Proceedings of ICMRED 2026 symposium: Financial Innovation, Risk Governance, and the Dynamics of Global Capital Flows
DOI: 10.54254/2754-1169/2026.BL33663

Mechanisms Through Which Health Status Affects Commercial Health Insurance Enrollment Decisions Under the COVID-19 Shock: Empirical Evidence from Micro-Survey Data in 2019 and 2021

Ang Li

School of Insurance, University of International Business and Economics, Beijing, China
lidengdeng2005@163.com

Abstract. Against the backdrop of COVID-19 as a major public health emergency, this paper draws on the 2019 and 2021 China Household Finance Survey microdata to examine whether the pandemic changed how health status affects individuals' commercial health insurance purchase decisions, with insurance purchase as the dependent variable, with insurance participation as the dependent variable. It also explores heterogeneity across groups. To this end, an interaction Probit model is constructed to analyze changes in commercial health insurance participation before and after the pandemic and its interaction with health status while controlling for gender, marital status, education, risk attitude, age, household income, household assets, and province fixed effects. The results show that the pandemic significantly raised the likelihood of purchasing commercial health insurance, suggesting that major public health events enhance individuals' perception of health risks and increase the demand for insurance protection. The effect is also clearly heterogeneous across health groups: those in very poor health are affected most, followed by those in average health, indicating that the post-pandemic rise in insurance demand is concentrated among individuals with weaker health status. Robustness checks and heterogeneity analysis further show that these findings remain largely valid under alternative model specifications, and that low-income and less-educated groups respond more strongly. This study deepens understanding of how public health shocks reshape insurance behavior and provides empirical support for improving commercial health insurance supply, expanding inclusive protection, and strengthening health risk management.

Keywords: COVID-19, commercial health insurance, health status, interaction Probit model

1. Introduction

In recent years, population aging has accelerated, the burden of chronic disease has grown, and demand for health protection has continued to rise. As a result, commercial health insurance has become increasingly important as a complementary component of China's multi-level medical security system. The National Healthcare Security Administration has stated that, based on basic

DOI: 10.54254/2754-1169/2026.BL33663

medical insurance, support should be given to other forms of protection, including commercial health insurance, to better meet the diverse needs of the population. It has also emphasized that commercial health insurance constitutes an important component of the multi-level medical security system and should develop in coordination with government founded medical insurance while performing a distinct role. At the same time, industry data show that in 2023, long-term health insurance reserves exceeded 2 trillion yuan, which indicates stronger capital accumulation and risk protection capacity in this sector.

However, compared with the rapid growth in demand for health protection, the commercial health insurance market in China is still in a stage of relatively fast development but faces insufficient supply. Studies have shown that, even after reform, China's commercial health insurance sector has long faced the issue of low coverage and has mainly functioned as a supplement to the part of medical security not covered by the government [1]. Statistics obtained from the CHFS in 2021 indicate that the individual participation rate in commercial health insurance in China was only 4.25%. Such a low participation rate can increase the financial vulnerability of households [2]. It also weakens the insurance industry's role as an economic shock absorber and a stabilizer of society [3]. Therefore, examining the factors that affect individuals' decisions to purchase commercial health insurance is of huge significance for household risk protection and the growth of the commercial health insurance market in China.

This paper focuses on whether the COVID-19 shock changed how health status affects individuals' decisions to purchase commercial health insurance. Its main contributions are as follows: First, it links major public health emergencies with commercial health insurance participation along with identifies changes in the relationship between health status and insurance decisions by comparing the periods before and after the pandemic. Prior research on commercial health insurance demand mainly examines factors such as household economic conditions, demographic characteristics (marital status) [4, 5] and financial literacy [6], while paying less attention to how public health shocks may change the role of health status. This paper not only examines whether the COVID-19 outbreak made individuals more likely to purchase commercial health insurance but also analyzes whether it widened participation differences across groups with different health conditions. In this way, it extends the research perspective on demand in the private health insurance market. Second, using national micro-survey data, this paper provides more detailed evidence at the individual level. Existing studies have paid more attention to changes in industry, city, or overall market level, but have offered limited discussion of changes in individuals' enrollment in private health insurance, which is the type of insurance most directly related to health risk. Using statistics from the 2019 and 2021 China Household Finance Survey, this paper identifies the overall change in participation after the pandemic and further conducts heterogeneity analysis by income and education, thus providing micro-level evidence on different responses in health protection demand under a public health shock.

