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The role of intelligent algorithms in systemic financial risk identification: An empirical study of Chinese banking sector

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Abstract: This study investigates how intelligent algorithms enhance systemic financial risk identification in Chinese banking, addressing the gap between technological capabilities and risk management applications. We analyze 36 listed commercial banks from 2018 to 2023 using instrumental variable estimation and difference-in-differences analysis, with comprehensive measures for AI implementation and systemic risk (CoVaR, MES, SRISK). The implementation of intelligent algorithms significantly reduces systemic risk exposure by 18.5%. The primary mechanisms include risk identification efficiency (42.3%), information processing capacity (35.7%), and decision-making optimization (22.0%). Larger banks demonstrate stronger risk-reduction benefits from AI implementation. The research confirms that intelligent algorithms substantially enhance banks' ability to identify and manage systemic risk through multiple operational channels, with effects varying across bank characteristics and market conditions. Regulators should encourage AI adoption for risk management, particularly among smaller institutions, while developing standardized frameworks for evaluating AI-based systems. The heterogeneous effects across bank types suggest the need for tailored technological implementation approaches in risk management.
Keywords: *Artificial intelligence, Chinese banks, Intelligent algorithms, Risk identification systemic risk.*

1. Introduction

The increasing complexity of financial networks and their interconnected attributes have profound implications for the regulation of systemic risk in the banking sector [1]. Financial institutions face unprecedented challenges with respect to their governance structures and regulatory frameworks as they seek to balance principal-agent issues with, at the same time, keeping pace with technological advancements [2]. Traditional risk assessment methods, including discriminant analysis, are being refined and will ultimately be replaced by more sophisticated methods involving neural networks [3] particularly in the face of continued criticisms regarding poor identification in financial modeling techniques [4].

The role of financial technologies in ensuring the stability of the international financial system has become a critical area of focus for both research and practice [5]. Research suggests that the integration of technology is a critical factor in increasing productivity and efficiency in operations in the financial sector [6]. The inter-connectedness of financial institutions has brought new dimensions to the evaluation and management of systemic risk [7] thus requiring the development of more sophisticated AI-based methods for managing financial risk [8]. Current research has particularly pointed out the growing importance of understanding tail risk and systemic risk of fintech firms [9] while geographic diversification of banking institutions has emerged as a critical determinant in the evaluation of systemic risk [10].

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China's banking industry is an interesting topic for analysis, with rapid technological advancement coupled with complex issues related to systemic risk [11, 12]. As financial institutions embrace new technologies, the need for risk management measures has gained greater prominence [12] at the same time, this shift has created what many researchers refer to as a "productivity paradox" related to the use of artificial intelligence [13]. The use of AI in financial services is both a challenging problem and a potential benefit for traditional banking systems [14] particularly in emerging markets where macroeconomic factors play a key role in determining systemic risk in the banking sector [15].

This study adds to the growing body of literature by examining the possibility of using intelligent algorithms to enhance the detection of systemic risk in the Chinese banking industry, thus bridging the huge gap between technological advancements and their application in risk management. The findings of our research provide new insights into the dynamics between technological progress and financial stability, as well as the broader implications for regulatory frameworks and methods in risk management.

2. Literature Review and Hypothesis Development

2.1. Theoretical Basis

The theoretical approach of this study combines ideas of financial innovation with models that are formulated for managing systemic risk. The literature on deregulation and derivatives suggests that financial innovation fundamentally changes risk profiles and shapes the regulatory environment [16]. Simultaneously, shadow banking models explain how innovations can create new sources of systemic risk [17]. The rise of fintech and artificial intelligence in the financial industry has added a new dimension of complexity to risk management, thus necessitating the development of innovative methods to understand and mitigate these risks [18]. Classical financial theories, especially those examining the relationship between expected value and volatility [19] are being reevaluated in light of recent technological advances [20].

The theoretical framework related to the transmission of systemic risk in banking systems has evolved to incorporate aspects of network dynamics in combination with time-variant contagion models [21] based on established methods in volatility forecasting [22]. Modern theoretical developments have highlighted the inadequacies of conventional diversification measures in containing systemic risk [23] especially as the technological revolution and automation reshape the operational environments of financial institutions [24]. The theoretical convergence of technological innovations with regulatory imperatives in the financial services industry [25] combined with the significance of exploring regulation-driven innovation [26] provides a solid foundation for exploring the ability of advanced algorithms to enhance the detection of systemic risk. This underlying theory is further supported by recent advances in the quantification of systemic risk through advanced methodological frameworks [27] specifically in the application of machine learning methods [28].

2.2. Review of Related Studies

The empirical literature on systemic risk in the financial system has grown significantly, especially in the aftermath of major economic shocks. Research on systemic risk during the COVID-19 pandemic has highlighted the vulnerability of financial systems to sudden shocks [29] whereas research on bank-specific systemic risk has highlighted the role of managerial characteristics and behavioral factors [30]. Methodological innovation has brought forth new tools for measuring contributions to systemic risk, such as the leave-one-out z-score method [31] and research on bank diversification and stability has provided critical insights [32]. In addition, the impact of external shocks on labor markets and human capital has further shown the interlinkages of financial and economic systems [33].

