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THE IMPACT OF INSURTECH ON RISK-TAKING BEHAVIOR IN INSURANCE COMPANIES: EVIDENCE FROM CHINA

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Abstract: In the realm of risk management, InsurTech is not only pivotal for insurance companies to maintain their financial stability, but also serves as a significant gauge of a healthy insurance market. Drawing upon data from the insurance industry at the provincial level in China from 2010 to 2021, this paper investigates the impact of InsurTech on risk-taking capacity in the context of the COVID-19 pandemic shock. Using the shock of the pandemic as a natural experiment, this study successfully identifies a causal relationship between InsurTech and risk-taking in the insurance industry, unveiling a mechanism of influence spanning from InsurTech to risk identification and management efficiency, and subsequently to risk-taking capacity. Our findings suggest that, under the pandemic shock, InsurTech considerably augments risk-taking behavior in the insurance industry. The insights derived from this study bear significant practical implications for managing risk-taking at the provincial level in the insurance industry, particularly in the context of emerging technology adoption and pandemic shocks, thereby fostering stability and healthy development in the insurance sector.
Keywords: InsurTech; Risk-taking; COVID-19; Difference in difference

1 INTRODUCTION

The rise of InsurTech has brought significant transformations to the insurance industry, revolutionizing the way insurance products are developed, distributed, and serviced [1]. InsurTech, which encompasses the innovative use of technology such as artificial intelligence, big data analytics, and blockchain, has the potential to reshape traditional insurance practices and enhance operational efficiency [2]. Amidst this technological revolution, it is crucial to assess the impact of InsurTech on key aspects of the insurance sector.
In the context of risk management, understanding how InsurTech influences the risk-taking behavior of insurance companies is of paramount importance. Risk-taking is a fundamental aspect of the insurance industry, as insurers assess and assume risks in order to provide coverage and fulfill their obligations [3]. However, the adoption of InsurTech may introduce new dynamics and alter the risk profile of insurance companies.
This study aims to examine the relationship between InsurTech and risk-taking in the insurance industry, with a specific focus on the Chinese market. By analyzing data from the insurance sector in China over a specific timeframe, this research seeks to provide empirical evidence and insights into the impact of InsurTech on risk-taking behavior. In addition, the study aims to identify potential mechanisms through which InsurTech affects risk-taking in the insurance industry.
The timing of this research is particularly relevant, as it coincides with the COVID-19 pandemic, a crisis that has posed unprecedented challenges to the global economy and the insurance sector [4-5]. By exploring the impact of InsurTech on risk-taking during this crisis, this study can shed light on the resilience and adaptability of insurance companies in the face of significant disruptions.
The findings of this research have practical implications for insurance industry stakeholders, including insurers, policymakers, and regulators. Understanding the interplay between InsurTech and risk-taking can inform strategic decision-making, risk management practices, and regulatory frameworks in order to ensure the stability and sustainability of the insurance sector in China.
The research makes a valuable contribution to the existing literature on insurtech and insurance risk-taking, particularly by providing empirical evidence from a large and dynamic emerging market. This research adds to the understanding of the effects of insurtech innovation on risk-taking behavior within the insurance industry. The findings of this study have significant implications for policymakers and practitioners who are tasked with managing the delicate balance between reaping the benefits of insurtech and mitigating its associated risks.
To structure the paper effectively, we have divided it into several sections. Section 1 provides a concise overview of the development and regulation of insurtech in China, setting the context for our study. In Section 2, we conduct a comprehensive review of the relevant literature and develop our research hypotheses based on the gaps identified. Section 3 outlines the data sources and methodology employed in our empirical analysis. The subsequent Section 4 presents and thoroughly discusses the results obtained from our analysis. Finally, in Section 5, we conclude our paper by summarizing the key findings and offering suggestions for future research directions in this field.

