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# How is Fintech reshaping the traditional financial markets? New evidence from InsurTech and insurance sectors in China

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A B S T R A C T

We examine the effect of Fintech on the market structure of traditional financial markets, and focus particularly on InsurTech and the insurance sector. We find that InsurTech has significantly reduced the non-life insurance sector's market concentration but plays a limited role in the life insurance sector's market structure. The results are not driven by potential reverse causality and remain unchanged when we employ an instrumental variables approach and use an alternative supply-side InsurTech index. We further explore the underlying mechanisms and find that, instead of competing directly with insurance companies, Fintech companies provide insurance technologies to traditional insurers and help them lower entry barriers and reduce operating costs. Our paper sheds light on how InsurTech is reshaping traditional insurance sectors, and the results are generalizable to Fintech and financial markets.

## 1. Introduction

The global financial crisis of 2008 caused a sharp loss of public trust in traditional financial institutions; this loss of trust became an important trigger for the rise of Fintech. Fintech innovations started in payments and lending with the emergence of Bitcoin and various peer-to-peer (P2P) lending platforms. The existing academic research traces that the evolution of Fintech focuses primarily on cryptocurrencies and marketplace lending (e.g., Berg, Burg, Gombović, & Puri, 2020; Foley, Karlsen, & Putniņš, 2019; Hu, Parlour, & Rajan, 2019; Jain, Mclnish, & Miller, 2019; Lin, Prabhala, & Viswanathan, 2013). As the investments in those two areas have become mature and even saturated, many investors see insurance as the next great opportunity (IAIS, 2017; KPMG, 2017).

As a branch of Fintech, InsurTech resembles other typical Fintech business in being characterized by BigTech companies providing a platform and adopting new technologies at the same time. InsurTech refers to a variety of emerging technologies and innovative business models that have the potential to transform the insurance industry (IAIS, 2017). As summarized by existing academic research and industry reports (Capgemini and Efma, 2018; Mueller, 2018; Neale, Drake, & Konstantopoulos, 2020), we classify InsurTech firms into three types: distributors, technology solution providers, and full-stack carriers. Distributors refer to various digital agents/brokers that focus on the sales and distribution, and collaborate with incumbent insurers to sell insurance on their platforms. Technology

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solution providers, such as software vendors, data originators and processors, target part of the value chain in insurance and help incumbent insurers improve their operating efficiency. Full-stack carriers are fully licensed insurance companies that use state-of-the-art technologies to underwrite policies and manage claims independently.

Unlike the direct competition and substitution between Fintech lending and traditional banking (Fuster, Plosser, Schnabl, & Vickery, 2019), InsurTech is characterized by the emergence of super-digital distributors like the Sure insurance platform based in the United States and the Ant insurance platform based in China. Considering that more than 50% of InsurTech deals flows into insurance distributors or brokers (Watson, Re, & Insights, 2020) and that the premiums collected from full-stack InsurTech insurers are less than 1% of premiums from all insurers,[1] the story of InsurTech and the insurance industry is different from the competition between Fintech lending and traditional banking. While some Fintech topics such as cryptocurrencies and NFTs are different from InsurTech, our discussion of InsurTech is generalizable to Fintech areas that involve a digital platform and incorporate new technologies such as AI, cloud computing, and big data.

Specifically, we investigate InsurTech's effect on the market structure of the insurance sector, which fits into a central theme in the literature on "disruptive innovation" and industrial development (Braun & Schreiber, 2017; Cappiello, 2018; Schumpeter, 1942). The recently emerged digital distributors[2] automate online premium payments through smart contracts, cooperate with traditional insurers to create new scenario-based insurance products, and achieve digitalized marketing and claim management with the application of blockchain. The digital distributor could be a game-changer for the competition among existing insurers and reshape the market structure of the insurance sector.

Based on several unique datasets from six sources, this study makes a key finding that InsurTech significantly reduces the non-life insurance sector's market concentration, but plays a limited role in the life insurance sector's market structure. Although we are not able to explore and identify the importance of all aspects of InsurTech itself, we piece together information for premiums and costs where data are available to capture the changes in different insurance sectors. Our estimates should be viewed as suggestive in understanding the economic impacts of InsurTech. The implications for consumer welfare and market competitiveness would be of great importance for regulators who supervise the insurance industry, given the significant differences between the non-life and life insurance sectors.

InsurTech's effect on non-life insurers is intuitive, since most non-life insurance products are simple and commodity-like. The digital distribution channel levels the playing field for insurers of different scales and allows small and medium-sized non-life insurers to reach the huge customer base of the digital platform with reduced search costs, lower commission expenses, and less geographic limitations. In addition, the digitized marketing, underwriting, and claim management with the blockchain and smart contracts on the platform lower the operating costs, which are particularly important for small and medium-sized non-life insurers. However, due to the complexity of life insurance products, which have long durations and high premiums, the branding and reputation of insurers play a more important role in customers' purchase decisions. As a result, consumers may prefer to purchase a product from large life insurers with good reputations on the digital platform or to purchase a product offline with the help of an agent. In our study, we find that InsurTech plays a limited role in the life insurance sector's market structure, which accords with several prior studies on Fintech and digital platforms such as Brynjolfsson and Smith (2000) and Hong, Lu, and Pan (2020). The significant difference between the non-life and life insurance sectors has great implications for the entire insurance sector in terms of technology advances, market competitiveness, and consumer welfare.

China's insurance market provides an ideal setting for our study. First, China has been playing a leading role in Fintech development.[3] China is also one of the largest InsurTech markets around the globe. Fig. 1 presents the InsurTech funding volumes and the number of deals over the period of 2012–2019. The global investments in InsurTech firms were $347 million in 2012, and rose up to about $6.3 billion in 2019. The number of deals showed a similar pattern, increasing from 46 in 2012 to 314 in 2019. China is one of the largest InsurTech markets, ranked the third place in terms of InsurTech deals, following the United States and United Kingdom. The findings on China's InsurTech market provide important insights for other countries that will take advantage of InsurTech. Second, in 2016, China surpassed Japan to become the second-largest insurance market after the United States.[4] Although a large body of the literature has examined the development of the U.S. insurance market, research on China's insurance market is scarce.

We start our study by merging the city-level demand-side InsurTech index, with the city-level branch data of Chinese insurers, to explore InsurTech's effect on the market structure of the insurance sector. We find that InsurTech reduces the non-life insurance sector's market concentration significantly, irrespective of the market structure measures used in the regressions; InsurTech plays a limited role in the life insurance sector's market concentration.

[1] The data on full-stack InsurTech carriers is scarce and lacks comparability among different countries. We manually collected the statistics from the annual reports of several full-stack InsurTech carriers to calculate the ratio.

[2] While the internet comparison sites emerged as early as 1995 in the United States and reduced the price of some insurance products, individuals only compare the quotes on these sites and seldom purchase insurance online (Brown & Goolsbee, 2002).

[3] According to an analysis by Accenture, the value of Fintech deals in China in 2018 was $25.5 billion, which accounted for 46% of all global Fintech investments in 2018. https://newsroom.accenture.com/news/global-Fintech-investments-surged-in-2018-with-investments-in-china-taking-the-lead-accenture-analysis-finds-uk-gains-sharply-despite-brexit-doubts.htm

[4] In 2014, China surpassed Germany to become the second-largest non-life insurance market. In 2017, China surpassed Japan to become the second-largest life insurance market. Moreover, growth potential remains for China's insurance market: in 2018, China's insurance density and insurance penetration were only $406 and 4.22%, respectively; in contrast, the world average insurance density and insurance penetration were $682 and 6.09%, respectively.

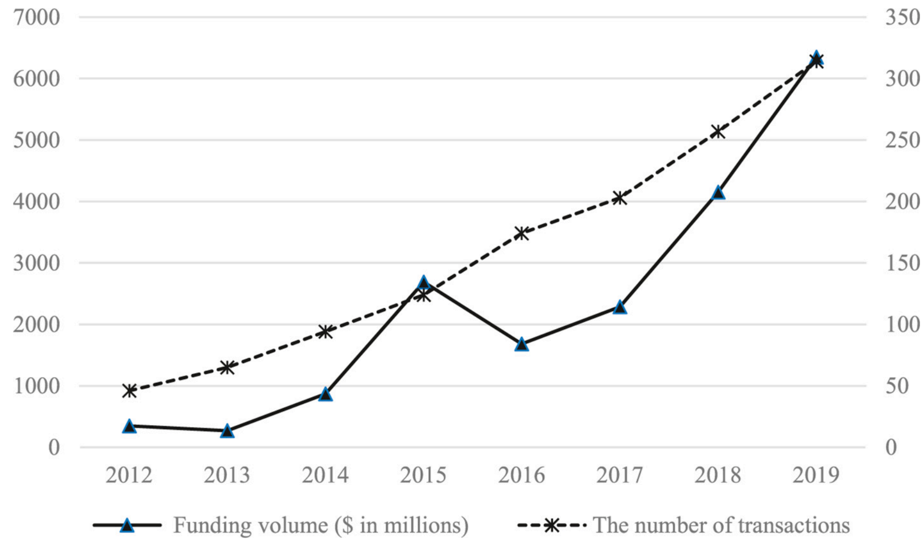


**Fig. 1.** Global InsurTech development from 2012 to 2019.
Data source: Willis Towers Watson Securities, Willis Re, and CB Insights.