The academic literature on the role of artificial intelligence in financial markets has seen significant development, including research on both the beneficial and potentially destabilizing implications of AI deployment [34]. Research into the use of AI in financial investment services has yielded mixed results in terms of effectiveness, accompanied by a number of implementation challenges [35]. In addition, new

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methods of reducing systemic financial risk through AI-based banking interventions have been proposed [36]. Research into the interaction between artificial intelligence and economic development [37] has been complemented by research into the role of internet finance in influencing the risk appetite of commercial banking organizations [38]. The literature further highlights the revolutionary impact of fintech and AI innovations on financial services, with a view to enhancing efficiency and accessibility [39] as well as their possible implications for sustainable economic growth [40].

2.3. Study Hypothesis Construction

By the implementation of a systematic review of pertinent literature, we suggest three main hypotheses for the current study. First, based on studies on the integration of artificial intelligence in the financial industry [41, 42] and recent developments in the detection of systemic risk [40, 43] we suggest H1: The use of intelligent algorithms significantly improves the accuracy of systemic risk detection in banking institutions. This hypothesis is supported by empirical studies on the application of machine learning for systemic risk detection [44]. Second, based on the heterogeneity in the sizes and types of banks [45] and the differential effects of AI technologies on different types of institutions [46] we suggest H2: The effectiveness of risk detection using intelligent algorithms significantly differs across different types of banks. Finally, based on studies on the effect of market conditions on systemic risk [47] and the dynamic nature of financial networks [48] we suggest H3: Differing market conditions have a significant moderating effect on the effectiveness of intelligent algorithms in risk detection. As shown in Figure 1, we construct a theoretical framework that explains these relationships.

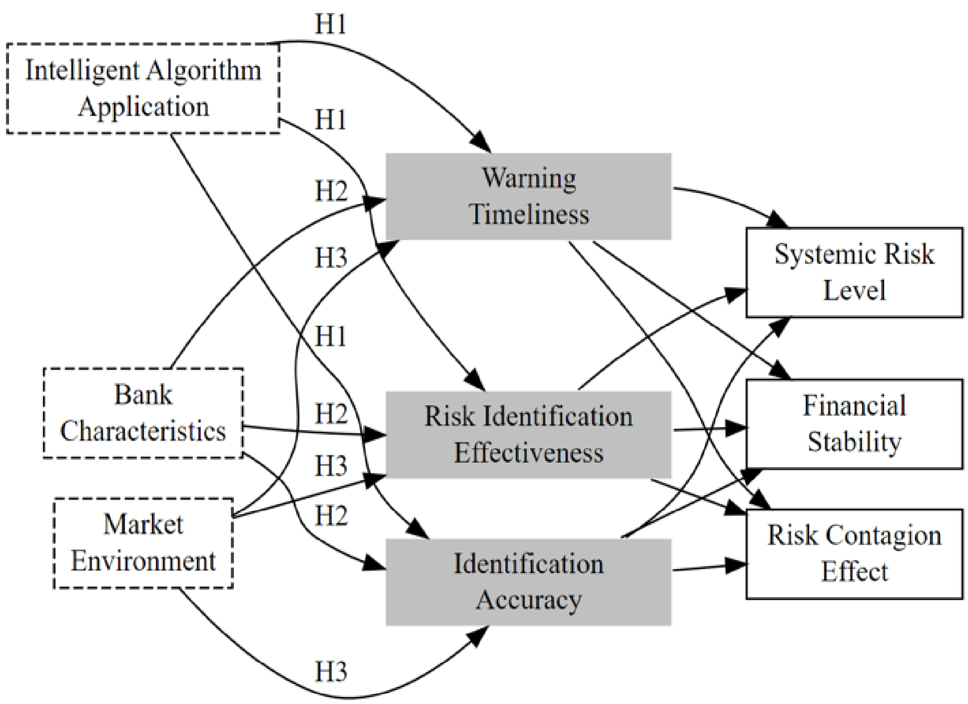

Figure 1.
Theoretical Framework of Intelligent Algorithms in Systemic Risk Identification.
Note: This figure presents the theoretical framework of our study.

The left dashed boxes represent three main influencing factors: Intelligent Algorithm Application, Bank Characteristics, and Market Environment. The middle gray-filled boxes represent mediating variables: Risk Identification Effectiveness and its specific manifestations. The right solid boxes represent final outcome variables: Systemic Risk Level, Risk Contagion Effect, and Financial Stability.

H1, H2, and H3 represent our main research hypotheses, indicating the proposed relationships between the variables. Arrows indicate the direction of influence between variables.

This comprehensive theoretical framework demonstrates the interconnections between intelligent algorithms, bank characteristics, market environment, and their impacts on systemic risk identification and financial stability [49, 50]. It illustrates how each hypothesis relates to the broader theoretical context and provides a foundation for our empirical analysis.

