Interregional Population Flow and Open Growth of Insurance — Empirical Analysis Based on Provincial Panel Spatial Econometrics

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Abstract

With China being gradually transformed into an open society where population can flow freely, it deserves more attention that interregional population flow will bring about the interactive growth of insurance. Based on the traditional insurance growth theory, this paper focuses on the internal mechanism how interregional population flow can affect insurance growth, uses the provincial panel data from 2012 to 2015 to construct a flow spatial weighting matrix based on the interregional population flow scale, and sets up a spatial econometric model for empirical analysis. Results show that, if the population flow increases by 1 percentage point, the region's insurance industry will grow 0.0794 percentage points, and other regions' insurance will grow 0.184 percentage points, making the national insurance industry increase by 0.264 percentage points., which is to say, the indirect effects of spatial knowledge spillover on insurance growth account for more than two thirds of the overall effects. This conclusion provides the policy enlightenment for promoting the interregional population flow, adjusting the product structure and marketing strategy in time by insurance companies, and promoting the balanced and coordinative development of the insurance industry in China.

Keywords: Population Flow, Insurance Growth, Spatial Spillover

Competing interests:

The authors declare that there is no conflict of interest.

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1. Introduction

Population factors are an important resource to promote insurance growth and have always been one of the focal points of academic attention. Earlier literature has included structural differences in age, household registration, and education in the factors affecting insurance growth, and based on my country's development reality, has focused on the special role played by phenomena such as population aging, urbanization (citizenization), and higher education in insurance growth. However, a common feature of most studies is that they only take the population factors of the region as the research object and explore the impact of population factors and their structural differences on insurance growth from a static perspective. The lack of mobility between regions of population factors has become a default premise for these studies to conduct theoretical and empirical analysis, and the potential impact of the dynamic flow of population factors between regions on insurance growth has been ignored for a long time.

If population factors are relatively static and stable within a region due to migration and market control under closed conditions, then even if the dynamic flow of population factors between regions can theoretically play a role in insurance growth, its impact is not great. However, this situation is increasingly inconsistent with China's reality. With the acceleration of the household registration system reform process and the close exchanges and cooperation between regions, China is gradually becoming an open society with free flow of population factors. According to the "China Migrant Population Development Report" released by the Migrant Population Department of the National Health and Family Planning Commission (formerly the Migrant Population Service Management Department of the National Population and Family Planning Commission), from 2009 to 2015, the scale of China's migrant population has always been above 200 million, accounting for about one-sixth of the total population of the country (see Figure 1). We can also find that in the same period, the aging of the population has intensified, urbanization and education system reform have entered the deep water zone, the traditional population factors that drive insurance growth are generally weak, and other traditional influencing factors under the new normal of the economy lack strong driving force, China's insurance industry has still maintained rapid growth. According to statistics, from 2009 to 2015, the premium income of China's insurance industry also increased from 1113.73 billion yuan to 2428.25 billion yuan, with an average annual growth rate of 13.87%. The above data suggest that the dynamic flow of population factors between regions may have a certain impact on insurance growth. During the " Thirteenth Five-Year Plan " period, the scale of population mobility in China is expected to remain above 200 million. If we can understand the mechanism of the dynamic flow of population factors in promoting insurance growth and make good use of it, it will find a new driving force for the sustainable development of China's insurance industry in the future. In addition, the insurance growth in various regions of China is not balanced. Studying the role of population factor flow on insurance growth can also provide policy inspiration for strengthening regional insurance industry exchanges and promoting balanced development of China's insurance industry between regions. Therefore, in-depth exploration of the mechanism of population factor flow in an open environment and analysis of its potential impact on insurance growth have become an important issue that needs to be solved in reality.

