introducing our baseline model, which examines the direct effect of FinTech development on connectedness. We then explore the moderating effects of internal FinTech innovation and market competition. Finally, we conduct a series of robustness checks and heterogeneity analyses.

3.1. Baseline model

To examine the relationship between FinTech development and financial institution connectedness, we estimate the following baseline model:

$$\begin{aligned}\text{ConnectPC}_{i,t} &= \beta_0 + \beta_1 \text{DFII}_{i,t} + \beta_2 \text{HHI}_{j(i),t} + \beta_3 \text{FinTechTrans}_{i,t} \\ &\quad + \delta \text{Controls}_{i,t} + u_i + v_t + \varepsilon_{i,t},\end{aligned} \tag{2}$$

where i, j and t denote institution, industry and year, respectively. The dependent variable $\text{ConnectPC}_{i,t}$ measures institution i's contribution to connectedness in year t, calculated using Eq. (1). Our main analysis uses ConnectPC3, based on the first three principal components. The key independent variable $\text{DFII}_{i,t}$ represents the FinTech development level in the province where institution i is headquartered. Control variables are defined in Table 1. We include institution fixed effects (u_i) and year fixed effects (v_t) to control for unobserved time-invariant institutional characteristics and common time trends.

We estimate this model using panel fixed effects regression with standard errors clustered at the provincial level to account for potential spatial correlation. This clustering approach is appropriate because institutions within the same province are subject to similar regional economic environments and regulatory implementations, creating correlations in their error terms.

The results in Table 3 provide strong support for our hypothesis. The coefficient of DFII is consistently positive and significant at the level 5% in all specifications. The economic significance is substantial: In column (3), a one-standard deviation increase in DFII (102.25) is associated with a 26.99 point increase in ConnectPC3 (approximately 91% of its mean value of 29.741).

Although market concentration (HHI) shows no significant direct effect, internal FinTech transformation (FinTechTrans) demonstrates a positive and significant relationship with connectedness. This suggests that institutions' active engagement with FinTech innovations increases their systemic importance.

Table 3
Baseline results: the impact of FinTech on financial connectedness.

	Dependent variable			
	ConnectPC3			
	(1)	(2)	(3)	(4) IV
DFII_PROV	0.580**	0.562**	0.264**	0.295***
	(0.229)	(0.224)	(0.102)	(0.079)
HHI		40.819	−35.239	−8.670
		(59.914)	(60.678)	(38.813)
FinTechTrans			0.183**	0.129**
			(0.061)	(0.052)
STATE_OWN	97.019**	96.151**	23.134***	21.284***
	(33.208)	(32.953)	(6.602)	(6.489)
SIZE	−7.282**	−6.923**	−4.446	−4.566
	(2.660)	(2.469)	(2.933)	(3.344)
LEV	42.966**	45.604**	37.936**	35.864**
	(17.852)	(19.287)	(15.375)	(15.020)
ROA	32.906	34.491	23.833	33.375
	(19.410)	(20.185)	(26.260)	(25.481)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	744	744	562	506
R^2	0.455	0.456	0.697	0.732

Note: This table reports the baseline results on the impact of FinTech on financial connectedness. Column (1) presents the baseline model with only DFII_PROV, Column (2) adds HHI, Column (3) further includes FinTechTrans, and Column (4) employs an instrumental variable approach. All specifications include industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Endogeneity concerns are inherently mitigated in our setting, as our primary explanatory variable (DFII) is measured at the province level while the outcome variable is at the institution level. An individual financial institution's connectedness is unlikely to significantly influence province-wide FinTech development. However, to further address potential reverse causality, we perform an instrumental variable analysis in column (4), using a one-year lagged DFII as an instrument. The IV results remain identical to our baseline estimates, confirming the robustness of our findings on the relationship between FinTech development and financial connectedness.

These results provide strong evidence for the impact of FinTech development on financial institution connectedness. However, to gain a more nuanced understanding of this relationship, we next explore potential channels that may influence the strength of this effect.