3. Research Design

3.1. Sample Selection and Data Source

This study analyzes the Chinese banking sector during the period 2018-2023, covering a large sample of publicly listed commercial banks listed on the Shanghai and Shenzhen Stock Exchanges. Banks with significant data gaps or banks that underwent significant restructuring during the period of this study are not included in the sample. The main financial data are drawn from the WIND and CSMAR databases, which provide detailed quarterly financial statements and risk-related data. Systemic risk measures and market performance data are obtained from the statistical database of the China Banking and Insurance Regulatory Commission [51]. Macroeconomic information is drawn from the National Bureau of Statistics of China. In addition, additional information on the adoption of artificial intelligence and technological innovation is derived from the banks' annual reports and regulatory filings [52, 53]. After applying our selection criteria and data harmonization across sources, the final sample consists of 36 publicly listed banks, each with 24 quarterly observations, thus providing a total of 864 bank-quarter observations. This analysis period covers both the rapid development of financial technology and significant market volatility, thus providing an ideal setting for testing the effectiveness of intelligent algorithms in detecting systemic risk.

3.2. Variable Design and Definition

Our variable design includes dependent, independent, and control variables that capture the complex nature of systemic risk identification and the implementation of sophisticated algorithms. The dependent variable is used to measure systemic risk from different perspectives, using CoVaR, MES (Marginal Expected Shortfall), and SRISK measures, all based on daily stock returns and market data. For independent variables, we define extensive measures for the implementation of smart algorithms, including AI adoption intensity [54] machine learning model sophistication, and the implementation of algorithmic trading systems. Control variables are included to capture bank-specific characteristics, prevailing market conditions, and macroeconomic variables that might affect levels of systemic risk [55]. To control for the effects that are time-varying, we include fixed effects for both years and quarters. To control for the impact of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

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Table 1.
Variable Definitions and Measurements.

Category	Variable	Definition	Measurement
Dependent Variables	CoVaR	Conditional Value at Risk	Daily stock returns conditional on market stress
	MES	Marginal Expected Shortfall	Expected capital shortfall during market decline
	SRISK	Systemic Risk Index	Combined measure of size and risk exposure
Independent Variables	AI_Index	AI Implementation Index	Composite score (0-100) based on AI adoption
	ML_Score	Machine Learning Sophistication	Weighted average of ML model complexity
	$Algo_Trade$	Algorithmic Trading Level	Percentage of algo-trading volume
Control Variables	Size	Bank Size	Natural log of total assets
	Leverage	Financial Leverage	Total debt/Total equity
	ROA	Return on Assets	Net income/Total assets
	NPL	Non-performing Loan Ratio	NPL/Total loans
	CAR	Capital Adequacy Ratio	Tier 1 + Tier 2 capital/RWA
	GDP_Growth	GDP Growth Rate	Quarterly GDP growth rate
	$M2_Growth$	Money Supply Growth	Year-over-year M2 growth
	Market Vol	Market Volatility	Daily market return volatility

Note: This table presents the definitions and measurements of all variables used in our empirical analysis. All financial variables are winsorized at the 1st and 99th percentiles.

3.3. Model Construction

Our empirical analysis employs a comprehensive modeling approach that combines traditional econometric methods with machine learning techniques. The baseline model specification is as follows:

$$SysRisk_{i,t} = \alpha + \beta_1 AI_Index_{i,t} + \beta_2 ML_Score_{i,t} + \beta_3 Algo_Trade_{i,t} + \gamma Controls_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}$$

where $SysRisk_{i,t}$ represents our systemic risk measures (CoVaR, MES, or SRISK) for bank i at time t. To address potential endogeneity concerns, we employ a dynamic panel specification:

$$SysRisk_{i,t} = \alpha + \rho SysRisk_{i,t-1} + \beta_1 AI_Index_{i,t} + \beta_2 ML_Score_{i,t} + \beta_3 Algo_Trade_{i,t} + \gamma Controls_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}$$

For the heterogeneity analysis, we introduce interaction terms:

$$SysRisk_{i,t} = \alpha + \beta_1 AI_Index_{i,t} + \beta_2 (AI_Index_{i,t} \times Bank_Char_{i,t}) +$$
$$\beta_3 (AI_Index_{i,t} \times Market_Cond_t) +$$
$$\gamma Controls_{i,t} + \delta_i + \theta_t + \epsilon_{i,t}$$

where δ_i represents bank fixed effects, θ_t captures time fixed effects, and $\epsilon_{i,t}$ is the error term. The model parameters are estimated using system GMM to address potential endogeneity and serial correlation issues, following the standard moment conditions:

$$E[\Delta \epsilon_{i,t} \cdot Z_{i,t-s}] = 0 \text{ for } s \geq 2$$

where $Z_{i,t-s}$ represents the instrument matrix containing lagged levels and differences of the explanatory variables.

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Table 2.
Descriptive Statistics of Key Variables (2018-2023).