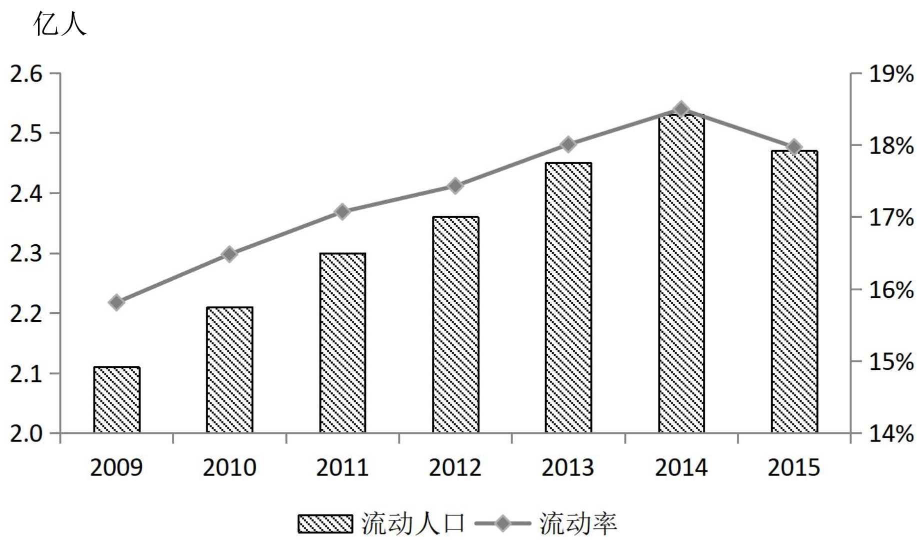

Figure 1 The size of my country's floating population and its proportion of the total population

Source: Calculated based on the China Migrant Population Development Report (2010-2016) and the China Statistical Yearbook (2016).

As mentioned above, due to the traditional research perspective, the mobility of population factors has not been included in the insurance growth theory and empirical analysis. In the absence of a systematic theoretical mechanism analysis, the empirical test of the dynamic flow of population factors between regions on insurance growth also lacks data and method support, and has not yet paid attention to the spatial correlation that may be caused by the flow of population factors between regions. Compared with previous studies, the contribution of this paper is mainly reflected in two aspects. First, based on the perspective of the dynamic flow of population factors, the mobility of population factors is incorporated into the theoretical framework of insurance growth, and the intrinsic mechanism of the flow of population factors affecting insurance growth is systematically analyzed. Second, the spatial correlation of the flow of population factors between regions is included in the empirical analysis, and a spatial econometric model is established using inter-provincial panel data to test the spatial transmission mechanism of the flow of population factors affecting insurance growth and measure the direct and indirect effects.

The rest of this article is as follows: The second part is a literature review, which systematically analyzes the internal mechanism of how the flow of population factors affects insurance growth; the third part establishes a measurement model, sets variables and performs descriptive statistics of data; the fourth part presents and analyzes the empirical results; finally, it summarizes and puts forward policy implications.

2. Literature Review

2.1 Population structure and insurance growth

Population structure refers to the proportion of heterogeneous population groups in a certain region or at a certain point in time, which are subdivided according to different standards. From a static research perspective, population structure mainly includes natural structure, social structure and geographical structure. The natural structure of the population divided by population biology includes age structure and gender structure , while the social structure of the population divided by population sociology mainly includes cultural structure, religious structure, ethnic structure, language structure, marriage structure, education structure, occupational structure, etc., while the geographical structure of the population divided by population geography mainly includes natural geographical structure, administrative division structure and urban-rural structure. Among them, the relevant population structures that have a significant impact on insurance growth mainly include gender structure, age structure, cultural and educational structure, marriage and family structure and urban-rural structure. (Liao Haiya and You Jie, 2012) With the development of economy and society, the role of population aging, urbanization (urbanization) and higher education in insurance growth has gradually become a key topic in insurance growth theory and empirical research. Huang Shan and Cao Weili (2008) used principal component analysis to combine multiple variables of population structure, such as the dependency ratio of the elderly population, urbanization rate, and educational level, and found that the above changes in China's population structure are generally in the same direction as insurance growth .