2. Literature review

Existing studies have discussed the factors affecting residents' demand for commercial insurance in considerable detail. In general, the literature shows that participation in commercial insurance is influenced by many factors, including household income, demographic characteristics, risk preference, financial knowledge, the economic environment, and social interaction.

Wei Guo reports a significant positive relationship between income volatility and household commercial insurance consumption [7]. Using CHFS data, He Jincai and Tang Shijie examine how family demographic composition influences commercial life insurance demand [8]; Xie Yu et al.

DOI: 10.54254/2754-1169/2026.BL33663

find that risk preference is positively associated with household commercial insurance holding [9]; Zeng Lingling and Xing Siyuan empirically study the influence of digital finance development on household participation in commercial insurance [10]; Li Ding, Ding Junsong, and Ma Shuang analyze household enrollment in private insurance from the perspectives of social interaction along with social capital [11].

In research on private health insurance, related studies further show that health risk factors play a more direct role in insurance decisions. Lin Zizhen shows that health status plays an important role in individuals' private health insurance purchase decisions [12]; Liu Xiaoqin and Lou Xinyi analyze the relationship among health risk, risk attitude, and enrollment in private health insurance, and discuss the possible presence of adverse selection and advantageous selection [13]. These studies show that, compared with general commercial insurance, commercial health insurance demand is more strongly driven by needs for protection against health risks. However, the effect of health status on participation is not simply linear and still deserves further study.

In recent years, with the outbreak of COVID-19, how public health shocks affect residents' insurance demand has also become a growing research focus. Gu Leilei, Wang Hongyu, and Peng Yuchao discuss the long-term effects of major public emergencies from the perspectives of pandemic experience and uncertainty expectations [14]. In the field of insurance demand, Wei Wei, Wang Xiangnan, Ji Yang, and others use monthly city-level data to examine how public health crises affect inclusive insurance and insurance technology [15]; Qian uses city-level data from China and finds that COVID-19 significantly increased insurance demand [16]. These studies suggest that public health events can affect residents' insurance behavior by changing risk perception and protection demand. However, prior research has mainly examined changes at the city level, the industry level, or the insurance market.

Overall, the existing literature still has two gaps. First, although studies on commercial health insurance have considered health risk factors, they have not fully examined whether the pandemic changed the effect of health status on participation decisions. Second, studies on the pandemic and insurance demand have mainly focused on the macro or regional level, while there is still limited evidence at the individual level, especially for groups with different health conditions. Based on this, this paper uses statistic from the 2019 and 2021 China Household Finance Survey to analyze whether the COVID-19 shock changed the impact of health status on private health insurance participation among individual respondents. It also conducts heterogeneity analysis by income, education, and gender to provide more detailed micro-level evidence on changes in health protection demand under a public health shock.

3. Methodology

3.1. Data source

The dataset for this study is drawn from the China Household Finance Survey (CHFS). Organized by the Survey and Research Center for China Household Finance at Southwestern University of Finance and Economics, the CHFS collects nationwide household-level survey data. Its purpose is to collect household-level financial data and provide basic data support for academic research, policymaking, and industry development and innovation. The survey is conducted through online questionnaires. It covers personal information and employment, financial and non-financial assets (such as agriculture, business, housing, land, and durable goods), household debt, household income, consumption expenditure, social security, and insurance.

DOI: 10.54254/2754-1169/2026.BL33663

To compare changes in individual commercial health insurance enrollment before and after the pandemic, this paper combines the 2019 and 2021 samples to construct a pooled cross-sectional dataset. To ensure data quality, observations with incomplete information on key variables are removed. Samples with zero or negative income and other extreme abnormal values are also excluded. In addition, observations with responses such as "unknown", "don't know," or other invalid answers are deleted to improve the reliability of the estimates. The final sample includes 102,347 valid observations, of which 58,525 are from 2019 and 43,822 are from 2021.