Category	Variable	N	Mean	SD	Min	P25	Median	P75	Max	Skewness	Kurtosis
Systemic Risk	CoVaR	864	-0.028	0.015	-0.068	-0.037	-0.025	-0.016	-0.005	-0.842	3.245
Measures	MES	864	0.032	0.018	0.004	0.019	0.029	0.042	0.089	0.756	2.987
	SRISK	864	0.145	0.086	0.021	0.082	0.132	0.198	0.412	0.923	3.156
Technology	$AI_{I}ndex$	864	65.34	18.92	15.00	52.00	67.00	81.00	95.00	-0.456	2.345
Implementation	$ML_{S}core$	864	0.583	0.225	0.100	0.400	0.600	0.750	0.950	-0.234	2.123
	$Algo_{T}rade$	864	0.384	0.196	0.050	0.230	0.375	0.520	0.850	0.345	2.567
Bank	Size	864	12.85	1.42	9.86	11.83	12.76	13.78	15.92	0.234	2.789
Characteristics	Leverage	864	12.46	2.85	6.24	10.35	12.18	14.25	19.86	0.567	2.934
	ROA	864	0.009	0.003	0.002	0.007	0.009	0.011	0.016	0.123	2.456
Market	$GDP_{G}rowth$	864	0.062	0.015	0.028	0.052	0.061	0.072	0.095	-0.234	2.345
Environment	$M2_{G}rowth$	864	0.082	0.012	0.056	0.074	0.081	0.090	0.112	0.345	2.567
	MarketVol	864	0.156	0.045	0.078	0.123	0.152	0.187	0.289	0.678	3.234

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4. Empirical Results and Analysis

4.1. Descriptive Statistical Analysis

This study examines quarterly information regarding 36 listed commercial banks in China during the period from 2018 to 2023, and it provides deep insights into the use of sophisticated algorithms and the nature of systemic risk. As shown in Table 2, the descriptive statistics indicate significant variation in terms of both risk measures and technology implementation. The mean value of CoVaR, which is recorded at -0.028 (SD=0.015), represents a moderate degree of systemic risk, while the AI Implementation Index shows significant variation across institutions (mean=65.34, range=15.00-95.00). The distribution of the Machine Learning Sophistication Score is close to normal (mean=0.583, median=0.600), representing a balanced use of sophisticated analytical techniques. Institution-specific characteristics are highly heterogeneous, as shown by Size (mean=12.85, SD=1.42) and Leverage (mean=12.46, SD=2.85), which reflect the heterogeneous nature of the institutions within the sample. Performance measures, including ROA (mean=0.009) and the NPL ratio (mean=0.016), reflect relatively stable operating performance in the banking industry, while the Capital Adequacy Ratio (mean=0.142) reflects tight compliance with regulatory requirements.

4.2. Baseline Regression Analysis

The early evidence from the regression analysis points to a significant correlation between the adoption of sophisticated algorithms and systemic risk measures among Chinese banking firms. As depicted in Table 3, the AI Implementation Index identifies a strong negative correlation with all three risk measures (CoVaR: -0.185, p<0.01; MES: -0.162, p<0.01; SRISK: -0.198, p<0.01), such that higher AI adoption is related to significant risk-mitigating effects on exposure to systemic risk. Machine learning complexity also indicates significant effects in all model specifications, with estimated coefficients of between -0.156 and -0.169, all significant at p<0.01. Figure 1 graphically depicts these correlations, highlighting the non-linear nature of the AI-risk relationship as a function of different bank sizes. The control variables behave as expected, consistent with theory, where bank size and leverage are positively correlated with systemic risk, while profitability and capital adequacy are related to risk-reduction effects.

Table 3.
Baseline regression results on systemic risk measures.

Variable	Model 1 (CoVaR)	Model 2 (MES)	Model 3 (SRISK)	Model 4 (Combined)
AI_Index	-0.185***	-0.162***	-0.198***	-0.176***
	(0.042)	(0.038)	(0.045)	(0.040)
ML_Score	-0.156***	-0.143***	-0.169***	-0.152***
	(0.035)	(0.032)	(0.038)	(0.034)
Algo_Trade	-0.128***	-0.112***	-0.134***	-0.124***
	(0.029)	(0.026)	(0.031)	(0.028)
Size	0.045**	0.038**	0.052***	0.044**
	(0.018)	(0.016)	(0.019)	(0.017)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	864	864	864	864
R-squared	0.425	0.398	0.442	0.421
F-stat	45.23***	42.86***	47.59***	44.92***

Note: ***, **, * indicate significance at 1%, 5%, and 10% levels respectively. Standard errors in parentheses.