However, the InsurTech index may be endogenous and thus merely reflect the competition outcomes in the insurance sector. We formally check for reverse causality through both the demand channel and the supply channel and conclude that the endogeneity of the InsurTech index is not a big concern and does not drive our main results. We also employ an instrumental variables approach to further mitigate the endogeneity concern. To make our results more convincing, we construct a new supply-side InsurTech index. The regression results are consistent with the main findings using the demand-side InsurTech index.

Next, we explore the underlying mechanisms through which InsurTech affects the market structure. Technology advancements and innovations in the financial sector have the potential to increase market access and lower operating costs (Financial Stability Board, 2019). We focus on these two aspects to pin down the underlying explanations: entry barriers and operating costs. We find that InsurTech has increased the number of both incumbent and new non-life insurance branches, but increased the number of incumbent life insurance branches only. In addition, InsurTech reduces the costs of non-life insurers but has no significant effect on the costs of life insurers. These findings help explain the main findings in the baseline regression.

Our study relates to the growing body of research on Fintech, the majority of which focuses on P2P lending and cryptocurrencies (Berg et al., 2020; Foley et al., 2019; Lin et al., 2013; Makarov & Schoar, 2020). We extend the Fintech literature by focusing on InsurTech, a relatively unstudied area of Fintech. Our study contributes to the emerging field of InsurTech by offering a comprehensive analysis on how InsurTech affects the insurance sector. Several studies focus on the application of telematics data in the automobile insurance market (Cather, 2020; Geyer, Kremslehner, & Muermann, 2020; Reimers & Shiller, 2019; Soleymanian, Weinberg, & Zhu, 2019). Based on six unique datasets, we provide the first empirical study of InsurTech's effect on the entire insurance sector, including the effect on market structure, entry barriers, and insurers' costs. Last, the structure-conduct-performance hypothesis in the industrial organization literature states that market concentration fosters collusion and facilitates firms' gaining on monopoly rents, which causes inefficient resource allocation (Bain, 1951; Bajtelsmit & Bouzouita, 1998; Njegomir & Stojić, 2011; Shepherd, 1972). We find that InsurTech significantly reduces the non-life insurance sector's market concentration, which provides an avenue to improve market efficiency and enhance consumer welfare.

The remainder of the paper is organized as follows. Section 2 describes the data, defines the variables, and introduces the econometric specification. Section 3 presents the results of the baseline model, explicitly tests the potential reverse causality, shows the results using an instrumental variables approach, and checks the robustness of the baseline results using the new supply-side InsurTech index. Section 4 considers two possible mechanisms through which InsurTech affects the market structure. Section 5 concludes.

## 2. Data, variables definitions, and research design

To examine InsurTech's effect on the market structure of the insurance sector and the underlying mechanisms, we manually collected several unique datasets at different levels of granularity from six sources: the *Yearbook of China's Insurance*, the Institute of Digital Finance at Peking University, the Insurance Association of China, the China Insurance Regulatory Commission, the *China Statistical Yearbook*, and the website of each insurer.

### *2.1. City-level branch data on premiums*

An appealing feature of the *Yearbook of China's Insurance* is that it releases not only the aggregate financial information on each insurer operating in China but the financial information on *all* city-level branches of each insurer as well. Specifically, it provides information on total premiums at each city-level branch as well as premiums for each line of business.[5] Using this dataset, we can calculate various market structure measures at city $i$ in year $t$. We manually collected the city-level branch data from the printed version of the *Yearbook of China's Insurance* over the period 2008–2018. Our initial sample includes 53,656 non-life insurance branch-year observations from an average of 14.41 branches in each city and 52,109 life insurance branch-year observations from an average of 14.20 branches in each city.

### 2.2. The demand-side InsurTech index

The city-level demand-side InsurTech index comes from the *Peking University Digital Financial Inclusion Index of China* (PKU-DFIIC), which is jointly compiled by the Institute of Digital Finance at Peking University and Ant Group.[6] The PKU-DFIIC, which is compiled from massive user transactions at Alipay, provides a comprehensive landscape of Fintech development and digital finance in China and shows how Fintech has improved financial inclusion (Guo et al., 2020).

In this paper, we focus on the city-level insurance sub-index (InsurTech index, hereafter) of PKU-DFIIC. This InsurTech index uses three indicators to capture the development of China's InsurTech and digital insurance across cities: the number of insureds per 10,000 Alipay users ($m_1$) in each city, the average number of insurance products purchased by each account ($m_2$) in each city, and the average coverage per account ($m_3$) in each city.

This index can well describe InsurTech development across cities in China. Ant Group claims that 570 million users used Ant Group insurance service to purchase insurance products sold by over 90 Chinese insurance companies from June 2019 to June 2020.[7] Given the huge number of Alipay users in China, insurers have strong incentives to cooperate with Alipay and sell their products on Alipay's digital platform. Since Alipay has huge amounts of big data on users' purchase preferences and payment behaviors, many insurers cooperate with Alipay and create scenario-based insurance products to sell on the platform, such as Alipay account security insurance, shipping return insurance, among others. Additionally, the adoption of blockchain and smart contracts at Alipay helps users achieve automated premium payments and online submission of claims. The digital insurance platform at Alipay is not a simple distributor but instead influences almost every value chain of insurers including product design, sales and distribution, premium payment, and claim management. The demand-side InsurTech index captures not only the level of digitalization of traditional insurance products, but also the sales of scenario-based innovative insurance utilizing big data and the attractiveness of automated premiums payments due to the adoption of blockchain and smart contracts.

On January 1, 2012, *Regulations on the Internet Insurance Business of Agents and Brokers* came into effect; this was the first regulation on online insurance distribution in China. The InsurTech index in our study covers the period of 2012–2018. We merge the city-level InsurTech index with the city-level branch data to examine InsurTech's effect on the market structure of the insurance sector.

### 2.3. The supply-side InsurTech index

Notably, the InsurTech index from PKU-DFIIC measures InsurTech development from users' behaviors. We also construct a supply-side InsurTech index to check the robustness of our baseline regression results. There are three possible ways to construct a supply-side index. The first is to collect information on insurers' inputs to facilitate insurers' InsurTech adoption, for example, their research and development (R&D) expenses on InsurTech. However, insurers are not required to release R&D expenses in their financial reports. The second way to construct a supply-side index is to compare insurers' outputs, which could be proxied by InsurTech-related patents. We manually collected insurers' patents from the China National Intellectual Property Administration and selected ones related to InsurTech by selecting those that included the keywords AI, big data, blockchain, machine learning or cloud computing. However, out of the 2430 patent applications from 2010 to 2020, there were only 139 patents applications before 2018, and only seven applications before 2016. Moreover, the patent applications of three InsurTech pioneers, Pingan, Taikang, and Zhongan, accounted for 90% of all patents. Thus, the patent variable during our sample period of 2012–2018 shows little variation both in the time dimension or the cross-sectional dimension. We then resort to the third way to proxy for insurers' InsurTech adoption—the time that insurers started to sell insurance products through digital platforms, either through their own website and mobile app or through third-party platforms. Note that the products sold on digital platforms are usually different from traditional offline products, with some traditional products redesigned using online big data and some innovative new insurance products designed based on online scenarios. In this sense, our self-constructed InsurTech supply-side index not only represents the InsurTech-based digital marketing but also reflects the development of InsurTech-based newly designed products.

Specifically, we first manually collected the information on the time when each insurer started to sell insurance products on its own website or mobile app and the time when each insurer started to collaborate with digital platforms to sell insurance products and/or create new insurance products. This information is derived from each insurer's website and the Digital Insurance Information Disclosure Section on the website of the Insurance Association of China. Second, we construct an indicator variable ($InsurTech\_h_{j,t}$) that

[5] According to the *Basic Element Data Directory of the Insurance Industry* released by the China Insurance Regulatory Commission, the total premiums at each city-level branch contain both offline premiums and online premiums. When a customer purchases insurance from an insurer through the digital channel, the premiums are considered to be premiums of the branch operating in the city where the customer resides.

[6] See Guo et al. (2020) for detailed descriptions on the construction of this index.

[7] Data source: http://static.sse.com.cn/stock/information/c/202008/e731ee980f5247529ea824d20fcdb293.pdf.

equals one if insurer *j* has performed either of the two above strategies in year *t*, and zero otherwise. Given that $InsurTech\_h_{j,t}$ reflects the InsurTech adoption from the headquarters of each insurer, we need to construct a variable that can proxy for the InsurTech development in city *i* in year *t*. To do so, we calculate an InsurTech index for the branch of insurer *j* operating in city *i* ($InsurTech\_b_{i,j,t}$) by multiplying $InsurTech\_h_{j,t}$ by the proportion of premiums at the branch operating in city *i* for insurer *j*. The rationale is that the headquarters' decision of insurer *j* is supposed to have a stronger influence on city *i* if the premiums from the branch that belongs to insurer *j* and operates in city *i* contributes more to total premiums at insurer *j*. Then we sum the values of $InsurTech\_b_{i,j,t}$ for *all* branches operating in city *i* to obtain the new supply-side InsurTech index for city *i* ($InsurTech\_c_{i,t}$).