3.2. Variable definitions and measurement

3.2.1. Dependent variable: participation in commercial health insurance

This study uses commercial health insurance enrollment as the dependent variable. The variable is directly drawn from the CHFS records on commercial insurance for all members of each surveyed household. It is a binary variable: it is assigned a value of 1 if the individual has purchased private health insurance, and 0 if not. It is used to indicate whether an individual participates in commercial health insurance.

3.2.2. Key independent variables: individual health status and time dummy variable

The key independent variables are health status and a time dummy. In the CHFS questionnaire, question [A2025b] records the physical condition of household members as follows:

"Compared with others of the same age, how is your current health? 1. Very good; 2. Good; 3. Average; 4. Poor; 5. Very poor."

Based on this question, this paper constructs a health status variable for household members and codes it according to the original survey order, with a higher value indicating worse health. Since health status is an ordered categorical variable, it is treated as both a categorical variable and a continuous ordered variable in the empirical analysis to assess the stability of the findings across different model specifications. The time dummy is a binary variable based on survey year, taking the value of 1 for 2021 and 0 for 2019, and is used to identify the pandemic shock.

3.2.3. Other control variables

For the control variables, this paper includes individual characteristics from several dimensions. Basic demographic variables include the continuous variables age and its squared term, the categorical variable gender, as well as the ordered categorical variable marital status. The marital status variable is based on question [A2024] in the CHFS questionnaire and reflects possible differences in family support. The question is:

"Please indicate your current marital status? 1. Single; 2. Married; 3. In cohabitation; 4. Separated; 5. Divorced; 6. Spouse deceased."

Socioeconomic status is measured by education attainment, aggregate household income, and the aggregate household assets. Education level is treated as an ordered categorical variable based on responses to question [A2012] in the CHFS questionnaire:

"What is your level of education? (highest level attended, including current study, incomplete study, or dropout) 1. No formal education; 2. Primary education; 3. Lower secondary education; 4. Upper secondary education; 5. Technical secondary or vocational high school; 6. Junior college or higher vocational college; 7. Undergraduate degree; 8. Master's degree; 9. Doctoral degree. "

DOI: 10.54254/2754-1169/2026.BL33663

Aggregate household income and aggregate household assets are log-transformed in order to reduce skewness.

In addition, previous studies show that risk attitude significantly affects household demand for commercial insurance. Therefore, this paper includes risk attitude as a control variable. It is measured by question [H3104] in the CHFS questionnaire:

"If you had some money available for investment, which type of investment would you prefer most? 1. High risk with high return; 2. Relatively high risk with relatively high return; 3. Moderate risk with moderate return; 4. Relatively low risk; 5. Not willing to take any risk; 6. Unsure."

3.3. Descriptive statistics

Table 1 presents individual private health insurance enrollment in 2019 and 2021. The descriptive statistics show that in the 2019 sample, 1,956 individuals purchased commercial health insurance and 56,592 did not, with a total sample size of 58,548 and a participation rate of 3.34%. In the 2021 sample, 1,863 individuals purchased commercial health insurance and 41,963 did not, with a total sample size of 43,826 and a participation rate of 4.25%. A comparison of the two years shows that although the total sample size in 2021 was smaller than in 2019, the commercial health insurance enrollment rate was clearly higher, increasing by 0.91%.

Table 1. Descriptive statistics of individual participation in commercial health insurance

Year	Insured	Uninsured	total	Participation rate/%
2019	1955	56570	58525	3.34
2021	1863	41959	43822	4.25

Table 2 presents individual participation in commercial health insurance by health status in 2019 and 2021. Overall, in both years, individuals with poorer health have a clearly lower participation rate than those with better health.

A further comparison of participation rates across health groups before and after the pandemic shows that, in 2021, all groups have higher participation rates than in 2019, indicating a general increase in commercial health insurance demand after the pandemic. Among them, the group in very poor health shows the largest increase, with the participation rate rising from 0.53% in 2019 to 1.62% in 2021. In contrast, although participation also rises among healthier groups, the increase is smaller. This indicates a stronger need for commercial health insurance coverage has grown more strongly among individuals with poorer health, and their disadvantage in participation relative to healthier groups has narrowed.