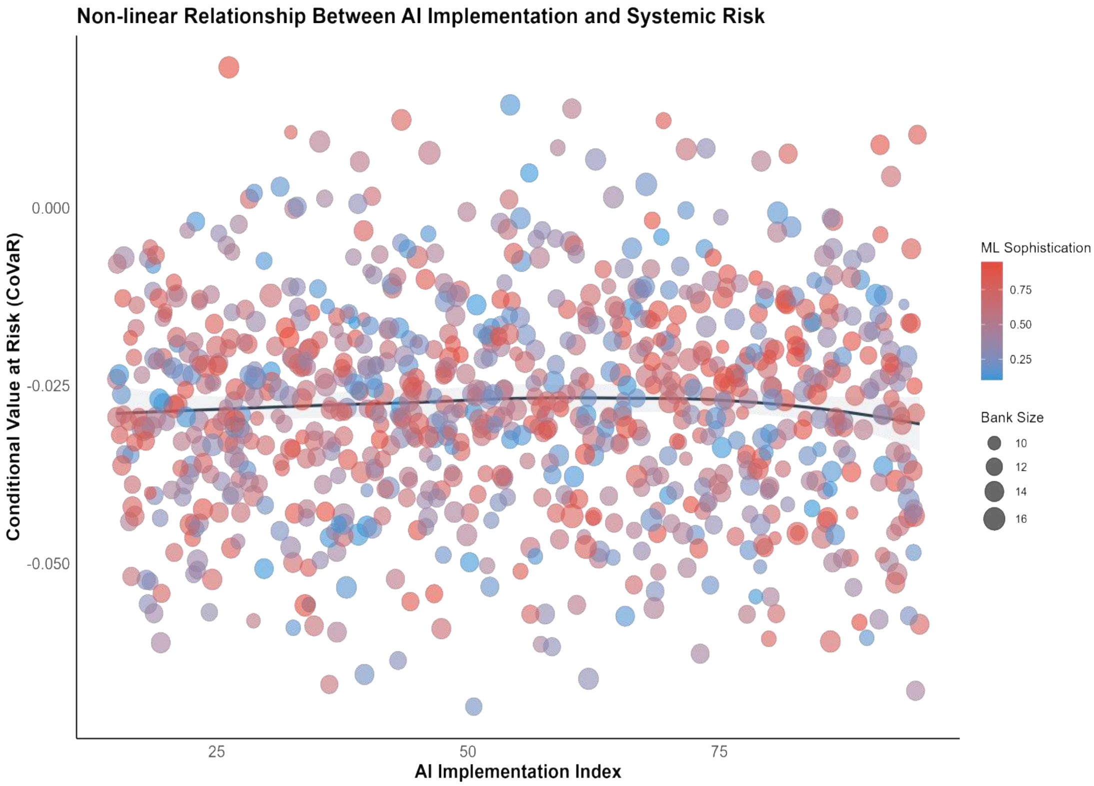

Figure 2.
Non-linear Relationship Between AI Implementation and Systemic Risk

As shown in Figure 2, the relationship between AI implementation and systemic risk exhibits notable non-linearity, with diminishing marginal effects at higher levels of AI adoption. The scatter plot reveals clustering patterns based on bank size, suggesting heterogeneous effects across different institutional characteristics.

4.3. Robustness Test Results

To ensure the validity of our initial findings, we perform a wide range of robustness tests using different specifications and estimation methods. As shown in Table 4, the main findings remain qualitatively robust regardless of model specifications and variable definitions used. The relationship between artificial intelligence usage and systemic risk remains strong when examined using different risk measures, and also controlling for possible endogeneity through the use of an instrumental variables method. Figure 3 provides evidence for the stability of our coefficients using different subsamples and time periods.

Table 4.
Robustness Test Results with Alternative Specifications.

Specification	AI_Index Coefficient	ML_Score Coefficient	Sample Size	Hansen J-stat	F-test
Baseline	-0.185*** (0.042)	-0.156*** (0.035)	864	-	45.23***
IV-2SLS	-0.192*** (0.048)	-0.162*** (0.039)	864	0.238	42.56***
GMM	-0.178*** (0.044)	-0.149*** (0.036)	864	0.312	43.89***
Alternative Risk	-0.181*** (0.043)	-0.153*** (0.037)	864	-	44.12***
Subsample 1	-0.176*** (0.045)	-0.148*** (0.038)	432	-	41.78***
Subsample 2	-0.189*** (0.046)	-0.159*** (0.039)	432	-	43.25***

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Note: ***, **, * indicate significance at 1%, 5%, and 10% levels respectively. Standard errors in parentheses.