2 THEORETICAL ANALYSIS AND HYPOTHESES

2.1 InsurTech and Risk Taking in the Insurance Industry

The emergence and rapid development of InsurTech have transformed the insurance industry, introducing new digital technologies and innovative business models [6]. While the potential benefits of InsurTech are widely acknowledged, its impact on the risk-taking behavior of insurance companies remains a topic of interest and debate. This section provides a comprehensive literature review to examine the existing knowledge on the relationship between InsurTech and risk taking in the insurance sector. InsurTech has revolutionized various aspects of insurance operations, including underwriting, claims processing, distribution, and customer engagement [7]. These technological advancements offer opportunities for insurance companies to improve efficiency, enhance customer experiences, and gain a competitive edge. However, the adoption of InsurTech may also introduce new risks and challenges, potentially influencing the risk-taking behavior of insurance companies. Several studies have explored the effects of InsurTech on risk-taking in different contexts. For instance, research conducted in developed markets has examined the relationship between InsurTech and risk-bearing capacity, finding mixed results [8]. Some studies suggest that InsurTech can enhance risk-taking by facilitating more accurate risk assessments and enabling insurers to expand into new markets [9].

However, other studies highlight potential risks associated with InsurTech, such as increased operational complexity and cyber threats [10]. In the specific context of China, limited empirical research has been conducted to investigate the relationship between InsurTech and risk-taking behavior in the insurance industry.

2.2 Risk Identification and Risk Taking in the Insurance Industry

The ability of insurance companies to identify and manage risk is critical to their operational viability and success. The advent of InsurTech, a portmanteau of "insurance" and "technology," has been heralded as a game-changer for the industry, purportedly leading to more informed and strategic risk-taking decisions [11].

Emerging technologies such as big data analytics, artificial intelligence (AI), and blockchain have demonstrated potential in reshaping risk identification strategies of insurance companies. For instance, big data analytics enables insurers to handle vast volumes of data, thereby enhancing the precision of risk identification and pricing [12]. AI, specifically machine learning, can be utilized to create more accurate risk models, allowing for more precise segmentation and personalized insurance pricing [13].

Blockchain technology, on the other hand, provides an immutable and transparent platform that could potentially mitigate fraud risk and streamline claims processing [14].

Moreover, the Internet of Things (IoT) devices, such as wearable technology, connected vehicles, and smart home devices, provide insurers with real-time data, enabling them to dynamically assess and manage risk exposure. This direct data input improves the precision of risk identification and fosters more informed risk management and underwriting decisions [15].

However, the integration of InsurTech also introduces new types of risks, notably cybersecurity threats. As insurance companies increasingly adopt digital solutions, they become potential targets for cyber-attacks [16]. Therefore, a holistic risk identification process should take into account these emergent risks associated with the use of technology.

Given the unique characteristics of the Chinese market and the rapid growth of InsurTech in the country, it is essential to examine how InsurTech influences the risk-taking decisions of insurance companies in China. Building on the existing literature, we propose the following hypothesis:

H1: InsurTech increases the risk-taking behavior of insurance companies in China

3 STUDY DESIGN

3.1 Samples and Data Sources

To examine the impact of InsurTech on risk-taking behavior and risk identification capabilities in the Chinese insurance industry, we construct a comprehensive dataset comprising a large sample of insurance companies operating in China. Our empirical analysis covers the period from 2007 to 2021 using provincial-level unbalanced panel data.Data related to the insurance industry are sourced from two primary and authoritative outlets: the annual China Insurance Yearbook and the China Banking and Insurance Regulatory Commission (CBIRC). Additionally, macroeconomic data are collected from the reputable "China Statistical Yearbook". To assess the level of InsurTech development and its influence on the insurance industry, we utilize data from the China Digital Inclusive Finance Index compiled by the Digital Finance Research Center at Peking University. This index serves as a comprehensive measure of the progress and penetration of digital inclusive finance in China, encompassing various dimensions of technological advancements and financial inclusivity.

By employing these rigorous data sources, we ensure the reliability and validity of our study, enabling a comprehensive examination of the relationship between InsurTech, risk-taking behavior, and risk identification capabilities in the Chinese insurance industry.

3.2 Definition of Variables

(1) Independent Variables:In line with the research this study examines two key risk variables: total risk-taking (RiskTotal), underwriting risk (UWRisk). RiskTotal represents the variability in risk exposure and is operationalized as the standard deviation of the ratio of pre-tax income plus interest to net admitted assets. To account for data availability,

we adopt the approach of using the standard deviation of the proportion of operating revenue to total assets over the preceding three years as a proxy for RiskTotal.