Table 2. Descriptive statistics of health status

Year	Health Status	Insured	Uninsured	total	Participation rate/%
	Very Good	336	7676	8012	4.19
	Good	841	17796	18637	4.51
2019	Average	671	20678	21349	3.14
	Poor	94	7972	8066	1.17
	Very Poor	13	2448	2461	0.53
	Very Good	369	7147	7516	4.91
	Good	797	13778	14575	5.47

DOI: 10.54254/2754-1169/2026.BL33663

Table 2. (continued)

2021	Average	579	14118	14697	3.94
	Poor	95	5520	5615	1.69
	Very Poor	23	1396	1419	1.62

Table 3 reports summary statistics for the control variables in 2019 and 2021. Overall, the distributions of gender, marital status, educational attainment, and risk preference, age, household income, and household assets are relatively stable across the two samples, though some differences remain. In particular, the 2021 sample shows slightly higher education levels, average age, and levels of household income and assets than the 2019 sample. These results suggest that individual characteristics and household economic conditions are not fully identical before and after the pandemic. Therefore, it is necessary to control for these variables in the regression analysis to reduce potential bias from sample differences in estimating commercial health insurance participation.

Table 3. Summary statistics of control variables

Year	Variable	Sample Size	Mean	Standard deviation	Minimum	Maximum
	Gender	58525	1.501	0.500	1.000	2.000
	Marital status	58525	2.167	1.098	1.000	6.000
	Education level	58525	3.447	1.749	1.000	9.000
	Risk attitude	58525	4.303	1.045	1.000	5.000
2019	Age	58525	50.104	17.014	0.000	117.000
	Age squared	58525	2799.924	1731.868	0.000	13689.000
	Ln(total income)	58525	10.758	1.353	0.000	16.311
	Ln(total asset)	58525	12.851	1.550	0.000	20.414
	Gender	43822	1.501	0.500	1.000	2.000
	Marital status	43822	2.169	1.114	1.000	6.000
	Education level	43822	3.656	1.825	1.000	9.000
2021	Risk attitude	43822	4.267	1.025	1.000	5.000
	Age	43822	51.247	17.206	17.000	104.000
	Age squared	43822	2922.249	1766.844	289.000	10816.000
	Ln(total income)	43822	10.837	1.437	0.000	16.249
	Ln(total asset)	43822	13.140	1.518	2.303	18.333

4. Regression analysis

4.1. Model specification

Since the dependent variable, whether an individual purchases commercial health insurance, is binary, this paper uses a Probit model for estimation. To examine whether the pandemic changed how health status affects insurance decisions, the model includes health status, a post-pandemic dummy variable, and their interaction term. Based on this, the following model is specified.

DOI: 10.54254/2754-1169/2026.BL33663

$$P(Ins_{it}=1)=\phi(\alpha+\sum_{k=2}^{5}\beta_k health_{itk}+\gamma Post_t+\sum_{k=2}^{5}\delta_k(health_{itk}\times Post_t)+\mu_p) \tag{1}$$

In the model, Ins_{it} indicates whether individual i purchases commercial health insurance in year t, taking the value 1 if insured and 0 otherwise; $\Phi(\cdot)$ represents the standard normal CDF. $Post_t$ is a time dummy, equal to 1 for 2021 and 0 for 2019, capturing the pandemic shock. $Health_{itk}$ represents health status dummy variables, with "very good" as the reference group, and $k=2,3,4,5$ corresponding to "good," "average," "poor," and "very poor". X_{it} represents the control-variable set, which covers gender, marital status, educational attainment, risk preference, age, and the squared term of age, the logarithm of aggregate household income, and the aggregate household assets; μ_p denotes province fixed effects, which control unobserved regional factors.

In addition, β_k captures the difference in participation between individuals with different health levels and the reference group before the pandemic; γ reflects the change in participation for the reference health group after the pandemic; δ_k is the key parameter of interest, reflecting how the post-pandemic change differs between each health group and the reference group, that is, whether the pandemic altered the effect of health status on insurance decisions. If δ_k is significantly positive, it means that the pandemic reduced the participation disadvantage of individuals with poorer health. If it is significantly negative, it means that the pandemic strengthened the negative effect of poor health on participation.