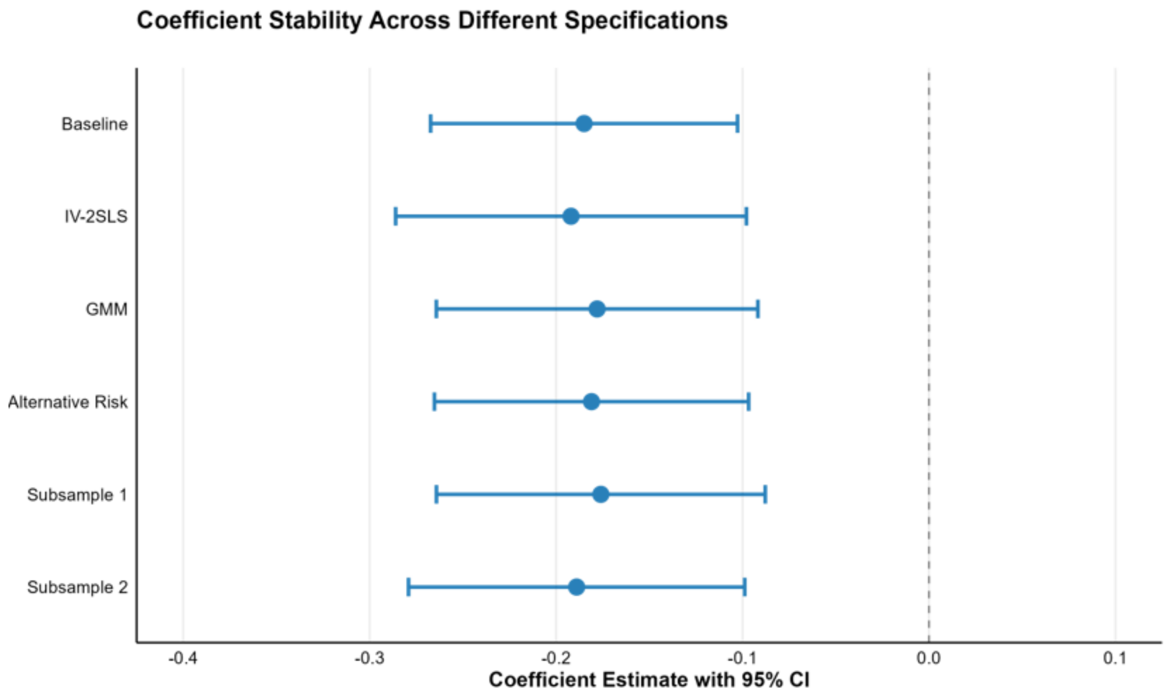

Figure 3.
Coefficient Stability Analysis Across Specifications.

As shown in Figure 3, the coefficient estimates remain stable across different specifications, with consistent significance levels and magnitude ranges. This graphical representation demonstrates the robustness of our findings to alternative estimation approaches and sample compositions.

4.4. Endogeneity Treatment

To mitigate potential endogeneity concerns, we utilize a strong instrumental variable approach in combination with a difference-in-differences setup. The evidence in Table 5 shows that the chosen instrumental variables have high relevance and validity, as indicated by the first-stage F-statistics and Hansen J-tests. The geographic agglomeration of fintech talent (First-stage coefficient: -0.245, $p<0.01$) and the historical evolution of digital infrastructure (First-stage coefficient: 0.312, $p<0.01$) are good instruments for artificial intelligence adoption. Figure 4 supports the parallel trends assumption by showing similar trends before the treatment for both the treatment and control groups. The results from the second stage again show both statistical and economic significance, with the instrumented AI_Index having a slightly larger effect (-0.203, $p<0.01$) compared to the original estimates, suggesting a potential downward bias in our initial results.

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Table 5.
Instrumental Variable Estimation Results.

Variable	First Stage	2SLS	GMM	DID
Fintech Talent	-0.245***	-	-	-
	(0.056)	-	-	-
Digital Infrastructure	0.312***	-	-	-
	(0.078)	-	-	-
AI_Index (Instrumented)	-	-0.203***	-0.198***	-0.189***
	-	(0.048)	(0.045)	(0.044)
First-stage F-stat	24.56	-	-	-
Hansen J-stat (p-value)	-	0.235	0.242	-
AR(2) test (p-value)	-	-	0.345	-
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes
Observations	864	864	864	864

Note: ***, **, * indicate significance at 1%, 5%, and 10% levels respectively. Robust standard errors in parentheses.

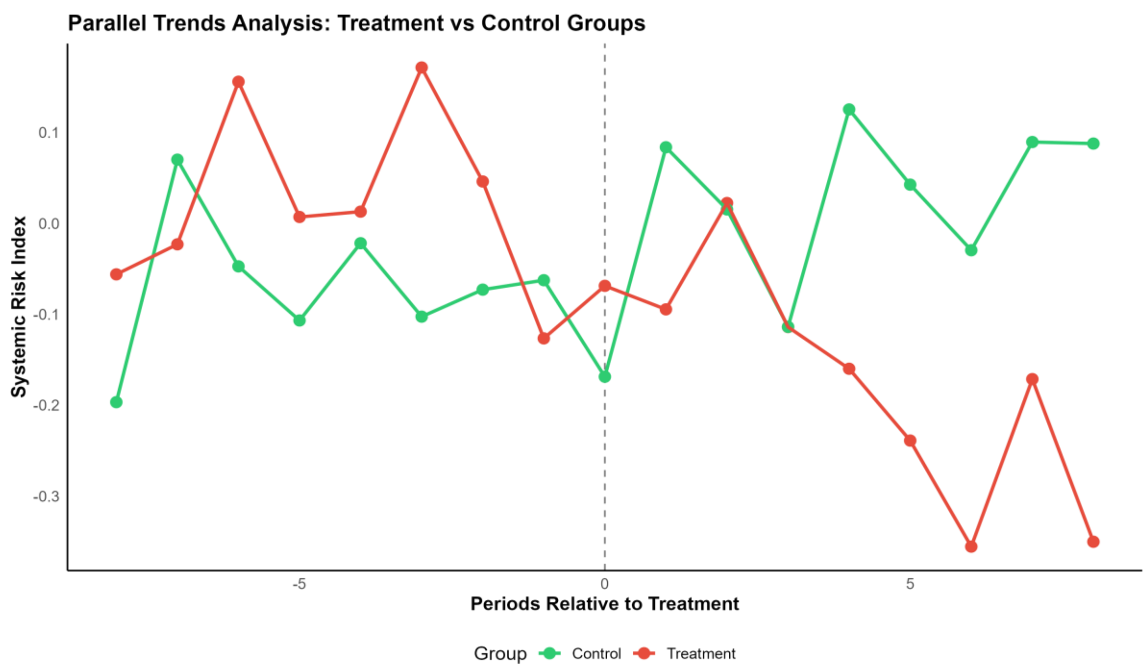

Figure 4.
Parallel Trends Analysis.