On the one hand, aging means an increase in life expectancy and a longer survival time, which is usually accompanied by a decline in income levels, resulting in a gap in pension costs. On the other hand, the incidence of chronic diseases and major diseases among the elderly is high, and medical expenses are large. When medical expenses continue to rise and basic medical insurance is insufficient, the gap in medical expenses will increase. Therefore, as the aging of the population deepens, the demand for insurance such as pension insurance and health insurance with protection functions will increase, thereby driving insurance growth (Yin Chengyuan et al., 2008). Zhuo Zhi (2001), Zhang Lianzeng and Shang Ying (2011) concluded through empirical analysis of personal insurance (or life insurance) in China that the aging rate of the population has a positive promoting effect on it. However, it should be pointed out that since automobile insurance accounts for a large proportion of property insurance (or non-life insurance), and car owners are mainly middle-aged people with higher incomes, population aging may have an adverse impact on property insurance (Guo Jinlong and Zhang Hao, 2015). More far-reaching is that the problem of population aging not only reduces human resources and slows economic development, but also may have a serious impact on insurance growth through the distribution of national income (Sun Xiuqing, 2004; Zhang Jinlin, 2005). Beck and Webb (2002) conducted a comparative analysis of the factors affecting insurance growth in 63 developing countries and 23 OECD countries in the past 20 years and found that compared with developed countries, the increase in the elderly dependency ratio in developing countries has a negative impact on insurance growth, and pointed out that the reason may be the decline in income and the large gap between the rich and the poor in developing countries.

Urbanization (citizenization) has changed the lifestyle of residents. First, it has weakened the residents' dependence on blood relatives and land. Second, as the size of the family decreases, they face new risks and seek insurance protection. Urbanization promotes economic growth, and residents' income increases accordingly, which in turn generates or increases the awareness of maintaining the safety of their own lives and property, and promotes insurance growth. Based on my country's macro data from 1990 to 2011, Guo Jinlong and Zhang Lei (2014) used a vector autoregression model to examine the impact of changes in population structure such as urbanization rate on insurance growth, and found that the deepening of urbanization will have a sustained and strong growth effect on insurance growth. Zhang Chong (2013), Yuan Cheng (2017) and many other literatures have supported this argument through empirical analysis.

In theory, higher education can promote insurance growth in the following three ways: (1) increase human capital, change risk attitudes, and be more inclined to avoid risks; (2) enhance the understanding of financial management tools and personal risks, and effectively use various risk management techniques and insurance means to diversify risks; (3) increase income levels, improve quality of life, increase life expectancy, and expand insurance demand. (Guo Jinlong and Zhang Hao, 2005) In empirical analysis, Outreville (1996) conducted an empirical analysis of insurance growth in several developing countries and found that education level has a significant promoting effect on it. Kakar and Shukla (2010) conducted a regression analysis on the growth of life insurance in India and found that it is positively correlated with education level. The more educated the household head is, the more inclined he is to buy life insurance. Sun Xiuqing (2013) selected regional data from 2001 to 2010 in China to compare and analyze the factors affecting the growth of life insurance in the east, middle and west, and found that education level is the main reason why the development level of life insurance in the middle and west lags behind that in the east. Zhang Lianzeng and Wang Jiao (2014) used a provincial panel to empirically test the factors affecting life insurance growth in my country and found that illiteracy rate has a reverse impact on life insurance density, which also supports the view that education level promotes insurance growth. Guo Jinlong and Zhang Lei (2014) found that a positive shock to education level will have a long-term and sustained pulling effect on insurance growth after a short-term reduction in insurance growth. In addition, some empirical studies, such as Zhang Chong (2013) and Yuan Cheng (2017), found that the existence of regional differences may lead to the fact that the role of education level in promoting insurance growth is not significant.

2.2 Internal mechanism of population mobility affecting insurance growth

Limited by the research perspective, population mobility has not been truly included in the scope of factors affecting insurance growth. Only a few studies have conducted a simple analysis of the potential impact of rural population mobility on urban and rural growth in the analysis of the mechanism of action of urban-rural structural changes on insurance growth (Liao Haiya and You Jie, 2012). Based on previous studies, this paper systematically sorts out the internal mechanism of population mobility on insurance growth, provides a certain theoretical basis for the subsequent empirical test, and proposes expected propositions.