To make it comparable to the demand-side InsurTech index from the PKU-DFIIC, we follow the construction of that index and use the efficacy function to transform $InsurTech\_c_{i,t}$:

$$InsurTech\_s_{i,t} = \frac{InsurTech\_c_{i,t} - InsurTech\_c^{l}_{i,t}}{InsurTech\_c^{h}_{i,t} - InsurTech\_c^{l}_{i,t}}, \tag{1}$$

where $InsurTech\_c^{h}_{i,t}$ and $InsurTech\_c^{l}_{i,t}$ are the 95% percentile and the 5% percentile of $InsurTech_c_{i,t}$for cities in the base year 2012, respectively. This efficacy function is both monotonic and convex to ensure that a higher value of $InsurTech\_c_{i,t}$ indicates a higher value of$InsurTech_s_{i,t}$.[8]

### 2.4. City-level control variables

In the baseline regression, we also control for several city-level variables that may correlate with the InsurTech index and the market structure of the insurance sector, including local GDP, the average wage, the number of high schools, the number of workers in the financial sector, foreign direct investments, and total deposits. We manually collected these control variables from the *China City Statistical Yearbook* compiled by the Department of Urban Surveys at the National Bureau of Statistics of China.

### 2.5. Headquarters-level financial information of each insurer

To rule out the potential reverse causality in the main regression, we explicitly examine the determinants of InsurTech adoption by insurers. In the mechanism analysis, we explore how InsurTech affects insurers' costs. The above two analyses need financial information of each insurer, such as operating costs, total assets, total premiums across lines of business, ceded premiums, the age of each insurer, and so forth. We manually collected the financial information from the annual reports of each insurer from the Insurance Association of China and the website of each insurer.

### 2.6. Variables definitions and the baseline model specification

The main goal of this study is to examine InsurTech's effect on the market structure of the insurance sector. We have three measures to capture the market structure of the city-level insurance market. The Herfindahl-Hirschman Index (*HHI*) is a widely recognized measure of market structure (Rhoades, 1995). We calculate the ratio of premiums from each branch operating in city *i* in year *t* to total premiums in city *i* in year *t*, and then sum the squared market share of each branch and denote it as $HHI_{i,t}$. A higher value of $HHI_{i,t}$ indicates a higher level of market concentration. We also consider two alternative measures for market structure: $CR3_{i,t}$ and $CR5_{i,t}$, which capture the market shares of the largest three or five branches at city *i* in year *t*. Likewise, a higher value of $CR3_{i,t}$ and $CR5_{i,t}$ indicates a higher level of market concentration. Notably, we calculate the market structure measures for the non-life insurance sector and the life insurance sector separately.

In the baseline model, we first examine the effect of the city-level demand-side InsurTech index on the market structure of the insurance market. We use the natural logarithm of the InsurTech index ($Insurtech_{i,t}$) in the regression due to its highly skewed characteristics. We also control for several city-level variables that may correlate with the InsurTech index and the market structure of the insurance sector: the natural logarithm of local GDP ($lnGDP_{i,t}$) and the natural logarithm of the average salary ($lnsalary_{i,t}$) to proxy for economic development and income level; the number of high schools ($num\_school_{i,t}$) to proxy for the education level; the ratio of foreign direct investments to local GDP ($r\_foreign_{i,t}$) to proxy for the degree of openness; the proportion of the number of workers in the financial sector ($r\_fin\_work_{i,t}$) and the ratio of total deposits to local GDP ($r\_deposit_{i,t}$) to proxy for financial development.

To investigate InsurTech's effect on the market structure of the insurance sector, we use the ordinary least square (OLS) technique to estimate the following regression model:

$$MS_{i,t} = \beta_0 + \beta_1 InsurTech_{i,t\text{-}1} + \gamma' X_{i,t\text{-}1} + \alpha_i + \delta_t + \varepsilon_{i,t}, \tag{2}$$

where *i* denotes the city, and *t* denotes the year. All independent variables are lagged one year to alleviate the simultaneity concerns. The dependent variable $MS_{i,t}$ represents three alternative measures for the market structure of the non-life (life) insurance sector ($HHI_{i,t}$, $CR3_{i,t}$, and $CR5_{i,t}$). The key independent variable of interest is $InsurTech_{i,t\text{-}1}$, which is the natural logarithm of the city-level demand-side InsurTech index. We also use the supply-side InsurTech index to check the robustness of the baseline regression results. $X_{i,t\text{-}1}$

[8] To alleviate the influence of extreme values, we also winsorize $InsurTech\_c_{i,t}$ in 2012 at the 5% and the 95% levels.

represents a set of city-level control variables that may affect the market structure. In addition, both city fixed effects, $\alpha_i$, and year fixed effects, $\delta_t$, are included in the regression to control for other demand-side factors in specific cities and macroeconomic trends across years.

Table 1 presents the summary statistics of the variables used in our baseline regression model. Our final sample in the baseline model consists of 1633 city-year observations in 253 cities over the period 2012–2018. The mean of the natural logarithm of the demand-side InsurTech index ($InsurTech_{i,t}$) is 5.701, with a standard deviation of 0.430. There is not much difference in the supply-side InsurTech index between the non-life insurance sector and the life insurance sector. For the non-life insurance sector, the average *HHI* is 0.231, and the premiums of the largest three (or five) non-life insurance branches account for 69.5% (82.8%) of total premiums in the city-level insurance market, suggesting a high degree of concentration. The life insurance market shows a lower degree of concentration, with a mean of *HHI* 0.195, and the average of the proportion of the premiums from the largest three (or five) life insurance branches 62.6% (77.5%). On average, a city has a local GDP of 165.52 billion RMB ($e^{16.622}$), a salary of 52.52 thousand RMB ($e^{10.869}$), 9.423 high schools, a ratio of foreign direct investments to local GDP 1.727%, a proportion of the number of workers in the financial sector of 1.425%, and a ratio of total deposits to local GDP of 143.901%.

## 3. Main findings

### 3.1. Effect of the demand-side InsurTech index on market structure

We start our analyses by examining the effect of the InsurTech index on the market structure of the non-life and life insurance sectors, respectively. The "InsurTech effect" may be heterogeneous in these two sectors due to different features of insurance products and branding concerns. First, most non-life insurance products are simple and commodity-like, which is particularly suitable for the application of technologies and digital sales. For instance, a customer can instantly obtain quotes for automobile insurance after inputting basic information such as car type, driving experience, age, etc. As the contract is almost the same across non-life insurers, customers may have no specific preference among brand names of insurers; this affords small and medium-sized non-life insurers more opportunities to expand business. In contrast, most life insurance products are characterized by complex terms, high premiums, and long durations. Moreover, the investment-oriented insurance products such as universal life insurance and variable life insurance

**Table 1**
Descriptive statistics.

| Variable | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| InsurTech index | | | | | |
| $InsurTech_{i,t}$ | 1633 | 5.701 | 0.430 | 3.907 | 6.516 |
| $InsurTech\_s_{i,t}(non\text{-}life)$ | 1633 | 2.823 | 1.394 | 0.000 | 7.932 |
| $InsurTech\_s_{i,t}(life)$ | 1633 | 2.860 | 1.494 | 0.000 | 8.164 |
| Non-life insurance sector | | | | | |
| $HHI_{i,t}$ | 1633 | 0.231 | 0.070 | 0.077 | 0.552 |
| $CR3_{i,t}$ (%) | 1633 | 0.695 | 0.087 | 0.370 | 1 |
| $CR5_{i,t}$ (%) | 1633 | 0.828 | 0.078 | 0.530 | 1 |
| Life insurance sector | | | | | |
| $HHI_{i,t}$ | 1633 | 0.195 | 0.088 | 0.057 | 0.670 |
| $CR3_{i,t}$ (%) | 1633 | 0.626 | 0.133 | 0.310 | 1 |
| $CR5_{i,t}$ (%) | 1633 | 0.775 | 0.123 | 0.422 | 1 |
| City-level controls | | | | | |
| $lnGDP_{i,t}$ | 1633 | 16.622 | 0.886 | 14.243 | 19.605 |
| $lnsalary_{i,t}$ | 1633 | 10.869 | 0.267 | 10.169 | 11.917 |
| $num\_school_{i,t}$ | 1633 | 9.423 | 15.858 | 0 | 92 |
| $r\_foreign_{i,t}$ (%) | 1633 | 1.727 | 1.754 | 0 | 11.526 |
| $r\_fin\_work_{i,t}$ (%) | 1633 | 1.425 | 1.760 | 0 | 7.308 |
| $r\_deposit_{i,t}$ (%) | 1633 | 143.901 | 61.449 | 37.109 | 531.334 |