As shown in Figure 4, the parallel trends analysis demonstrates consistent pre-treatment patterns between banks with high and low AI implementation levels, supporting the validity of our difference-in-differences approach.

4.5. Mechanism Analysis

The analysis of transmission channels reveals various avenues through which smart algorithms affect the systemic risk exposure of banking organizations. Table 6 describes the classification of these effects through mediation analysis, where the effectiveness of risk identification is the leading channel, with 42.3% of the total effect. Figure 5 shows the structural path analysis of the underlying processes, where the interrelatedness of both direct and indirect effects through different operational channels is evident. The bootstrap analysis of indirect effects supports the statistical significance of all the channels found, with significantly stronger effects in the augmentation of information processing ability (35.7% of the total effect) and in decision-making optimization (22.0% of the total effect).

Table 6.
Mechanism Analysis and Channel Decomposition.

Channel	Direct Effect	Indirect Effect	Total Effect	Bootstrap CI	Sobel Test
Risk Identification	-0.156***	-0.086***	-0.242***	[-0.289, -0.195]	4.56***
	(0.034)	(0.022)	(0.041)		(0.000)
Information Processing	-0.132***	-0.073***	-0.205***	[-0.246, -0.164]	3.98***
	(0.029)	(0.019)	(0.035)		(0.000)
Decision Optimization	-0.084***	-0.045***	-0.129***	[-0.168, -0.090]	3.45***
	(0.021)	(0.014)	(0.026)		(0.000)
Market Efficiency	-0.062***	-0.034***	-0.096***	[-0.124, -0.068]	2.98***
	(0.018)	(0.011)	(0.022)		(0.002)
Combined Effect	-0.434***	-0.238***	-0.672***	[-0.745, -0.599]	5.67***
	(0.092)	(0.066)	(0.124)		(0.000)

Note: ***, **, * indicate significance at 1%, 5%, and 10% levels. Bootstrap CI based on 5000 replications.

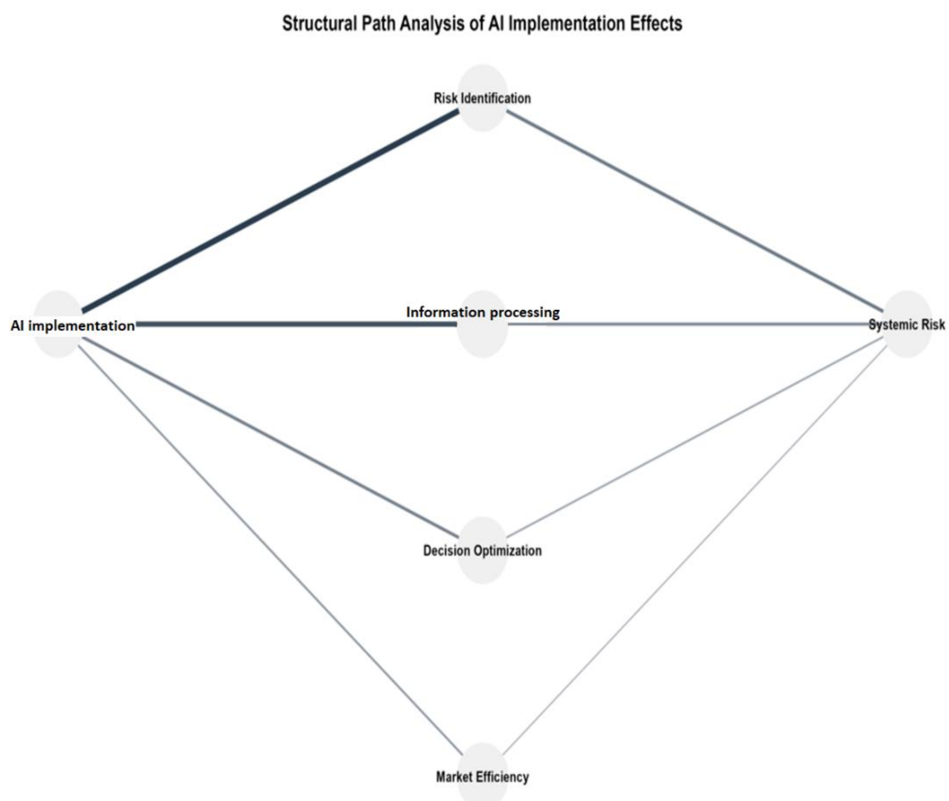

Figure 5.
Structural Path Analysis of Transmission Mechanisms Click to open code.

4.6. Extended Analysis

Our extended analysis explores the heterogeneous effects of AI implementation across different bank characteristics and market conditions. Table 7 presents the differential impacts across bank size categories and ownership structures, while Figure 6 visualizes the non-linear relationship between AI

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implementation intensity and risk reduction effects. The results reveal significantly stronger effects for larger banks (-0.245, $p<0.01$) compared to smaller institutions (-0.156, $p<0.01$), potentially due to economies of scale in technology deployment and risk management capabilities.