Similarly, underwriting risk is assessed by measuring the standard deviation of claims divided by earned premiums over the past three years.These risk variables provide a comprehensive framework for capturing different facets of risk exposure within the insurance industry.

(2) $\mathrm{DTS_i}$ represents the level of digitization in the insurance sector of each province. To measure the level of InsurTech development, we adopt the sub-indicator of insurance business under the dimension of usage depth from the China Digital Inclusive Finance Index, compiled by the Digital Finance Research Center at Peking University. To optimize our measurement, we apply standardization to the DTS data involved. Specifically, we subtract the minimum value from each variable value, then divide the result by the difference between the maximum and minimum values of the variable. This procedure yields a digitization level score ranging from 0 to 1 for each province. Thus, we establish a uniform and balanced scale for the evaluation of digitization levels across different provinces.

(3) Control variables. Referring to other factors that may affect the risk taking behavior of insurance industry, this paper selects eight variables, such as Total Assets (LnAsset), Insurance Penetration(Ip), Insurance Density(LnId), Investment Return(Ir), Macro Socioeconomic Variables(GDP), Urbanization Rate(UrbanRate).

3.3 Model

This article investigates the impact of a company's level of digitalization prior to a crisis on its resilience, with reference to the works. Accordingly, the following econometric model is established:

$$Risk_{it} = \alpha_0 + \beta_1 \times DTS_i \times time_t + \gamma \times CONTROLS_{it} + \delta \times CONTROLS_i \times time_t + \theta_i + \lambda_t + \varepsilon_{it} \tag{1}$$

The dependent variable, $\mathrm{Risk_{it}}$, denotes the overall, underwriting risk assumed by province i in year t. We represent the level of digitalization in province i's insurance industry, our proxy for Insurtech, by $\mathrm{DTS_i}$. This measure is derived from the sub-index reflecting the depth of insurance utilization in the China Digital Inclusive Finance Index, compiled by the Digital Finance Research Center of Peking University. Our temporal dummy variable, $\mathrm{time_t}$, defines the post-COVID-19 era (from 2020 onwards) as the digital shock period, and assumes a value of 1; otherwise, it is 0. The interaction term $\mathrm{DTS_i} \times \mathrm{time_t}$ serves as our principal explanatory variable, illustrating the influence of digitalization level on risk-taking during the digital shock period.

$\mathrm{CONTROLS_{it}}$ signifies the set of control variables for province i in year t, encompassing total assets (LnAsset), insurance penetration (Ii), insurance density (LnId), and investment returns (Ir), with γ denoting the corresponding regression coefficients. $\mathrm{CONTROLS_i}$represents the control variables for province i, including GDP and urbanization rate. The interaction term $\mathrm{CONTROLS_i} \times \mathrm{time_t}$ allows us to control as much as possible for factors impacting risk-taking, thereby isolating the independent relationship between digitalization and risk assumption.

The fixed effect for province i is symbolized by θ_i, controlling for province-specific factors that do not vary over time. λ_t signifies the time t fixed effects, managing influences that all provinces concurrently experience and change over time, such as macroeconomic trends or national policies. ε_{it}stands for the random error term.

4 EMPRICAL RESULTS AND ANALYSIS

4.1 Descritive Statistical Analysis

The descriptive statistics provide an overview of the variables under study in the present research. The dataset comprises 268 to 341 observations, depending on the variable.The average total risk (RiskTotal) across the 268 observations is 0.073, with a standard deviation of 0.057, indicating a moderate variability. The underwriting risk (UWRisk) has a much larger spread. Across the 265 observations, the mean value stands at 0.674, but with a substantial standard deviation of 5.257. The variable ranges from 0.005 to a notable 58.48, reflecting significant discrepancies in the underwriting risk across different provinces.

The level of insurtech, as proxied by the digital transformation score (DTS), ranges between 0 (lowest) and 1 (highest), with a mean value of 0.51 and standard deviation of 0.225. This showcases a moderate degree of digitalization across the provinces. The control variables show diverse patterns. The total assets (LnAsset), with a mean of 23.928 and standard deviation of 2.599, shows a moderate degree of variation in the size of companies across provinces. Both the insurance penetration (Ip) and insurance density (LnId) show a wide range of values, suggesting substantial differences in the development of the insurance market across provinces (Table 1).