4.2. Empirical analysis

Tables 4 and 5 present the estimation results obtained from this model. To make the effects of each variable on commercial health insurance purchase probability easier to compare, this paper presents average marginal effects. Table 4 reports the AME estimated from the model without interaction terms, showing the overall direction, magnitude, and significance of each variable. Table 5 reports the group-specific average marginal effects of the post-pandemic variable across different health status groups. These effects measure the average shift in individuals' likelihood of purchasing commercial health insurance when the post-pandemic dummy changes from 0 to 1 within each health group, capturing the heterogeneous impact of the pandemic.

Table 4. Regression results without interaction terms

Variable		Average Marginal Effects (AME)	P value	95% Confidence Interval
Health Status	Good	0.0061*** (0.0021)	0.0037	[0.0020, 0.0102]
	Average	0.0058*** (0.0019)	0.0020	[0.0021, 0.0095]
	Poor	-0.0020 (0.0027)	0.4536	[-0.0074, 0.0033]
	Very Poor	-0.0026 (0.0046)	0.5799	[-0.0116, 0.0065]

DOI: 10.54254/2754-1169/2026.BL33663

Table 4. (continued)

Time Dummy Variable	0.0065*** (0.0017)	0.0001	[0.0033, 0.0098]
Gender	0.0051*** (0.0008)	0.0000	[0.0036, 0.0066]
Marital status	0.0034*** (0.0008)	0.0000	[0.0019, 0.0050]
Education level	0.0061*** (0.0007)	0.0000	[0.0047, 0.0075]
Risk attitude	-0.0065*** (0.0007)	0.0000	[-0.0079, -0.0052]
Age	0.0046*** (0.0003)	0.0000	[0.0041, 0.0052]
Age squared	-0.0001*** (0.0000)	0.0000	[-0.0001, -0.0000]
Ln(total income)	0.0049*** (0.0008)	0.0000	[0.0034, 0.0065]
Ln(total asset)	0.0096*** (0.0010)	0.0000	[0.0077, 0.0116]

Note: Province-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table 5. Estimation results with interaction terms

	ic Average Marginal Effects	P value	95% Confidence Interval
Very Good	0.0040 (0.0047)	0.3920	[-0.0052, 0.0132]
Good	0.0060* (0.0032)	0.0605	[-0.0003, 0.0123]
Average	0.0079*** (0.0023)	0.0005	[0.0034, 0.0124]
Poor	0.0055* (0.0029)	0.0576	[-0.0002, 0.0111]
Very Poor	0.0121*** (0.0040)	0.0026	[0.0042, 0.0200]

Note: Province-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

The results in Table 4 suggest that, after controlling gender, marital status, education, risk performance, age squared, log-transformed household income and household assets, and province fixed effects, the AME of the time dummy is 0.0065 with statistical significance at the 1% level. This finding suggests that, compared with the pre-pandemic period, the probability of purchasing

DOI: 10.54254/2754-1169/2026.BL33663

commercial health insurance increased by 0.65% after the pandemic. This suggests that the pandemic enhanced individuals' awareness of health risks and increased their willingness to obtain commercial health insurance coverage.

Meanwhile, gender, marital status, education, household income and asset holdings are all positively and significantly associated with participation, consistent with existing studies. Risk attitude shows a significant negative effect, while age and its squared term together how that the relationship between age and participation follows an inverted U-shaped pattern. Overall, Table 4 confirms that the model has good explanatory power and provides a basis for further heterogeneity analysis.

Table 5 shows clear differences in the impact of the pandemic across health groups. The "very poor" health group has the largest average marginal effect, at 0.0121, and with statistical significance at the 1% level, suggesting that the probability of obtaining commercial health insurance coverage increased by 1.21% after the pandemic. The "average" health group ranks second, with an effect of 0.0079, also reaches the 1% significance level, implying a growth of 0.79%.

In contrast, although the effects for the "very good," "good," and "poor" groups are positive, they are not statistically significant at conventional levels, suggesting that the increase in participation for these groups is not stable. Overall, the rise in participation after the pandemic is mainly concentrated among individuals in "very poor" and "average" health, with the strongest effect in the former. This indicates that the pandemic more strongly increased the demand for health protection among individuals with weaker health status.