3.2. Mechanism analysis

To better understand how FinTech development affects financial institution connectedness, we examine two potential channels: market competition and internal FinTech innovation. These channels may moderate the relationship between FinTech development and connectedness by affecting institutions' technological adoption patterns and risk-sharing behaviours.

To investigate these moderating effects, we augment our baseline model with interaction terms. We estimate two separate models:

$$\begin{aligned}\text{ConnectPC}_{i,t} &= \beta_0 + \beta_1 \text{DFII}_{i,t} + \beta_2 \text{HHI}_{j(i),t} + \beta_3 \text{FinTechTrans}_{i,t} \\ &\quad + \beta_4 (\text{DFII}_{i,t} \times \text{HHI}_{j(i),t}) + \delta \text{Controls}_{i,t} \\ &\quad + u_i + v_t + \varepsilon_{i,t},\end{aligned} \tag{3}$$

$$\begin{aligned}\text{ConnectPC}_{i,t} &= \beta_0 + \beta_1 \text{DFII}_{i,t} + \beta_2 \text{HHI}_{j(i),t} + \beta_3 \text{FinTechTrans}_{i,t} \\ &\quad + \beta_4 (\text{DFII}_{i,t} \times \text{FinTechTrans}_{i,t}) + \delta \text{Controls}_{i,t} \\ &\quad + u_i + v_t + \varepsilon_{i,t},\end{aligned} \tag{4}$$

The results in Table 4 reveal two important mechanisms. First, columns (1) and (2) show that market concentration amplifies the impact of FinTech development on connectedness, as evidenced by the

Table 4
The moderating effects of market competition and internal FinTech innovation..

	Dependent variable			
	ConnectPC3			
	(1)	(2)	(3)	(4)
DFII_PROV	0.186**	0.183*	0.173**	0.177*
	(0.083)	(0.097)	(0.073)	(0.081)
HHI	−135.494***	−117.848***	−68.247*	−42.402
	(38.259)	(36.646)	(36.511)	(34.165)
FinTechTrans	0.163***	0.172***	−0.541***	−0.460**
	(0.047)	(0.048)	(0.168)	(0.208)
DFII_PROV×HHI	0.374***	0.383***		
	(0.060)	(0.072)		
DFII_PROV×FinTechTrans			0.002***	0.002**
			(0.001)	(0.001)
STATE_OWN		22.807***		22.673**
		(8.087)		(9.492)
SIZE		−6.041***		−4.588
		(2.206)		(2.809)
LEV		43.222		36.889
		(27.124)		(27.022)
ROA		25.935		16.956
		(19.215)		(22.700)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	570	562	570	562
R^2	0.694	0.710	0.693	0.705

Note: This table reports the moderating effects of market competition and internal FinTech innovation. Columns (1) and (2) examine the interaction between DFII_PROV and HHI, while Columns (3) and (4) examine the interaction between DFII_PROV and FinTechTrans. Columns (1) and (3) include only key variables, while Columns (2) and (4) include full controls. All specifications include industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 5
Robustness tests: city-level FinTech development and financial connectedness.

	Dependent variable		
	ConnectPC3		
	(1)	(2)	(3)
DFII_CITY	0.240**	0.133	0.110
	(0.100)	(0.110)	(0.087)
HHI	−23.987	−124.734***	−26.809
	(34.343)	(40.802)	(33.714)
FinTechTrans	0.191***	0.170***	−0.556*
	(0.060)	(0.048)	(0.306)
DFII_CITY×HHI		0.560***	
		(0.114)	
DFII_CITY×FinTechTrans			0.002**
			(0.001)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	540	540	540
R^2	0.691	0.705	0.698