This table presents descriptive statistics of the variables used in our baseline regression model. The sample consists of 1,633 city-year observations for the life (non-life) insurance sector over the period 2012–2018. The city-level branch data of Chinese insurers were manually collected from the *Yearbook of China's Insurance*. The demand-side InsurTech index is jointly compiled by the Institute of Digital Finance at Peking University and Ant Group. The supply-side InsurTech index is calculated based on the data each insurer adopted InsurTech. Other control variables were manually collected from the *China City Statistical Yearbook*. The dependent variables are three alternative measures for the market structure of the insurance sector: $HHI_{i,t}$, $CR3_{i,t}$, and $CR5_{i,t}$. The key independent variable of interest is $InsurTech_{i,t}$, which is the natural logarithm of the demand-side InsurTech index. We also replace the demand-side InsurTech index ($InsurTech_{i,t}$) with the supply-side InsurTech index ($InsurTech\_s_{i,t}$) to check the robustness of the main regression results. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t}$ (unit: 10,000 RMB), the natural logarithm of city-level average wage $lnsalary_{i,t}$ (unit: RMB), the number of high schools in the city $num\_school_{i,t}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t}$.

require that customers have a basic knowledge of both insurance and investments; otherwise, it is difficult for them to understand the calculation of cash value. In this case, customers may still need an agent to explain the contract terms and offer professional suggestions even though the life insurance products can be sold online. In addition, due to the complexity of life insurance products with long durations and high premiums, the branding and reputation of insurers may play a more important role in customers' purchase decisions, where large insurers have great advantages over small and medium-sized insurers in the life insurance sector. Therefore, we expect that InsurTech has a more significant effect on the non-life insurance sector's market structure.

Tables 2 and 3 present the regression results for the non-life and the life insurance sectors, respectively. For the non-life insurance sector, the coefficients on the demand-side InsurTech index are negative and significant at the 1% level across different market structure measures. To get a sense of the economic magnitude, a 1% increase of the InsurTech index is associated with a 0.16% (1% *0.037/0.231) decrease in *HHI* with respect to the sample average (column 2 of Table 2). For the life insurance sector, the coefficients on the InsurTech index are negative but statistically insignificant, irrespective of market structure measures used in the regression (see Table 3). These findings suggest that InsurTech significantly reduces the non-life insurance sector's market concentration, but plays no relevant role in the life insurance' sector's market structure. The contrasting differences of the regression results between the non-life and life insurance markets increase our confidence that the findings here are not spurious, but the real impact of InsurTech on the market structure of these two markets.

### 3.2. Endogeneity concerns

Although we use the one-year lagged values of the independent variables as well as both city and year fixed effects, the InsurTech index may still raise some endogeneity concerns. It is likely that the InsurTech index reflects the endogenous competition outcomes in the non-life and life insurance sectors. First, when there are more local branches offering non-life insurance, online customers are more likely to purchase products from those companies because of brand recognition and higher product awareness (*the demand channel*). Second, higher market competition may lead local insurers to shift their businesses online. Most non-life insurance products are homogeneous with short durations and low premiums, which is particularly suitable for the application of up-to-date technologies and digital sales. In contrast, life insurance products are complex with long durations and high premiums. The features of non-life insurance products may lead to higher local market competition and force more non-life insurers to shift their businesses online to capture more customers (*the supply channel*).

In this section, we will conduct formal tests on the potential reverse causality and further mitigate the endogeneity concerns using an instrumental variables approach.

#### 3.2.1. Test on the demand channel

Regarding the demand channel, we need detailed information on the premiums from the online distribution channel for each insurer to check whether insurers with more offline branches would collect more online premiums. Unfortunately, this information is not publicly available from the Insurance Association of China or the insurers' websites. To check whether the significant "InsurTech effect" in the non-life insurance sector is driven by the reverse causality arising from the demand channel, we contacted the non-life and life insurance departments at the Insurance Association of China, and they provided us with each non-life insurer's online premiums collected from 2016 to 2018.

Using the firm-level data of non-life insurers, we perform a simple regression of the logarithm of online premiums collected (*online_prem*) on the logarithm of the number of branches (*lnbranch*), with both firm and year fixed effects included. As seen from Table 4, the coefficient on *lnbranch* is statistically insignificant. This finding suggests that the main findings in our study are not driven by the demand channel.

#### 3.2.2. Test on the supply channel

As discussed above, another channel for reverse causality comes from insurers' choices to shift their business online due to higher local competition. Since non-life insurance products are characterized by short durations, low premiums, and homogeneous products, online shifting is more likely to occur in the non-life sector, which could drive our baseline results. To rule out this concern, we carefully compare the market structure patterns between the non-life and life insurance sectors and analyze the InsurTech adoption choices by insurers.

According to the descriptive statistics in Table 1, the means of *HHI*, *CR3*, and *CR5* are 0.195, 62.6%, and 77.5% for the life insurance sector and 0.231, 69.5%, and 82.8% for the non-life insurance sector. The local market competition in the non-life insurance sector is not higher than that in the life insurance sector. Moreover, the *HHI* changed from 0.258 in 2012 to 0.161 in 2018 for the life insurance sector and from 0.260 in 2012 to 0.225 in 2018 for the non-life insurance sector. Competition within the non-life insurance sector did not increase more rapidly than in the life insurance sector. This summary alleviates our concern that higher market competition forces more non-life insurers to shift their business online, which contributes to a higher InsurTech index.

Since we also manually collected the information on InsurTech adoption by each insurer (see Section 2.3), we can directly compare the digital strategy of non-life insurers versus life insurers. In 2012, 32.20% of life insurers had their own websites or mobile apps to sell insurance products; that percentage rose to 77.22% in 2018. This ratio is lower for non-life insurers, with 29.82% having a website or mobile app to sell insurance products in 2012 and 67.86% in 2018. In 2012, 13.56% of life insurers collaborated with digital platforms to sell traditional insurance products and/or create new products; this rose to 74.68% in 2018. For non-life insurers, this ratio was 17.54% in 2012 and 73.81% in 2018. These summary statistics show that not only homogeneous non-life products with short durations and low premiums were sold online, but life insurers also have been active in selling their products online. This suggests that

**Table 2**
The demand-side InsurTech index and the non-life insurance sector's market structure.

| | $HHI_{i,t}$ | | $CR3_{i,t}$ | | $CR5_{i,t}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $InsurTech_{i,t-1}$ | −0.034*** | −0.037*** | −0.052*** | −0.054*** | −0.048*** | −0.052*** |
| | (0.010) | (0.010) | (0.015) | (0.015) | (0.013) | (0.013) |
| $lnGDP_{i,t-1}$ | | 0.050*** | | 0.047** | | 0.050*** |
| | | (0.015) | | (0.018) | | (0.016) |
| $lnsalary_{i,t-1}$ | | −0.015 | | −0.034* | | −0.003 |
| | | (0.018) | | (0.019) | | (0.016) |
| $num\_school_{i,t-1}$ | | −0.000 | | −0.001 | | −0.001 |
| | | (0.001) | | (0.002) | | (0.001) |
| $r\_foreign_{i,t-1}$ | | −0.001 | | −0.001 | | −0.001 |
| | | (0.001) | | (0.001) | | (0.001) |
| $r\_fin\_work_{i,t-1}$ | | 0.001 | | 0.001 | | 0.000 |
| | | (0.002) | | (0.002) | | (0.002) |
| $r\_deposit_{i,t-1}$ | | 0.000 | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | 0.384*** | −0.401 | 1.002*** | 0.562 | 1.063*** | 0.205 |
| | (0.051) | (0.373) | (0.079) | (0.447) | (0.065) | (0.362) |
| *Observations* | 1400 | 1400 | 1400 | 1400 | 1400 | 1400 |
| *Adjusted* $R^2$ | 0.872 | 0.874 | 0.879 | 0.880 | 0.904 | 0.906 |

This table reports the effect of the demand-side InsurTech index on the non-life insurance sector's market structure. The dependent variables are three alterative measures for the non-life insurance sector's market structure, with $HHI_{i,t}$ in columns (1)–(2), $CR3_{i,t}$ in columns (3)–(4), and $CR5_{i,t}$ in columns (5)–(6). The main independent variable of interest is $InsurTech_{i,t-1}$, which is the natural logarithm of the demand-side InsurTech index from the PKU-DFIIC. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t-1}$, the natural logarithm of city-level average wage $lnsalary_{i,t-1}$, the number of high schools in the city $num\_school_{i,t-1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t-1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t-1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t-1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 3**
The demand-side InsurTech index and the life insurance sector's market structure.