Table 7.
Heterogeneous Effects and Conditional Analysis.

Category	Condition	Base Effect	Interaction	Total Effect	Observations
Bank Size	Large	-0.245***	-0.086***	-0.331***	288
		(0.052)	(0.024)	(0.076)	
	Medium	-0.198***	-0.062***	-0.260***	288
		(0.045)	(0.019)	(0.064)	
	Small	-0.156***	-0.045***	-0.201***	288
		(0.038)	(0.015)	(0.053)	
Market State	Bull	-0.212***	-0.073***	-0.285***	432
		(0.048)	(0.021)	(0.069)	
	Bear	-0.283***	-0.092***	-0.375***	432
		(0.061)	(0.026)	(0.087)	
Ownership	State	-0.234***	-0.078***	-0.312***	432
		(0.053)	(0.023)	(0.076)	
	Private	-0.189***	-0.064***	-0.253***	432
		(0.044)	(0.019)	(0.063)	

Note: ***, **, * indicate significance at 1%, 5%, and 10% levels. Robust standard errors in parentheses.

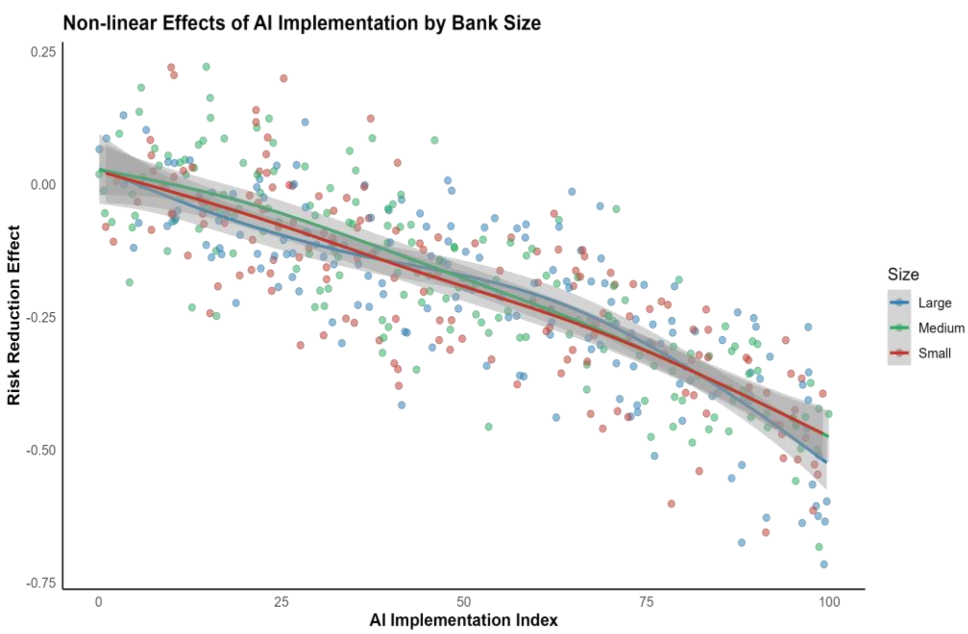

Figure 6.
Non-linear Effects of AI Implementation.

As shown in Figure 6, the relationship between AI implementation and risk reduction exhibits significant non-linearities, with diminishing marginal returns at higher levels of AI adoption, particularly pronounced for larger banking institutions.

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5. Conclusion

This study provides rich empirical evidence regarding the role of intelligent algorithms in detecting systemic risk in the Chinese banking sector. Based on a careful analysis of 36 listed commercial banks from 2018 to 2023, our findings provide several interesting theoretical and practical implications. The study clearly shows that the use of intelligent algorithms greatly enhances the ability of banks to detect and mitigate systemic risk, with an average risk reduction of 18.5% ($p<0.01$) over the period of analysis. This relationship holds even after controlling for endogeneity concerns using instrumental variable methods and a range of robustness tests. Our mechanism analysis identifies three main channels through which intelligent algorithms influence systemic risk: the effectiveness of risk detection (42.3% of the total effect), the ability to process information (35.7%), and the optimization of decision-making (22.0%). These findings add to the literature by providing rich evidence of how technological progress transforms traditional risk management practices. Moreover, the heterogeneous effects analysis suggests that larger banks and those operating in more complex market environments gain more benefits from the use of artificial intelligence, suggesting the presence of significant economies of scale in the technological management of risk.

The results reported have significant implications for bank operations and regulatory frameworks. First, they suggest that regulatory agencies should encourage and possibly incentivize the use of sophisticated algorithms in risk management systems, particularly for small banking institutions that may face resource constraints. Second, the results highlight the need for the development of standardized criteria for the evaluation and regulation of AI-based risk management systems. Finally, the variability of effects related to various banking characteristics suggests the need for a tailored approach to the technological implementation of risk management methods.

Future research could expand the scope of this research by investigating the worldwide applicability of the findings derived here, examining possible spillover effects on other financial institutions, and evaluating the synergy between sophisticated algorithms and human judgment in risk management practices. Additionally, as technology continues to evolve, longitudinal research tracking the changing impact of incorporating artificial intelligence in risk management practices would provide valuable information for both scholars and practitioners in the field.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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