Note: This table reports robustness tests using city-level FinTech index (DFII_CITY) instead of provincial-level index. Column (1) presents the baseline model with DFII_CITY, Column (2) examines the interaction between DFII_CITY and HHI, and Column (3) examines the interaction between DFII_CITY and FinTechTrans. All specifications include industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

positive and significant interaction term (DFII_PROV×HHI). The economic intuition is straightforward: in concentrated markets, fewer institutions dominate the landscape, making them more likely to adopt similar FinTech solutions and interact with the same technology providers. This convergence in technological choices creates common risk exposures and operational dependencies that strengthen interconnections. The total effect of market concentration can be expressed as $-117.848 + 0.383 \times$DFII_PROV. This relationship becomes positive when DFII_PROV exceeds 307.697, suggesting that high levels of FinTech development make market concentration more conducive to interconnectedness.

To illustrate the economic significance of this interaction, we examine the marginal effect of FinTech development across different market structures. Based on our estimates from column (2), the marginal effect of FinTech on connectedness is $(0.383 \times \mathrm{HHI} + 0.183)\times\, \Delta\mathrm{DFII}$. Consider two markets with different concentration levels—one at the 25th percentile of HHI (0.054) and one at the 75th percentile (0.212). Given a one standard deviation increase in DFII (102.256), the difference in the impact on financial connectedness between these two markets is 6.19, representing approximately 20.8% of the mean connectedness value (29.74).

To contextualize this effect against real-world events, we convert this impact to the same scale as our connectedness measure (by dividing by 10^5 and multiplying by the number of institutions, 116). The resulting change of approximately 0.00718 represents about 14% of the observed increase in market connectedness during the COVID-19 pandemic (when ConnectPC3 rose from 0.50 to 0.55, as shown in Fig. 1). This comparison demonstrates that the differential impact of FinTech development across market structures is economically significant, approaching the magnitude of connectedness changes observed during major systemic stress events.

Second, columns (3) and (4) demonstrate that internal FinTech innovation strengthens the relationship between FinTech development and connectedness. The positive and significant coefficient of DFII_PROV×FinTechTrans (0.002) indicates that institutions actively pursuing FinTech transformation become more interconnected as the overall FinTech environment develops. This finding supports two potential explanations. First, institutions with stronger internal innovation capabilities are more efficient at absorbing and integrating external FinTech technologies, making them more susceptible to external FinTech developments. Second, innovation-oriented institutions tend to adopt similar cutting-edge FinTech solutions, leading to more correlated risk exposures across these institutions.

3.3. Robustness tests

To ensure the reliability and stability of our main findings, we conduct a series of robustness tests. These tests involve using alternative measures for our key variables and examining the consistency of our results across different specifications.

3.3.1. Alternative measure for FinTech development

First, we examine whether our results hold when using a more granular measure of FinTech development. Although our main analysis uses DFII at the provincial level, local variations in FinTech development could be better captured at the city level.

Table 5 presents the results using DFII_CITY as the measure of FinTech development. While the direct effect of DFII_CITY is positive but not statistically significant, the interaction effects remain robust and economically meaningful. The coefficient of DFII_CITY×HHI (0.560) is larger than its provincial-level counterpart (0.383 in Table 4), suggesting that the effects of market concentration are more pronounced at the local level. In addition, the interaction with FinTechTrans maintains its significance and magnitude (0.002), confirming that internal FinTech innovation consistently enhances the relationship between FinTech development and connectedness.

The consistency of these interaction effects across different geographical measures strengthens our main conclusions about the mechanisms through which FinTech development affects financial institution connectedness. The stronger effects at the city level particularly highlight the importance of local market conditions in shaping the relationship between FinTech development and financial interconnectedness.

Table 6
Robustness tests: alternative measures for connectedness.