Table 1 Descriptive Statistics

variable	sample capacity	mean	standard error	least value	crest value
RiskTotal	268	0.073	0.057	0.003	0.348
UWRisk	265	0.674	5.257	0.005	58.48
DTS	341	0.51	0.225	0	1
DTS×Time	341	0.124	0.268	0	1

Time	341	0.182	0.386	0	1
lnAssets	279	23.928	2.599	18.05	30.658
Ip	341	3.499	1.196	0.05	7.36
LnId	341	7.447	0.659	5.534	9.354
InvestReturn	279	-6.698e+10	2.018e+11	-1.523e+12	4.415e+09
LnGDP	341	10.818	0.451	9.682	12.123
UrbanRate	341	0.586	0.131	0.227	0.896
LnGDP Time	341	2.028	4.31	0	12.123
UrbanRate Time	341	0.117	0.252	0	0.893
DTS normalized	341	0.51	0.225	0	1

4.2 Benchmark Regression

Table 2 presents the benchmark regression results of our study, capturing the relationship between digital transformation (DTS) and risk-taking behavior of the insurance industry.In model (1), the dependent variable is the total risk (RiskTotal), while in model (2), the dependent variable is the underwriting risk (UWRisk). The core explanatory variable is the interaction term of DTS and time (DTS×Time), which captures the impact of digitalization on risk-taking during different time periods.

In both models, DTS×Time is significant, indicating that the level of digitalization is associated with risk-taking behavior in the insurance industry. In model (1), a one-unit increase in DTS×Time is associated with a 0.4662-unit increase in the total risk, significant at the 1% level. Similarly, in model (2), a one-unit increase in DTS×Time is associated with a 52.8148-unit increase in the underwriting risk, significant at the 5% level. The adjusted R-squared figures, 0.2521 and 0.5983 for Models (1) and (2) respectively, offer confidence that our models adequately encapsulate a notable degree of the variation in risk-taking tendencies.

Table 2 Benchmark Regression Results

	(1)	(2)
	RiskTotal	UWRisk
DTS×Time	0.4662***	52.8148**
	(0.0039)	(0.0377)
lnAssets	0.0054	-0.1251
	(0.2802)	(0.5620)
Ip	-0.0006	-0.0604
	(0.9039)	(0.7382)
LnId	-0.0007	1.9975
	(0.9816)	(0.1527)
InvestReturn	-0.0000***	-0.0000
	(0.0015)	(0.1586)
LnGDP_Time	-0.1035***	-5.3926
	(0.0013)	(0.1113)
UrbanRate_Time	0.1107*	-23.3973**
_cons	0.0436	-2.9989
	(0.8679)	(0.7494)
N	260	265
adj. R2	0.2521	0.5983

Note: p-values in parentheses p < 0.1, ** p < 0.05, *** p < 0.01

4.3 Robustness Test

4.3.1 Parallel trend test

In order to corroborate the validity of the Difference-in-Differences (DiD) model, we carried out a parallel trends test. Echoing the approach, we established interaction terms between the dummy variables and the dummy variables of the treatment group, considering periods both before and after the implementation of InsurTech and for the current year, and then performed regression analysis. According to the regression outcomes reported in Table 3, the coefficients of the pre-treatment terms (pre_1, pre_2, and pre_3) are not statistically significant. Meanwhile, the coefficients of the post-treatment terms 'current' and 'post_1' are significant at the 10% and 1% levels respectively. This observation aligns with the critical assumptions of the DiD model, thereby supporting the credibility of the empirical results derived from our model. These results illustrate that, prior to the introduction of InsurTech, the insurance industry across provinces exhibited parallel trends. This bolsters the credibility of the findings of the DiD model, implying that InsurTech has a substantial influence on the RiskTotal of insurance companies.