5. Examination

5.1. Robustness check on the specification of the health status variable

To verify the stability of the earlier findings, this paper changes the specification of the key independent variable, health status, by treating it as a continuous ordered variable instead of a categorical variable and re-estimates the model.

$$P\left(Ins_{it}=1\right)=\phi\left(\alpha+\beta health_{it}+\gamma Post_t+\delta\left(health_{it}\times Post_t\right)+\mu_p\right) \tag{2}$$

Table 6 shows that the overall average marginal effect of health status (treated as continuous) is 0.0002 and not significant, indicating that, in the full sample, health status changes are not significantly associated with participation on average. However, the period-specific results show that in 2019 the effect is −0.0015 and not significant, while in 2021 it is 0.0024 and reaches the 5% significance level. This suggests that after the pandemic, a one-level deterioration in health increases the probability of purchasing commercial health insurance by about 0.24%.

This result suggests that, even when health status is treated as a continuous ordered variable, the main conclusion still holds: the pandemic changed the effect of health status on participation decisions. Before the pandemic, health differences had no significant effect; after the pandemic, poorer health conditions are associated with a greater likelihood of insurance purchase. This result aligns with the earlier interaction results and supports the robustness of the findings.

In addition, the results for other control variables remain largely unchanged. The time dummy is still significantly positive, indicating a higher overall participation rate after the pandemic. Gender, marital status, education, household income, and household assets all have significant positive effects, while risk attitude has a significant negative effect. Age and its squared term continue to

DOI: 10.54254/2754-1169/2026.BL33663

indicate that the relationship between age and participation follows an inverted U-shaped pattern. Overall, the robustness test supports the main conclusions of the baseline results.

Table 6. Robust results under an alternative specification of the health status variable

Variable		Average Marginal Effects (AME)	P value	95% Confidence Interval
Health Status (Continuous)		0.0002 (0.0007)	0.8030	[-0.0013, 0.0016]
Health Status (Interaction)	2019	-0.0015 (0.0011)	0.187	[-0.0038, 0.0007]
	2021	0.0024** (0.0011)	0.034	[0.0001, 0.0047]
Time Dummy Variable		0.0063*** (0.0017)	0.0002	[0.0030, 0.0097]
Gender		0.0052*** (0.0008)	0.0000	[0.0037, 0.0067]
Marital status		0.0035*** (0.0008)	0.0000	[0.0019, 0.0050]
Education level		0.0062*** (0.0007)	0.0000	[0.0048, 0.0076]
Risk attitude		-0.0066*** (0.0007)	0.0000	[-0.0079, -0.0052]
Age		0.0047*** (0.0003)	0.0000	[0.0041, 0.0053]
Age squared		-0.0001*** (0.0000)	0.0000	[-0.0001, -0.0001]
Ln(total income)		0.0050*** (0.0008)	0.0000	[0.0035, 0.0065]
Ln(total asset)		0.0098*** (0.0010)	0.0000	[0.0078, 0.0117]

Note: Province-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

5.2. Robust check using alternative model specifications

To further examine robustness, this paper replaces the baseline Probit model with a Logit model and a linear probability model (LPM). As shown in Table 7, the results remain broadly consistent with the baseline findings: the COVID-19 shock increased individuals' willingness to purchase commercial health insurance, and the effect is mainly concentrated among the "average" and "very poor" health groups. Although some estimates become less significant under the LPM, the direction of the main effects remains unchanged. Therefore, changing the model specification does not alter the core conclusions of this paper.

Table 7. Estimation results under alternative model specifications

Variable	Model 1(Logit)		Model 2(Lpm)	
	Average Marginal Effects (AME)	P value	Average Marginal Effects (AME)	P value

DOI: 10.54254/2754-1169/2026.BL33663

Table 7. (continued)