The most direct impact of population mobility is the generation and increase of mobility risks. During the process of migration, settlement and employment, residents have increased risks of personal and property accidents, such as traffic accidents, damage to personal property, and work-related injuries. At the same time, due to the significant changes in lifestyle before and after migration, especially after rural residents migrated to large cities, the original mutual insurance mechanism of blood and land has been greatly weakened. Based on the inadequacy of the basic social security system and personal self-protection ability, the security gap of migrant residents in terms of pension and medical care has further widened and needs to be filled urgently. With the deepening of social integration of migrant residents and the increase of family income, insurance awareness and insurance ability have been qualitatively improved, releasing the effective demand for corresponding insurance, thereby driving insurance growth.

Another impact of population mobility is the spread of insurance awareness, insurance culture and insurance knowledge along with the pendulum-like population mobility and population return, which we collectively refer to as the spatial spillover of insurance cognition. The pendulum-like mobility theory of An Husen and Liu Junhui (2014) believes that when the technical productivity of underdeveloped regions is improved to the point where they can undertake industrial transfer from developed regions, the labor force will return. Before that, affected by the household registration system and the fact that close relatives did not migrate with them, the floating population still maintained contact with the original outflow area, and even returned intermittently. Insurance cognition in developed regions then spread, improving insurance cognition in underdeveloped regions, thereby promoting insurance growth.

In addition, the flow of population factors establishes a connection between the inflow and outflow areas, making the factors affecting insurance growth mutually affect each other: first, population mobility breaks the static structure of the population in the two places, and the age structure, urban-rural structure and education structure all change, changing human capital; second, population mobility promotes economic growth and income improvement, and increases residents and social asset reserves; third, population mobility drives industrial transfer and agglomeration, and corporate and social property risks are transferred and agglomerated accordingly; finally, population mobility promotes the allocation of insurance factors, optimizes the layout of insurance institutions' business outlets and the form of the insurance market. The above factors constitute a complex linkage network, which has a long-term impact on insurance growth.

Based on the above mechanism analysis, we propose the following two expected propositions:

Expected Proposition 1: The inter-regional mobility of population factors can not only promote the insurance growth of the inflow area, but also promote the insurance growth of the outflow area through the insurance cognitive spatial spillover effect, thereby promoting the overall growth of my country's insurance industry;

The second expected proposition is that the inter-regional flow of population factors will link the various factors that affect insurance growth in the inflow and outflow areas, forming a complex linkage network, which will jointly act on insurance growth.

3. Empirical Methods

3.1 Establishment of spatial measurement model

This paper first incorporates the population factor mobility factor into the insurance growth model to obtain the corresponding least squares model (hereinafter referred to as the OLS model):

$$ln\, ins_{it} = \beta_0 + \beta_1 \, ln\, flow_{it} + \beta_2 \, ln\, L_{it} + \beta_3 \, ln\, K_{it} + \beta_4 X_{control} + \varepsilon_{it} \quad (1)$$

Among them, ins_{it} is the total output value of the insurance industry in each region, $flow_{it}$ is the population flow in each region, L_{it} is the number of insurance industry employees in each region, K_{it} and is the stock of fixed assets in the insurance industry in each region. $X_{control}$ is the control variable group, which mainly includes population structure variables, economic and industrial variables, insurance market variables, etc. according to previous literature. ε_{it} is a random disturbance term, which obeys independent and identical distribution, that is $\varepsilon_{it} \sim iid\left(0,\sigma^2\right)$.