	Dependent variable					
	ConnectPC1			ConnectPC5		
	(1)	(2)	(3)	(4)	(5)	(6)
DFII_CITY	0.250***	0.098	0.185***	0.173	0.139	0.058
	(0.074)	(0.061)	(0.058)	(0.135)	(0.107)	(0.149)
HHI	−74.038*	−77.326*	−155.572***	−2.774	−3.518	−111.001**
	(38.363)	(36.246)	(45.415)	(39.080)	(39.508)	(42.871)
FinTechTrans	0.095**	−0.775***	0.086**	0.248***	0.051	0.225***
	(0.037)	(0.240)	(0.035)	(0.067)	(0.343)	(0.054)
DFII_CITY×FinTechTrans		0.003***			0.001	
		(0.001)			(0.001)	
DFII_CITY×HHI			0.454***			0.602***
			(0.114)			(0.117)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	540	540	540	540	540	540
R^2	0.655	0.672	0.673	0.738	0.738	0.746

Note: This table reports robustness tests using alternative measures of financial connectedness. Columns (1)–(3) use the largest principal component (ConnectPC1) while Columns (4)–(6) use the largest five principal component (ConnectPC5). For each connectedness measure, the first column presents the baseline model, the second column examines the interaction with FinTechTrans, and the third column examines the interaction with HHI. All specifications include industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

3.3.2. Alternative measures for connectedness

We employ two approaches to validate our findings using alternative connectedness measures. First, we examine whether our results hold using different numbers of principal components (ConnectPC1 and ConnectPC5 instead of ConnectPC3).[3] Second, we utilize network-based measures to provide complementary evidence from a different methodological perspective.

Table 6 shows remarkable consistency across different ConnectPC specifications. While the magnitude of coefficients varies, the key relationships remain stable. The interaction between DFII_CITY and HHI shows increasing coefficients from ConnectPC1 (0.454) to ConnectPC5 (0.602), suggesting that market concentration effects become more pronounced when considering more comprehensive measures of connectedness. The DFII_CITY×FinTechTrans interaction maintains significance for ConnectPC1 but becomes insignificant for ConnectPC5, indicating that internal innovation effects may be more relevant for primary connectivity channels.

While principal component analysis provides robust evidence for our main findings, we further explore the relationship between connectedness and systemic risk using network centrality measures. The determination of which financial institutions contribute the most to systemic risk can be made using notions of financial centrality (Jackson and Pernoud, 2021). This complementary approach allows us to examine the structure of financial networks more directly.

For our network analysis, we construct financial institution networks using Granger causality tests following Billio et al. (2012). Fig. 2 compares the network density with our PCA-based measure. The blue line represents the network density, which measures the proportion of significant Granger-causal relationships among all possible pairs of institutions. The red line shows the previously calculated connectedness measure with $m = 1$. To facilitate comparison, both measures are normalized using min–max scaling to the [0,1] interval. The remarkable similarity in their temporal patterns, particularly during market stress periods, validates our main connectedness measure from a different methodological perspective.

We also employ various network centrality measures obtained form the above Granger-causal network as dependent variables, including out-degree and out-degree percentage (measuring an institution's influence on others), in-degree and in-degree percentage (measuring an institution's susceptibility to others' influence), closeness (measuring connection efficiency), and eigenvector centrality (measuring overall network importance).

The results in Table 7 show that FinTech development maintains significantly positive coefficients for in-degree, in-degree percentage, and eigenvector centrality, while HHI shows significantly negative coefficients in these specifications. These findings support our baseline results about the role of FinTech development in enhancing financial institution connectedness. Moreover, the predominant effect on in-degree suggests that FinTech development primarily makes institutions more receptive to market-wide shocks rather than enhancing their capacity to transmit shocks to others. Digital technologies enable institutions to process and respond to market signals more rapidly, increasing their sensitivity to external developments without necessarily expanding their systemic influence over other institutions.

3.4. Heterogeneity analysis

We explore two key dimensions of heterogeneity in the relationship between FinTech development and financial institution connectedness. First, we decompose the DFII into its constituent components to identify which aspects of FinTech development drive our main results. Second, we examine how institutional characteristics, particularly ownership structure, moderate these effects.

3.4.1. Heterogeneous effects of DFII sub-indices

The DFII is a comprehensive measure composed of three sub-indices: digitization level, usage depth, and coverage breadth. To investigate which aspects of FinTech development are most influential in shaping connectedness, we replace the aggregate DFII with these sub-indices in our model.