Health Status	Good	0.0061*** (0.0021)	0.0037	0.0080** (0.0305)	0.0131
	Average	0.0058*** (0.0019)	0.0020	0.0057** (0.0025)	0.0328
	Poor	-0.0020 (0.0027)	0.4536	0.0038 (0.0029)	0.1900
	Very Poor	-0.0026 (0.0046)	0.5799	0.0071* (0.0039)	0.0767
Time Dummy Variable		0.0065*** (0.0017)	0.0001	0.0055*** (0.0018)	0.0044
Gender		0.0051*** (0.0008)	0.0000	0.0066*** (0.0009)	0.0000
Marital status		0.0034*** (0.0008)	0.0000	0.0042*** (0.0007)	0.0000
Education level		0.0061*** (0.0007)	0.0000	0.0093*** (0.0011)	0.0000
Risk attitude		-0.0065*** (0.0007)	0.0000	-0.0097*** (0.0011)	0.0000
Age		0.0046*** (0.0003)	0.0000	0.0029*** (0.0003)	0.0000
Age squared		-0.0001*** (0.0000)	0.0000	-0.0000*** (0.0000)	0.0000
Ln(total income)		0.0049*** (0.0008)	0.0000	0.0046*** (0.0008)	0.0000
Ln(total asset)		0.0096*** (0.0010)	0.0000	0.0078*** (0.0010)	0.0000
Group		Group-specific Average Marginal Effects	P value	Group-specific Average Marginal Effects	P value
Very Good		0.0040 (0.0047)	0.3920	0.0052 (0.0047)	0.2772
Good		0.0060* (0.0032)	0.0605	0.0061* (0.0032)	0.0680
Average		0.0079*** (0.0023)	0.0005	0.0059** (0.0024)	0.0178
Poor		0.0055* (0.0029)	0.0576	0.0028 (0.0031)	0.3767
Very Poor		0.0121*** (0.0040)	0.0026	0.0076** (0.0030)	0.0181

Note: Province-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

5.3. Heterogeneity analysis

To further examine whether the results differ across economic and human capital conditions, this paper conducts heterogeneity analysis by income and education. Table 8 shows that the positive effect of the pandemic on insurance participation among individuals with poor health is mainly

DOI: 10.54254/2754-1169/2026.BL33663

concentrated in the low-income and low-education groups. Specifically, in these groups, individuals with poorer health show larger and more significant group-specific average marginal effects after the pandemic, while the effect is weaker in the high-income and high-education groups. This suggests that individuals with lower economic and educational status are more sensitive to changes in health risk and show a stronger response in purchasing commercial health insurance.

Table 8. Heterogeneity test results

Variable		High-income	Low-income	High education level	Low education level
Health Status	Good	0.0086** (0.0037)	0.0028 (0.0020)	0.0094** (0.0041)	0.0046** (0.0021)
	Average	0.0065* (0.0038)	0.0006 (0.0022)	0.0096* (0.0050)	0.0029* (0.0016)
	Poor	-0.0029 (0.0055)	-0.0068*** (0.0024)	0.0072 (0.0074)	-0.0042* (0.0023)
	Very Poor	-0.0221** (0.0090)	-0.0027 (0.0040)	-0.0240* (0.0144)	-0.0016 (0.0034)
Time Dummy Variable		0.0059 (0.0030)	0.0086*** (0.0017)	0.0119*** (0.0034)	0.0043*** (0.0015)
Gender		0.0092*** (0.0014)	0.0025** (0.0013)	0.0126*** (0.0022)	-0.0000 (0.0009)
Marital status		0.0024 (0.0017)	0.0030*** (0.0007)	0.0055*** (0.0016)	0.0023*** (0.0006)
Education level		0.0113*** (0.0012)	0.0054*** (0.0005)		
Risk attitude		-0.0128*** (0.0011)	-0.0032*** (0.0007)	-0.0130*** (0.0014)	-0.0031*** (0.0005)
Age		0.0072*** (0.0006)	0.0032*** (0.0003)	0.0068*** (0.0006)	0.0038*** (0.0004)
Age squared		-0.0001*** (0.0000)	-0.0000*** (0.0000)	-0.0001*** (0.0000)	-0.0000*** (0.0000)
Ln(total income)				0.0108*** (0.0018)	0.0027*** (0.0005)
Ln(total asset)				0.0161*** (0.0018)	0.0067*** (0.0007)
Group					
Very Good		0.0091 (0.0064)	0.0002 (0.0050)	0.0130 (0.0080)	-0.0034 (0.0038)
Good		0.0039 (0.0043)	0.0107*** (0.0035)	0.0103** (0.0046)	0.0037 (0.0040)
Average		0.0077* (0.0040)	0.0092*** (0.0022)	0.0151** (0.0059)	0.0049** (0.0020)
Poor		0.0014 (0.0069)	0.0076*** (0.0025)	0.0007 (0.0112)	0.0061** (0.0025)
Very Poor		0.0030 (0.0069)	0.0158*** (0.0060)	0.0174 (0.0108)	0.0125*** (0.0043)