| | $HHI_{i,t}$ | | $CR3_{i,t}$ | | $CR5_{i,t}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $InsurTech_{i,t-1}$ | −0.015 | −0.017 | −0.023 | −0.023 | −0.022 | −0.022 |
| | (0.012) | (0.012) | (0.017) | (0.017) | (0.014) | (0.015) |
| $lnGDP_{i,t-1}$ | | 0.042** | | 0.013 | | 0.003 |
| | | (0.017) | | (0.028) | | (0.025) |
| $lnsalary_{i,t-1}$ | | −0.041** | | −0.015 | | −0.010 |
| | | (0.019) | | (0.023) | | (0.024) |
| $num\_school_{i,t-1}$ | | 0.003*** | | 0.003* | | 0.003** |
| | | (0.001) | | (0.002) | | (0.002) |
| $r\_foreign_{i,t-1}$ | | −0.000 | | 0.001 | | −0.001 |
| | | (0.001) | | (0.002) | | (0.001) |
| $r\_fin\_work_{i,t-1}$ | | 0.000 | | −0.001 | | −0.002 |
| | | (0.002) | | (0.002) | | (0.002) |
| $r\_deposit_{i,t-1}$ | | 0.000** | | 0.000 | | −0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | 0.200*** | −0.457 | 0.544*** | 0.195 | 0.672*** | 0.453 |
| | (0.061) | (0.411) | (0.086) | (0.639) | (0.075) | (0.560) |
| *Observations* | 1400 | 1400 | 1400 | 1400 | 1400 | 1400 |
| *Adjusted* $R^2$ | 0.898 | 0.900 | 0.911 | 0.912 | 0.918 | 0.918 |

This table reports the effect of the demand-side InsurTech index on the life insurance sector's market structure. The dependent variables are three alterative measures for the life insurance sector's market structure, with $HHI_{i,t}$ in columns (1)–(2), $CR3_{i,t}$ in columns (3)–(4), and $CR5_{i,t}$ in columns (5)–(6). The main independent variable of interest is $InsurTech_{i,t-1}$, which is the natural logarithm of the demand-side InsurTech index. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t-1}$, the natural logarithm of the city-level average wage $lnsalary_{i,t-1}$, the number of high schools in the city $num\_school_{i,t-1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t-1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t-1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t-1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 4**
The effect of the number of branches on online premiums for non-life insurers.

| | The dependent variable: online_prem |
|---|---|
| *lnbranch* | 1.525 |
| | (1.119) |
| *Firm FE* | YES |
| *Year FE* | YES |
| *Constant* | −2.216 |
| | (1.498) |
| *Observations* | 166 |
| *Adjusted $R^2$* | 0.888 |

This table reports the effect of the number of branches on online premiums for non-life insurers. The sample covers the period of 2016–2018. The dependent variable is the natural logarithm of online premiums for non-life insurer *j* in year *t* ($online\_prem_{j,t}$). The independent variable is the natural logarithm of the number of branches for insurer *j* in year *t* ($lnbranch_{j,t}$). Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the baseline results are not driven by different digital strategies between non-life and life insurers.

To formally check whether local market competition affects the InsurTech adoption of insurers, we use the firm-level data from annual reports of each insurer and regress the InsurTech adoption measure $InsurTech\_h_{j,t}$ for each insurer on local market competition and other firm-level factors. $InsurTech\_h_{j,t}$ is an indicator variable that equals one if an insurer either sells insurance on its websites or mobile app or collaborates with digital platforms to sell traditional insurance products and/or create new products in year *t*. In addition to the outcome variable $InsurTech\_h_{j,t}$, we construct two variables $Insur\_self_{j,t}$ and $Insur\_out_{j,t}$ to differentiate the two digital strategies. Specifically, $Insur\_self_{j,t}$ is an indicator variable that equals one if insurer *j* has started to sell insurance products on its own website or mobile app in year *t*, and zero otherwise; $Insur\_out_{j,t}$ is an indicator variable that equals one if insurer *j* has started to collaborate with other digital platforms to sell traditional insurance products and/or create new insurance products in year *t*, and zero otherwise. We calculate local market competition ($a\_compet\_hhi_{j,t}$) faced by each insurer as the weighted average of the market competition ($HHI_{i,j,t}$) in city *i* where the branch of insurer *j* operates. The weight is the ratio of total premiums at each city-level branch to total premiums at insurer *j*. Other firm-level control variables include the natural logarithm of total assets ($lnasset_{j,t}$), the age of each insurer ($Age_{j,t}$), the Herfindahl-Hirschman Index of premiums across lines of business for each insurer ($HHI\_line_{j,t}$), and the proportion of ceded premiums ($r\_cede_{j,t}$).[9] We also include two variables aggregated from the city-level branches to capture the operating diversities of each insurer across regions: the natural logarithm of the number of branches for insurer *j* ($lnbranch_{j,t}$) and the average ratio of total premiums at each branch of insurer *j* to total premiums in that city ($ar\_tot\_prem_{j,t}$).[10] Table 5 presents the regression results of the determinants of InsurTech adoption by non-life and life insurers, respectively. Note that the coefficients on the local market competition measure ($a\_compet\_hhi_{j,t}$) never approach significance for both non-life and life insurers. That suggests that local market competition does not lead insurers to shift online, which rules out the supply channel.

Also note that the coefficients on firm size ($lnasset_{j,t}$) are always negative and significant for non-life insurers but are insignificant for life insurers. This provides a plausible explanation for the baseline regression results. The smaller non-life insurers are more inclined to embrace InsurTech, but we fail to find a similar pattern for life insurers. Combining the baseline regression results with the summary statistics in this section, we can see that the active digital strategy of life insurers does not significantly affect the life insurance sector's market structure. As discussed earlier, the branding and reputation of insurers may play a more important role in the life insurance sector. Small and medium-sized life insurers realize that the adoption of InsurTech may have limited effects on the increase of their market shares, and as a result, they are more hesitant to adopt InsurTech and sell those products online. In contrast, small and medium-sized non-life insurers have strong incentives to shift their business online given the commodity-like features of non-life insurance products.

In sum, the potential reverse causality, either from consumers' preferences on the demand side or insurers' choices on the supply side, is not a big concern and does not drive the results in our baseline setting.

### 3.2.3. Instrumental variables and the 2SLS regression results

To further mitigate the endogeneity concern, we employ an instrumental variables approach to reexamine InsurTech's effect on the market structure. Note that a valid instrumental variable should meet the following two conditions: the relevance condition and the exclusion restriction (Wooldridge, 2008). The relevance condition requires the instrumental variable to be correlated with the

[9] Ceded premiums refer to premiums paid by the primary insurer to another insurer for reinsurance protection.

[10] The pairwise correlation between firm size *lnasset* and *lnbranch* (*ar_tot_prem*) is only 0.343 (0.608). This modest correlation exactly reflects diversified operating strategies for small and medium-sized insurers. Some small and medium-sized insurers choose to launch a large number of branches in different cities, but others prefer to launch few branches and gain high market shares in a small set of cities where large insurers do not have much business.

**Table 5**
The determinants of insurers' InsurTech adoption.

| | Non-life insurers | | | Life insurers | | |
|---|---|---|---|---|---|---|
| | *Insurtech_s* | *Insur_self* | *Insur_out* | *Insurtech_s* | *Insur_self* | *Insur_out* |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $a\_compet\_hhi_{j,t}$ | 0.108 | 0.691 | 1.830 | 0.847 | 1.943 | −0.259 |
| | (1.347) | (1.159) | (1.345) | (1.574) | (1.483) | (1.525) |
| $lnassetj_{,t}$ | −0.124** | −0.122*** | −0.115** | 0.010 | −0.002 | 0.031 |
| | (0.050) | (0.045) | (0.052) | (0.054) | (0.050) | (0.053) |
| $Age_{j,t}$ | 0.033** | −0.077** | 0.054*** | 0.084*** | 0.096*** | 0.099*** |
| | (0.015) | (0.036) | (0.013) | (0.017) | (0.016) | (0.017) |
| $HHI\_line_{j,t}$ | 0.022 | −0.264* | 0.449*** | −0.024 | 0.292*** | −0.143 |
| | (0.142) | (0.145) | (0.164) | (0.111) | (0.112) | (0.132) |
| $r\_cede_{j,t}$ | 0.002 | −0.001 | 0.002 | 0.002** | 0.001 | 0.002** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |
| $lnbranchj_{,t}$ | 0.220*** | 0.054 | 0.152*** | 0.004 | −0.016 | 0.015 |
| | (0.044) | (0.052) | (0.047) | (0.068) | (0.067) | (0.061) |
| $ar\_tot\_prem_{j,t}$ | 4.747*** | 4.636*** | 2.384 | 0.624 | 0.615 | −0.128 |
| | (1.294) | (1.301) | (1.750) | (0.981) | (1.063) | (1.029) |
| *Firm FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | −1.928** | 2.682* | −2.101** | −0.262 | −0.453 | −0.419 |
| | (0.936) | (1.509) | (1.060) | (0.584) | (0.551) | (0.557) |
| *Observations* | 480 | 480 | 480 | 442 | 442 | 442 |
| *Adjusted* $R^2$ | 0.673 | 0.763 | 0.643 | 0.560 | 0.712 | 0.604 |