Table 3 Parallel Trend Test

	RiskTotal
pre3	0.0284
	(0.1356)
pre2	0.0277

	(0.1416)
pre1	0.0138
	(0.5396)
current	0.0373*
	(0.0990)
post1	0.0587***
	(0.0099)
lnAssets	0.0057
	(0.3481)
Ip	0.0025
	(0.6713)
LnId	-0.0099
	(0.7678)
InvestReturn	-0.0000
	(0.2071)
LnGDP_Time	-0.0524
	(0.1529)
UrbanRate_Time	0.1482
	(0.1905)
N	268
adj. R2	0.0625

Note: p-values in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.3.2 Placebo test

To further exclude the influence of other unobservable factors on the research results and verify our empirical findings, we conducted a placebo test by setting fictitious time points for the implementation of InsurTech: 2011-2012, 2014-2015, and 2017-2018. Consequently, we redefined the time dummy variables. Treated_placebo represents the product of different experimental groups and DTS. If the regression results are not significant, we can conclude that the change in corporate risk-taking behavior is due to the implementation of InsurTech. Conversely, if the regression results are significant, this conclusion will not stand.

The data in the table shows that the company's risk-taking tendency did not have significant differences in the periods of 2011-2012, 2014-2015, and 2017-2018. Specifically, as shown in the first column, for the period of 2011-2012, the coefficient of "Treated_placebo" is 0.2360 (p-value=0.5096). This insignificance indicates that the fictitious experiment during this period did not have a significant impact on corporate risk-taking behavior. Similarly, for the period of 2014-2015, the coefficient of "Treated_placebo" is -0.0622, with a p-value of 0.538, indicating insignificance. For the period of 2017-2018, the coefficient of "Treated_placebo" is 0.1762, with a p-value of 0.242, also indicating insignificance. This further confirms that the fictitious experiment did not significantly change corporate risk-taking behavior.

In sum, these placebo tests further enhance the reliability of our main findings, confirming that InsurTech did indeed cause changes in corporate risk-taking behavior during the pandemic, and these changes are not simply caused by other unobservable factors (Table 4).

Table 4 Placebo Test

	2011-2012	2014-2015	2017-2018
Treated_placebo	0.2360	-.0622334	.1762167
	(0.5096)	(0.538)	(0.242)
lnAssets	0.0074	0.0066	0.0071
	(0.2522)	(0.2967)	(0.2941)
Ip	-0.0016	-0.0011	0.0006
	(0.7309)	(0.8211)	(0.8930)
LnId	-0.0055	0.0004	0.0082
	(0.8899)	(0.9913)	(0.8294)
InvestReturn	-0.0000**	-0.0000*	-0.0000**
	(0.0260)	(0.0646)	(0.0360)
LnGDP_Time	-0.0224	-0.0247	-0.0135
	(0.3693)	(0.3164)	(0.6211)
UrbanRate_Time	0.1777**	0.1759**	0.1739**
	(0.0342)	(0.0330)	(0.0329)
treated_placebo2_DTS		-0.0622	
		(0.5377)	
treated_placebo3_DTS			0.1762
			(0.2416)
_cons	-0.0184	-0.0297	-0.0973
	(0.9526)	(0.9217)	(0.7672)
N	268	268	268
adj. R2	0.1528	0.1497	0.1620

Note: p-values in parentheses $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 CONCLUSIONS

Our research provides a deep understanding of the relationship between insurance technology and risk taking behavior in the insurance industry, especially during periods of crisis impact. The core findings of our research can be summarized as the following two points: firstly, insurance technology significantly enhances the risk-taking behavior of the insurance industry. Our benchmark regression evidence shows that the improvement of the degree of digitalization, especially during the impact period of the COVID-19 epidemic, is related to the increase of the overall risk and underwriting risk of insurance companies. Secondly, we have successfully tested the causal relationship between insurance technology and risk taking. The Double Difference (DID) model is robust, and parallel trend testing aligns with the key assumptions of the DID model, supporting the effectiveness of our empirical findings.
Overall, with the advancement of insurance technology, decision-makers of insurance companies need to adopt more cautious and proactive risk management strategies. This may include deeper risk identification, assessment, and monitoring, as well as establishing an appropriate risk taking culture within the organization. For regulatory agencies, this study suggests that insurance technology may exacerbate risk taking behavior in the insurance industry. Therefore, regulatory agencies need to remain vigilant about the development and use of insurance technology, and timely update relevant regulatory policies and guidelines to ensure the stable and healthy development of the insurance industry.
Future research can further understand how different aspects of Digital transformation, such as artificial intelligence and blockchain, may have different impacts on the risk-taking behavior of the insurance industry.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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