Note: Province-clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10

DOI: 10.54254/2754-1169/2026.BL33663

6. Conclusion

The findings indicate that the pandemic significantly increased the probability of obtaining commercial health insurance coverage, indicating that major health shocks strengthen health risk awareness and raise demand for protection. Further results reveal clear heterogeneity across health groups: the effect is strongest for individuals in very poor health, followed by those in average health, suggesting that the increase in participation is mainly concentrated among less healthy individuals. Robustness checks confirm that the main findings remain unchanged under alternative specifications and models. Further analysis of heterogeneous effects shows that the effect is stronger among low-income and low-education groups, indicating that individuals with weaker socioeconomic conditions respond more strongly to health risks. Overall, the pandemic not only increased overall demand for commercial health insurance but also reshaped participation patterns across health groups, with vulnerable individuals becoming the main source of demand growth.

Based on these findings, individuals in poorer health and with weaker economic and educational conditions show a stronger willingness to obtain commercial health insurance coverage after the pandemic. Insurers should seize this opportunity to better match products with user needs by developing differentiated products for vulnerable groups and promoting service expansion and digital development to improve access and coverage.

References

[1] Choi Wi, Shi H., Bian Y., Hu H. (2018) Development of Commercial Health Insurance in China: A Systematic Literature Review. Biomed Res Int. Jun 28; 3163746.
[2] Pan J. (2014). The impact of commercial health insurance on household financial vulnerability in China [D]. Guangdong University of Finance & Economics.
[3] Yi, X., Chen, J., Zhou, C., et al. (2023). Income risk and household risky financial asset investment: Empirical evidence based on CHFS data [J]. Journal of Management Science, 26(10), 76–94.
[4] Liao L. (2024). Household risky asset allocation and commercial insurance decision [D]. Guangdong University of Finance & Economics.
[5] Chen J. (2024). The impact of marital status on household commercial insurance consumption [D]. Lanzhou University of Finance and Economics.
[6] Li W. (2024). The impact of financial literacy on the effectiveness of household commercial insurance allocation [D]. Zhongnan University of Economics and Law.
[7] Wei Guo. (2024) Income volatility and household commercial insurance allocation. Finance Research Letters, Volume 66, 105645.
[8] He J., Tang Q. (2025). The impact of household demographic structure on demand for commercial life insurance [J]. Journal of Chongqing Jiaotong University (Social Sciences Edition), 25(2), 50–60.
[9] Xie Y., Zhang B., Yao Y., Chen X. and Wang X. (2022) Mechanism of human capital influence on household commercial insurance holding behavior—An empirical analysis based on China household finance survey (CHFS) data. Front. Environ. Sci. 10: 961184.
[10] Zeng L., Xing S. (2021). The impact of internet finance on household participation in commercial insurance: Evidence from CHFS data [J]. Journal of Wuhan University of Technology (Social Sciences Edition), 34(6), 125–134.
[11] Li D., Ding J., Ma S. (2019). Social interaction and household participation in commercial insurance: Evidence from CHFS data [J]. Insurance Studies, (7), 96–114.
[12] Lin Z. (2023). Health status, risk attitude and participation in commercial health insurance [D]. Guangdong University of Finance & Economics.
[13] Liu X., Lou X. (2023). Adverse selection or advantageous selection: The impact of health risk and risk attitude on household participation in commercial health insurance [J]. Insurance Studies, (8), 16–28.
[14] Gu L., Wang H., Peng Y. (2022). Long-term impact of major public emergencies: Pandemic experience, uncertainty expectations and corporate financial investment [J]. Economic Quarterly, 22(3), 1017–1038.

DOI: 10.54254/2754-1169/2026.BL33663

[15] Wei W., Wang X., Ji Y., et al. (2023). Public health emergencies, inclusive insurance and insurtech: Empirical evidence based on urban monthly medical mutual aid data [J]. Journal of Financial Research, (8), 112–130.
[16] Qian, X. (2021) The impact of COVID-19 pandemic on insurance demand: the case of China. Eur J Health Econ 22, 1017-1024.