This table reports the determinants of insurers' decisions to adopt InsurTech. All the variables are aggregated at the headquarters-level. Columns (1)–(3) present the results for non-life insurers and columns (4)–(6) present the results for life insurers. The dependent variables are three alternative variables indicating whether an insurer sells insurance on its website or mobile app and whether an insurer collaborates with digital platforms to sell traditional insurance products and/or create new products in year *t*. The key independent variables of interest are the weighted average of local market competition faced by insurer *j* ($a\_compet\_hhi_{j,t}$). The control variables include the natural logarithm of total assets of insurer *j* ($lnasset_{j,t}$), the age of each insurer ($Age_{j,t}$), the Herfindahl-Hirschman Index of premiums across lines of business for each insurer ($HHI\_line_{j,t}$), and the proportion of ceded premiums ($r\_cede_{j,t}$). There are also two control variables aggregated from the city-level branches of each insurer: the natural logarithm of the number of branches for insurer *j* ($lnbranch_{j,t}$) and the average ratio of total premiums at each branch of insurer *j* to total premiums in that city ($ar\_tot\_prem_{j,t}$). Both firm fixed effects and year fixed effects are included in the regression. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

endogenous variable; the exclusion restriction requires the instrumental variable to have no correlation with the error term and to affect the outcome variable indirectly through the endogenous variable. We choose the natural logarithm of the number of mobile phones users in each city (*mobile*) and the natural logarithm of the number of patent applications in each province (*patent_aprv*) as the instrumental variables for the city-level InsurTech index from the PKU-DFIIC.[11] These data are obtained from the *China City Statistical Yearbook* and the WIND database. The rationale is that the mobile phones serve as the fundamental infrastructure for Alipay users to purchase insurance products and regional technology advances lay the foundation for InsurTech development and customer attitudes toward InsurTech, thereby affecting the market structure of the insurance sector. The number of applied patents reflects the preference for new knowledge and new technology in local areas, which is positively associated with the application of InsurTech. However, the market structure of a specific industry is unlikely to change the use of mobile phones in a city or the overall patent applications in a province. Note that we have two instrumental variables for the key variable of interest *InsurTech*, which allows us to explicitly test the relevance condition and the exclusion restriction. Table 6 presents the two-stage least squares (2SLS) regression results of InsurTech's effect on the market structure of the insurance sector. The first-stage regression results suggest that these two instrumental variables are positively associated with the InsurTech index, which is consistent with our expectation. The Wald *F-statistic* is 10.34, which indicates that the instrumental variables are not weak. The *p*-values of the Hansen *J-statistic* (Hansen, 1982; Sargan, 1958) are all above 0.1, which does not reject the null hypotheses that the instrumental variables are uncorrelated with the error term and are correctly excluded from the estimated equation. For the non-life insurance sector, the InsurTech index still presents a negative and significant effect on the market structure; For the life insurance sector, the coefficient of the InsurTech index is negative and becomes significant when the market structure measure is *HHI*, but it is still insignificant when the market structure is *CR3* or *CR5*. The 2SLS regression results support our main findings that InsurTech reduces the market concentration significantly but plays a limited role in the life insurance sector's market structure.

### 3.3. Effect of the supply-side InsurTech index on market structure

In this section, we use the new supply-side InsurTech index that we construct in Section 2.3 to further check the robustness of the

[11] The number of patent applications in each city is not available.

**Table 6**
InsurTech and the market structure of the insurance sector-2SLS regression.

| | Non-life insurance | | | Life insurance | | |
|---|---|---|---|---|---|---|
| | $HHI_{i,t}$ | $CR3_{i,t}$ | $CR5_{i,t}$ | $HHI_{i,t}$ | $CR3_{i,t}$ | $CR5_{i,t}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Insurtech_{i,t-1}$ | −0.289*** | −0.382*** | −0.265** | −0.347** | −0.184 | 0.084 |
| | (0.103) | (0.141) | (0.110) | (0.136) | (0.129) | (0.095) |
| $lnGDP_{i,t-1}$ | 0.076*** | 0.080*** | 0.072*** | 0.075*** | 0.029 | −0.009 |
| | (0.020) | (0.028) | (0.021) | (0.024) | (0.032) | (0.025) |
| $lnsalary_{i,t-1}$ | −0.001 | −0.015 | 0.009 | −0.016 | 0.003 | −0.013 |
| | (0.024) | (0.028) | (0.021) | (0.027) | (0.023) | (0.023) |
| $num\_school_{i,t-1}$ | 0.000 | −0.000 | −0.000 | 0.003** | 0.003* | 0.003** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| $r\_foreign_{i,t-1}$ | −0.001 | −0.001 | −0.001 | 0.000 | 0.001 | −0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $r\_fin\_work_{i,t-1}$ | 0.001 | 0.003 | 0.001 | 0.001 | −0.001 | −0.002 |
| | (0.002) | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| $r\_deposit_{i,t-1}$ | 0.000** | 0.000 | 0.000 | 0.000*** | 0.000 | −0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Observations* | 1378 | 1378 | 1378 | 1378 | 1378 | 1378 |
| | First Stage regression | | | | | |
| $mobile_{i,t-1}$ | 0.095** | 0.095** | 0.095** | 0.095** | 0.095** | 0.095** |
| | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) | (0.048) |
| $patent\_aprv_{i,t-1}$ | 0.055* | 0.055* | 0.055* | 0.055* | 0.055* | 0.055* |
| | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) | (0.030) |
| *Wald F-statistic* | 10.341 | 10.341 | 10.341 | 10.341 | 10.341 | 10.341 |
| *Hansen J-statistic* | 0.129 | 1.945 | 0.725 | 0.101 | 0.289 | 2.679 |

This table reports the results of the effect of the demand-side InsurTech index on the insurance sector's market structure using a 2SLS approach. The dependent variables are three alternative measures of market structure: $HHI_{i,t}$, $CR3_{i,t}$, and $CR5_{i,t}$. Columns (1)–(3) show the results for the non-life insurance sector and columns (4)–(6) show the results for the life insurance sector. The instrumental variables for the key explanatory variable $InsurTech_{i,t-1}$ are the natural logarithm of the number of mobile phone users in each city ($mobile_{i,t-1}$) and the natural logarithm of the number of patent applications in each province ($patent\_aprv_{i,t-1}$). The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t-1}$, the natural logarithm of city-level average wage $lnsalary_{i,t-1}$, the number of high schools in the city $num\_school_{i,t-1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t-1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t-1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t-1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

baseline regression results. The demand-side InsurTech index from the PKU-DFIIC is based on the insurance purchasing behavior of consumers. We replace it with the supply-side InsurTech index that reflects the adoption of InsurTech by insurers in the baseline regression.[12]

Tables 7 and 8 present the regression results of the effect of the new supply-side InsurTech index on the market structure of the non-life and the life insurance sectors, respectively. First, InsurTech still has a negative and significant effect on the non-life insurance sector's market concentration. Second, for the life insurance sector, the coefficients on InsurTech are insignificant when the market structure measures are *HHI* and *CR5,* and they become marginally significant when the market structure measure is *CR3* ($p$-value = 0.10 in column 3 and 0.08 in column 4). The regression results using the supply-side InsurTech index reach a similar conclusion and makes our main findings more convincing. The results show that InsurTech significantly reduces the non-life insurance sector's market concentration, while InsurTech's effect on the life insurance sector's market structure is limited.

## 4. The mechanisms through which InsurTech affects market structure

In this section, we explore the underlying mechanisms through which InsurTech affects the market structure. Specifically, we examine InsurTech's effect on entry barriers and insurers' costs.

### 4.1. Entry barriers

The development of InsurTech has broken geographic limitations for insurers and extends the sales distribution channels, which lowers entry barriers and improves competition in the insurance market. While InsurTech helps insurers achieve digital marketing and enables customers to purchase insurance and file claims online, insurers still need physical branches to better address customers' needs

[12] Relative to the demand-side InsurTech index, the supply-side InsurTech index is less likely to be endogenous since we have shown that local market competition does not lead insurers to shift online (see Table 5).