Table 8 reveals notable differences in how these components affect connectedness. The digitization level shows the strongest effect (0.138, significant at 1%), followed by usage depth (0.122, significant at 5%), while coverage breadth shows no significant impact. These findings suggest that the quality and sophistication of FinTech adoption, rather than mere accessibility, drive financial interconnectedness.

[3] We conducted additional robustness checks using the first 10 principal components (explaining 88% of total variance on average). While this captures more comprehensive risk factors, the resulting connectedness measures show limited temporal variation, leading to insignificant results for external FinTech development and internal transformation variables. Only the market concentration moderating effect remains significant. These analyses, available upon request, suggest the baseline three-component approach optimally balances comprehensiveness and statistical sensitivity.

Fig. 2. Comparison of network density and connectedness.

Table 7
Robustness tests: alternative network measures for connectedness.

	Dependent variable					
	Out_degree (1)	Out_pct (2)	In_degree (3)	In_pct (4)	Closeness (5)	Eigenvector (6)
DFII_CITY	0.062	0.0005	0.076*	0.001*	−0.00002	0.004**
	(0.049)	(0.0004)	(0.045)	(0.0003)	(0.00002)	(0.002)
HHI	4.426	0.034	−20.467**	−0.155**	−0.007	−1.036***
	(11.265)	(0.085)	(10.396)	(0.079)	(0.023)	(0.386)
FinTechTrans	0.0001	0.00000	0.006	0.00005	−0.00001	−0.0003
	(0.018)	(0.0001)	(0.016)	(0.0001)	(0.00004)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	540	540	540	540	531	540
R^2	0.494	0.494	0.465	0.465	0.183	0.530

Note: This table reports robustness tests using various network-based measures of financial connectedness instead of principal components. Columns (1) and (2) use out-degree measures (raw counts and percentages), Columns (3) and (4) use in-degree measures, Column (5) uses closeness centrality, and Column (6) uses eigenvector centrality. All specifications include the full set of control variables along with industry and year fixed effects. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8
Heterogeneous effects of sub-indices of DFII.

	Dependent variable		
	ConnectPC3 (1)	(2)	(3)
Digitization_PROV	0.138***		
	(0.057)		
Usage_PROV		0.122**	
		(0.051)	
Coverage_PROV			0.118
			(0.068)
HHI	−30.681	−38.731	−29.555
	(34.596)	(36.524)	(35.791)
FinTechTrans	0.180**	0.186**	0.187**
	(0.061)	(0.061)	(0.059)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	562	562	562
R^2	0.699	0.696	0.693

Note: This table presents the heterogeneous effects of different sub-indices of the DFII. Column (1) focuses on the digitization sub-index, Column (2) on the usage sub-index, and Column (3) on the coverage sub-index. All specifications include the full set of control variables along with industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The non-significant effect of coverage breadth likely stems from listed financial institutions being more responsive to the competitiveness and client reliance on new FinTech services, rather than merely how many people have access to them. Digitization level and usage depth create direct competitive pressures that compel institutions to adopt similar technologies and partner with comparable FinTech providers, generating common technological dependencies that increase interconnectedness. When digital services become more sophisticated or customers use them more intensively, financial institutions face immediate threats to their market share, forcing urgent strategic adaptations. In contrast, expanded access alone does not immediately threaten existing institutions' competitive positions or require adaptations that would lead to greater systemic interconnections.

3.4.2. Heterogeneous effects based on ownership structure

Given that state ownership is an important characteristic of China's financial markets, we examine how ownership structure moderates the relationship between FinTech development and connectedness. We classify institutions as state-owned if they have any government ownership and as private-owned otherwise.

Table 9 presents the results of this analysis, with odd-numbered columns showing results for state-owned institutions and even-numbered columns for private-owned institutions. Our analysis reveals striking differences between state-owned and private-owned institutions:

Table 9
Heterogeneous effects of ownership structure.