**Table 7**
The supply-side InsurTech index and the non-life insurance sector's market structure.

| | $HHI_{i,t}$ | | $CR3_{i,t}$ | | $CR5_{i,t}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $InsurTech\_s_{i,t-1}$ | −0.011*** | −0.012*** | −0.018*** | −0.019*** | −0.015*** | −0.016*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| $lnGDP_{i,t-1}$ | | 0.050*** | | 0.047** | | 0.050*** |
| | | (0.016) | | (0.018) | | (0.015) |
| $lnsalary_{i,t-1}$ | | −0.002 | | −0.014 | | 0.015 |
| | | (0.016) | | (0.017) | | (0.016) |
| $num\_school_{i,t-1}$ | | −0.000 | | −0.001 | | −0.001 |
| | | (0.001) | | (0.002) | | (0.001) |
| $r\_foreign_{i,t-1}$ | | −0.001 | | −0.001 | | −0.001 |
| | | (0.001) | | (0.001) | | (0.001) |
| $r\_fin\_work_{i,t-1}$ | | 0.001 | | 0.002 | | 0.001 |
| | | (0.002) | | (0.002) | | (0.001) |
| $r\_deposit_{i,t-1}$ | | 0.000 | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | 0.279*** | −0.679* | 0.846*** | 0.136 | 0.907*** | −0.179 |
| | (0.022) | (0.372) | (0.021) | (0.426) | (0.018) | (0.341) |
| *Observations* | 1400 | 1400 | 1400 | 1400 | 1400 | 1400 |
| *Adjusted* $R^2$ | 0.873 | 0.875 | 0.881 | 0.883 | 0.905 | 0.908 |

This table reports the effect of the supply-side InsurTech index on the non-life insurance sector's market structure. The dependent variables are three alterative measures for the non-life insurance sector's market structure, with $HHI_{i,t}$ in columns (1)–(2), $CR3_{i,t}$ in columns (3)–(4), and $CR5_{i,t}$ in columns (5)–(6). The main independent variable of interest is $InsurTech\_s_{i,t-1}$, which is the natural logarithm of the supply-side InsurTech index. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t-1}$, the natural logarithm of city-level average wage $lnsalary_{i,t-1}$, the number of high schools in the city $num\_school_{i,t-1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t-1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t-1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t-1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Table 8**
The supply-side InsurTech index and the life insurance sector's market structure.

| | $HHI_{i,t}$ | | $CR3_{i,t}$ | | $CR5_{i,t}$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $InsurTech\_s_{i,t-1}$ | −0.004 | −0.005 | −0.008* | −0.008* | −0.005 | −0.005 |
| | (0.003) | (0.003) | (0.005) | (0.005) | (0.005) | (0.005) |
| $lnGDP_{i,t-1}$ | | 0.041** | | 0.013 | | 0.002 |
| | | (0.017) | | (0.028) | | (0.024) |
| $lnsalary_{i,t-1}$ | | −0.041** | | −0.014 | | −0.010 |
| | | (0.019) | | (0.024) | | (0.024) |
| $num\_school_{i,t-1}$ | | 0.003*** | | 0.003* | | 0.003** |
| | | (0.001) | | (0.002) | | (0.002) |
| $r\_foreign_{i,t-1}$ | | −0.000 | | 0.001 | | −0.001 |
| | | (0.001) | | (0.002) | | (0.001) |
| $r\_fin\_work_{i,t-1}$ | | 0.000 | | −0.002 | | −0.002 |
| | | (0.002) | | (0.002) | | (0.002) |
| $r\_deposit_{i,t-1}$ | | 0.000** | | 0.000 | | −0.000 |
| | | (0.000) | | (0.000) | | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | 0.151*** | −0.506 | 0.480*** | 0.121 | 0.589*** | 0.393 |
| | (0.022) | (0.414) | (0.031) | (0.636) | (0.032) | (0.556) |
| *Observations* | 1400 | 1400 | 1400 | 1400 | 1400 | 1400 |
| *Adjusted* $R^2$ | 0.898 | 0.900 | 0.912 | 0.912 | 0.918 | 0.918 |

This table reports the effect of the supply-side InsurTech index on the life insurance sector's market structure. The dependent variables are three alterative measures for the life insurance sector's market structure, with $HHI_{i,t}$ in columns (1)–(2), $CR3_{i,t}$ in columns (3)–(4), and $CR5_{i,t}$ in columns (5)–(6). The main independent variable of interest is $InsurTech\_s_{i,t-1}$, which is the natural logarithm of the supply-side InsurTech index. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t-1}$, the natural logarithm of city-level average wage $lnsalary_{i,t-1}$, the number of high schools in the city $num\_school_{i,t-1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t-1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t-1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t-1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

and handle claims. Here we utilize the number of branches to proxy for entry barriers. To explicitly examine this mechanism, we calculate the number of non-life (life) insurance branches in city *i* in year *t* ($n\_branch_{i,t}$) and estimate the following regression model for the non-life and the life insurance sectors, respectively:

$$ln\_branch_{i,t} = \beta_0 + \beta_1 Insurtech_{i,t\text{-}1} + \gamma' X_{i,t\text{-}1} + \alpha_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

where $ln\_branch_{i,t}$ is the natural logarithm of the number of non-life (life) branches in city *i* in year *t*, and the explanatory variables are the same as those in the baseline model in Eq. (2).

According to the results in columns (1) and (4) of Table 9, InsurTech increases the number of both non-life and life insurance branches. In addition, the magnitude and the significance for the non-life insurance sector are larger than those for the life insurance sector. However, it does not tell us the source of the increase in the number of branches: does it stem from new entrants or incumbents? To determine the source of the increase in the number of branches, we further calculate the number of branches for new entrant insurers and the number of branches for incumbent insurers in city *i* in year *t*, respectively. We define an insurer as a "new entrant" if its age is below the 25th percentile of the age distribution; otherwise, it is an "incumbent" insurer. Then, we investigate InsurTech's effect on these two numbers for the non-life and the life insurance sectors, respectively. According to the results in columns (2) and (3) of Table 9, InsurTech increases the number of branches of both new entrant and incumbent non-life insurers. Moreover, the effect for new entrants is about 2.6 times as large as that for incumbents. For the life insurance sector, however, the increase in the number of branches mainly stems from incumbents (see columns 5 and 6 of Table 9).

We can better understand the main findings in the baseline and the 2SLS regressions through the results in Tables 5 and 9. In the non-life insurance sector, small and medium-sized insurers actively embrace InsurTech and enter local markets as new entrants, which reduces the market concentration. In the life insurance sector, insurers of various sizes show no difference in embracing InsurTech (column 4 of Table 5). In addition, InsurTech benefits the incumbents who enter local life insurance markets more than new entrants (column 6 of Table 9). As a result, InsurTech may reduce the *HHI* of the life insurance market to some extent (column 4 of Table 6), but has no effect on *CR3* and *CR5*.

### 4.2. *Insurers' costs*

InsurTech should also reduce costs for insurers, which is key to improving their competitiveness. First, the digital distribution

**Table 9**
InsurTech and entry barriers to the insurance sector.

| | Non-life insurance sector | | | Life insurance sector | | |
|---|---|---|---|---|---|---|
| | Total | New entrants | Incumbents | Total | New entrants | Incumbents |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $InsurTech_{i,t\text{-}1}$ | 0.124*** | 0.271* | 0.105*** | 0.081** | 0.167 | 0.066** |
| | (0.039) | (0.165) | (0.039) | (0.031) | (0.114) | (0.032) |
| $lnGDP_{i,t\text{-}1}$ | 0.063 | 0.540* | −0.004 | 0.059 | 0.271 | 0.042 |
| | (0.060) | (0.276) | (0.063) | (0.056) | (0.218) | (0.057) |
| $lnsalary_{i,t\text{-}1}$ | −0.066 | 0.018 | −0.060 | 0.020 | 0.167 | −0.009 |
| | (0.046) | (0.243) | (0.047) | (0.057) | (0.210) | (0.062) |
| $num\_school_{i,t\text{-}1}$ | 0.010** | 0.036 | 0.005* | −0.002 | −0.004 | −0.002 |
| | (0.004) | (0.026) | (0.003) | (0.003) | (0.015) | (0.003) |
| $r\_foreign_{i,t\text{-}1}$ | 0.003 | 0.027* | −0.001 | 0.006** | 0.019 | 0.005 |
| | (0.003) | (0.014) | (0.003) | (0.003) | (0.012) | (0.003) |
| $r\_fin\_work_{i,t\text{-}1}$ | 0.004 | −0.007 | 0.006 | 0.005 | 0.012 | 0.004 |
| | (0.007) | (0.027) | (0.006) | (0.005) | (0.018) | (0.005) |
| $r\_deposit_{i,t\text{-}1}$ | 0.000 | 0.001 | 0.000 | 0.000 | −0.003** | 0.001* |
| | (0.000) | (0.002) | (0.000) | (0.000) | (0.001) | (0.000) |
| *City FE* | YES | YES | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES | YES | YES |
| *Constant* | 1.465 | −13.358** | 3.123** | 2.176* | −4.305 | 2.634** |
| | (1.261) | (6.041) | (1.351) | (1.106) | (4.554) | (1.158) |
| *Observations* | 1400 | 1400 | 1400 | 1400 | 1400 | 1400 |
| *Adjusted* $R^2$ | 0.965 | 0.627 | 0.961 | 0.981 | 0.663 | 0.979 |

This table reports InsurTech's effect on entry barriers to the insurance sector. The dependent variables are the logarithm of the number of branches in columns (1) and (4), the logarithm of the number of "new entrant" branches in columns (2) and (5), and the logarithm of the number of "incumbent" branches in columns (3) and (6). We define an insurer as a new entrant if its age is below the 25th percentile of the age distribution; otherwise, it is an incumbent insurer. Columns (1)–(3) show the results for the non-life insurance sector and columns (4)–(6) show the results for the life insurance sector. The main independent variable of interest is $InsurTech_{i,t\text{-}1}$, which is the natural logarithm of the demand-side InsurTech index from the PKU-DFIIC. The city-specific control variables include the natural logarithm of city-level GDP $lnGDP_{i,t\text{-}1}$, the natural logarithm of city-level average wage $lnsalary_{i,t\text{-}1}$, the number of high schools in the city $num\_school_{i,t\text{-}1}$, the ratio of foreign direct investments to local GDP $r\_foreign_{i,t\text{-}1}$, the proportion of the number of workers in the financial sector $r\_fin\_work_{i,t\text{-}1}$, and the ratio of total deposits to local GDP $r\_deposit_{i,t\text{-}1}$. Both city fixed effects and year fixed effects are included in the regression. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

channel reduces agent's commission expenses for insurers. Second, advanced technologies such as blockchain and smart contracts (such as on the Ant Group platform) lower insurers' costs in underwriting and claim management. We check whether InsurTech indeed lowers insurer's costs. Before moving forward, note that we have no information on the cost of branches at the city level. Instead, we manually collected the headquarters-level financial information of each insurer from annual reports over the sample period of 2012–2018. As is discussed in the construction of the new supply-side InsurTech index, we created a dummy variable $InsurTech\_h_{j,t}$ that equals one if insurer *j* has either started to sell insurance products on its own website or mobile app or has started to collaborate with other digital platforms to sell traditional insurance products and/or create new insurance products in year *t*, and zero otherwise. We combine the above data and examine InsurTech's effect on the costs of non-life (life) insurers with following regression model:

$$cost_{j,t} = \alpha_0 + \alpha_1 Insurtech\_h_{j,t\text{-}1} + \gamma' Z_{j,t\text{-}1} + \lambda_j + \delta_t + \varepsilon_{i,t}, \tag{4}$$

where *j* denotes the insurer and *t* denotes the year. The dependent variable is the ratio of operating and administrative expenses to total premiums ($cost_{j,t}$). To account for other factors that may affect insurers' costs, we also include the natural logarithm of total assets ($lnasset_{j,t\text{-}1}$), the age of each insurer ($Age_{j,t\text{-}1}$), the Herfindahl-Hirschman Index of premiums across lines of business for each insurer ($HHI\_line_{j,t\text{-}1}$), and the proportion of ceded premiums ($r\_cede_{j,t\text{-}1}$). We include both firm fixed effects ($\lambda_j$) and year fixed effects ($\delta_t$) in our regression. The results in Table 10 show that, for non-life insurers, InsurTech reduces insurers' costs significantly; for life insurers, the "InsurTech effect" is negative but insignificant. One explanation would be that traditional agents still play an important role in online sales of life insurance products because customers need agents to explain the complex terms and offer professional guidance even if the product is sold online. The insignificant effect of InsurTech on the costs of life insurers also helps explain why small and medium-sized life insurers do not embrace InsurTech more actively than large life insurers. Overall, the analyses on the entry barriers and the insurers' costs are consistent with the baseline results that InsurTech significantly reduces the non-life insurance sector's market concentration but plays a limited role in the life insurance sector's market structure.

## 5. Conclusions

Although online trading has been prevalent over the past quarter century, the recent development of Fintech and the rising platform economy are entirely new phenomena (Hong et al., 2020). This paper examines the effect of technology innovations on traditional financial markets, with a special focus on the insurance sector. Before the emergence of Fintech platforms like Ant, insurers primarily delivered insurance products through agents and bancassurance. The new digital distribution channels directly threaten those traditional distribution channels. Customers can purchase not only traditional insurance products but scenario-based new insurance products that utilize big data from Fintech platforms. Blockchain and smart contracts on Fintech platforms allow customers to pay their premiums automatically and submit claims online. An increasing number of insurers are actively responding to the challenge of the Fintech platforms by adopting up-to-date technologies and collaborating with such Fintech platforms. Against this backdrop, we examine InsurTech's effect on the insurance sector, with a special focus on the market structure.

Based on several unique datasets with different levels of granularity from six sources in China, we provide a comprehensive landscape on how InsurTech is reshaping the insurance sector. Our results show that InsurTech significantly reduces the non-life insurance sector's market concentration, but plays a limited role in the life insurance sector's market structure. The results are not driven by reverse causality and remain unchanged when we employ an instrumental variables approach and use an alternative supply-side InsurTech index. We further explore the underlying mechanisms through which InsurTech affects the market structure of the insurance sector and find that InsurTech lowers entry barriers of new non-life insurers and reduces non-life insurers' costs. However, InsurTech does not help new life insurers enter local markets and fails to significantly reduce life insurers' costs, which helps explain the limited role of InsurTech in reducing the market concentration of the life insurance sector. The limited role of InsurTech in the life insurance sector's market structure is attributable to four factors: an insignificant effect of InsurTech on life insurers' costs, a limited role of InsurTech in helping new life insurers enter local markets, similar attitudes toward InsurTech adoption among life insurers of different sizes, and the branding and reputation concerns of customers toward small life insurers.

This study helps us better understand the dynamics of InsurTech and its effect on the insurance sector, and our findings have great policy implications. InsurTech is particularly suitable for the commodity-like and simple insurance products. Small and medium-sized non-life insurers should focus on digital sales and innovations of these products to gain more market shares. By contrast, the complexity of life insurance products induces customers to trust large insurers more, which contributes to the limited role of InsurTech in the life insurance sector's market structure, at least in the current early stage of InsurTech development. In addition, regulators should provide more flexible arrangements to facilitate the development of InsurTech such as establishing a regulatory sandbox and revising regulations to accommodate technology innovations and new business. However, regulators also need to address data protection and the potential cyber risks to ensure the benefits of policyholders.

The rich data in China's insurance market enable us to take the first step to provide a comprehensive analysis on whether and how InsurTech is reshaping the insurance sector, but there are some limitations for our study. First, the city-level analysis may not be granular enough to entirely address the endogeneity concern. In this study, we endeavor to alleviate the endogeneity concern to the best of our ability, which includes using one-year lagged independent variables, explicitly examining the potential reverse causality from both the supply and the demand channels, and performing 2SLS regressions with two instrumental variables. We also construct a new supply-side InsurTech index to further check the robustness of the baseline regression results. If we had the individual-level data, we would be able to directly examine how InsurTech influences the purchasing behavior of customers, which in turn affects the market structure. Second, our findings mainly reflect InsurTech's effect on the insurance in InsurTech's early stages of development. Although

**Table 10**
InsurTech and insurers' costs.

| | *The dependent variable: $cost_{j,t}$(%)* | | | |
|---|---|---|---|---|
| | Non-life insurers | | Life insurers | |
| | (1) | (2) | (3) | (4) |
| *$InsurTech\_h_{j,t-1}$* | −0.159** | −0.138*** | −0.094 | −0.081 |
| | (0.066) | (0.053) | (0.076) | (0.077) |
| *$lnasset_{j,t-1}$* | | −0.104** | | −0.167** |
| | | (0.049) | | (0.073) |
| *$Age_{j,t-1}$* | | 0.057*** | | 0.009 |
| | | (0.018) | | (0.035) |
| *$HHI\_line_{j,t-1}$* | | −0.046 | | −0.181 |
| | | (0.317) | | (0.154) |
| *$r\_cede_{j,t-1}$* | | 0.018*** | | −0.001 |
| | | (0.006) | | (0.001) |
| *Firm FE* | YES | YES | YES | YES |
| *Year FE* | YES | YES | YES | YES |
| *Constant* | 0.343*** | −0.471 | 0.260*** | 2.343*** |
| | (0.066) | (0.815) | (0.090) | (0.729) |
| *Observations* | 405 | 405 | 360 | 360 |
| *Adjusted $R^2$* | 0.477 | 0.580 | 0.301 | 0.321 |

This table reports InsurTech's effect on insurers' costs. The dependent variable is the ratio of operating and administrative expenses to total premiums. Columns (1)–(2) show the results for non-life insurers and columns (3)–(4) show the results for life insurers. The key independent variable of interest is *$InsurTech\_h_{j,t-1}$*, which is a dummy variable indicating whether an insurer has its own website or mobile app to sell insurance products or collaborates with other digital platforms to sell traditional insurance products and/or create new insurance products. The control variables include the natural logarithm of total assets (*$lnasset_{j,t-1}$*), the age of the insurer (*$Age_{j,t-1}$*), the Herfindahl-Hirschman Index of premiums across lines of business for each insurer (*$HHI\_line_{j,t-1}$*), and the proportion of ceded premiums (*$r\_cede_{j,t-1}$*). Both firm fixed effects and year fixed effects are included in the regression. Robust standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

the effect of InsurTech is not significant for life insurance at present, chances are that InsurTech may better resolve information asymmetries in complex insurance products and alleviate customers' concerns about branding in the future. However, our findings still provide great insights to other countries whose Fintech development lags behind the United States and China.

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## Data availability

The authors do not have permission to share data.

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