	Dependent variable					
	ConnectPC3					
	(1)	(2)	(3)	(4)	(5)	(6)
DFII_PROV	0.105	0.321**				
	(0.188)	(0.128)				
Digitization_PROV			−0.041	0.189**		
			(0.089)	(0.071)		
Usage_PROV					0.053	0.154**
					(0.052)	(0.063)
HHI	−31.223	−59.693	−18.962	−52.060	−28.840	−65.577
	(89.348)	(35.564)	(102.345)	(34.011)	(86.190)	(36.688)
FinTechTrans	0.223*	0.174**	0.238*	0.169**	0.227*	0.176**
	(0.117)	(0.071)	(0.113)	(0.072)	(0.116)	(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	140	422	140	422	140	422
R^2	0.883	0.687	0.883	0.691	0.883	0.686

Note: This table presents the heterogeneous effects of different types of ownership structure, with odd-numbered columns showing results for state-owned institutions and even-numbered columns for private-owned institutions. Columns (1) and (2) use the overall DFII_PROV index, Columns (3) and (4) use the Digitization sub-index, and Columns (5) and (6) use the Usage sub-index. All specifications include the full set of control variables along with industry and year fixed effects. Standard errors clustered at the provincial level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

for each FinTech measurement, the coefficients for private-owned institutions are larger and more significant than that for state-owned institutions. These results consistently show that private-owned institutions are more responsive to FinTech development in terms of increased connectedness.

Several mechanisms likely explain these differential effects. First, state-owned financial institutions in China often benefit from implicit government guarantees (Dong et al., 2014), which may reduce their sensitivity to market-based risk transmission channels that FinTech development amplifies. Second, private institutions possess greater operational flexibility and stronger profit-maximization incentives (Lin and Zhang, 2009), enabling them to more rapidly adopt FinTech innovations and forge new market connections. Third, state-owned institutions traditionally maintain stable relationships with other state-owned enterprises and government entities (Sapienza, 2004), creating networks that may be less affected by FinTech-driven transformations. Private institutions, by contrast, compete more aggressively for market share and would logically leverage FinTech technologies more intensively as strategic tools to expand their network connections.

It is important to note that these findings do not imply that state-owned institutions contribute less to overall connectedness. In fact, the positive coefficient on STATE_OWN in our main results suggests that, all else equal, state-owned institutions generally contribute more to connectedness. Rather, these results indicate that the marginal impact of FinTech development on connectedness is stronger for private-owned institutions.

4. Conclusion

This study investigates how FinTech development shapes the connectedness of financial institutions in China using data from 2011 to 2021. Our analysis reveals that FinTech development significantly enhances financial institutions' contributions to network connectedness. This effect is moderated by market structure and institutions' characteristics: the impact is stronger in concentrated markets and among institutions with robust internal FinTech capabilities.

Our heterogeneity analyses further reveal that the sophistication and intensity of FinTech services, rather than mere accessibility, drive connectedness. Additionally, private-owned institutions demonstrate greater sensitivity to FinTech development compared to state-owned institutions.

These findings carry important implications for both regulators and financial institutions. For regulators, oversight should extend beyond FinTech adoption rates to focus on how tightly technology connects institutions, particularly in concentrated markets where contagion risks are amplified. Regulatory frameworks must be proactive and adaptive, with disclosure, stress testing, and concentration caps calibrated to technology-driven interconnections. Financial institutions face the strategic challenge of leveraging FinTech's competitive advantages while managing their contribution to systemic vulnerability. These results also highlight important directions for future research, which should identify the specific technological channels that create institutional linkages and evaluate which regulatory tools work best to mitigate technology-induced systemic risk.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I do not have permission to share the raw data, but I have provided a Mendeley Data link containing synthetic data and the corresponding code.

Replication package for "Financial Connectedness in the Digital Age: The Impact of Regional FinTech Development" (Reference data) (Mendeley Data)

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