The premise of the above OLS model is that the variables in each region are independent of each other. However, as argued in the previous part of this paper, insurance growth and its influencing factors, especially the population flow that this paper focuses on, are not independent of each other in different regions. The scale of population flow in a certain region and its effect on insurance growth may be affected by other regions. The first law of geography proposed by Tobler (1970) points out that all things are related to each other, and are more closely related to similar things. Therefore, ignoring the spatial dependence of population flow between different regions may cause deviations in model setting. Based on this, this paper further selects a spatial econometric model that can effectively identify the spatial correlation of economic activities to examine the relationship between population flow between regions and insurance growth. The most general spatial econometric model for panel data should be:

$$ln\, ins_{it} = \beta_0 + \rho W \, ln\, Ins_{it} + \beta_1 \, ln\, flow_{it} + \beta_2 \, ln\, L_{it} + \beta_3 \, ln\, K_{it} + \beta_4 X_{control}$$

$$+\delta_1 W \, ln\, flow_{it} + \delta_2 W \, ln\, L_{it} + \delta_3 W \, ln\, K_{it} + \delta_4 W X_{control} + \mu_{it} \quad (2)$$

$$\mu_{it} = \lambda W \mu_{it} + \varepsilon_{it}$$

Among them, W is the spatial weight matrix. μ_{it} is the random disturbance term, which obeys independent and identical distribution, that is $\mu_{it} \sim iid\left(0,\sigma^2\right)$.

However, current empirical studies all use the following special forms to test different types of spatial transmission mechanisms. The first spatial Durbin model (hereinafter referred to as the SDM model) mainly considers the spatial interaction mechanism that the insurance growth of a certain region is not only affected by factors in the region, but also by the insurance growth and factors in other regions. The model is set as follows:

$$ln\,ins_{it} = \beta_0 + \rho W\,ln\,Ins_{it} + \beta_1\,ln\,flow_{it} + \beta_2\,ln\,L_{it} + \beta_3\,ln\,K_{it} + \beta_4 X_{control}$$

$$+\delta_1 W\,ln\,flow_{it} + \delta_2 W\,ln\,L_{it} + \delta_3 W\,ln\,K_{it} + \delta_4 W X_{control} + \varepsilon_{it} \quad (3)$$

The second spatial autocorrelation model (hereinafter referred to as the SAC model) mainly considers the interactive impact of insurance growth among regions, and the spatial spillover may also be subject to the random shock of unobservable factors. The model is set as follows:

$$ln\,ins_{it} = \beta_0 + \rho W\,ln\,Ins_{it} + \beta_1\,ln\,flow_{it} + \beta_2\,ln\,L_{it} + \beta_3\,ln\,K_{it} + \beta_4 X_{control} + \mu_{it} \quad (4)$$

$$\mu_{it} = \lambda W \mu_{it} + \varepsilon_{it}$$

If there is only spatial autocorrelation between regions, but no spatial interaction mechanism, that is, in the SDM model $\delta_i = 0$ (i = 1, ..., 4), and no spatial random shock, that is, in the SAC model λ=0 , then the third spatial econometric model, the spatial autoregressive model (hereinafter referred to as the SAR model), is established. The model is set as follows:

$$ln\,ins_{it} = \beta_0 + \rho W\,ln\,Ins_{it} + \beta_1\,ln\,flow_{it} + \beta_2\,ln\,L_{it} + \beta_3\,ln\,K_{it} + \beta_4 X_{control} + \varepsilon_{it} \quad (5)$$

If the insurance growth between regions is only subject to spatial random shocks, that is, it is satisfied in the SDM model $\delta_i = -\rho\beta_i$ or appears in the SAC model ρ=0 , then the fourth spatial econometric model, the spatial error model (hereinafter referred to as the SEM model), is established. The model is set as follows:

$$ln\,ins_{it} = \beta_0 + \beta_1\,ln\,flow_{it} + \beta_2\,ln\,L_{it} + \beta_3\,ln\,K_{it} + \beta_4 X_{control} + \mu_{it} \quad (6)$$

$$\mu_{it} = \lambda W \mu_{it} + \varepsilon_{it}$$

Different types of spatial econometric models examine different spatial mechanisms. In order to establish a spatial econometric model with the best fitting effect for empirical analysis, this paper conducts empirical measurement in the order of OLS model, $\rightarrow$SEM model , SAR model , $\rightarrow$SAC model and $\rightarrow$SDM model, and analyzes the results by statistical tests such as Wald and LR. (Bai Junhong et al., 2017)

3.2 Variable setting

(1)Spatial weight matrix

The premise of spatial econometric analysis is to measure the spatial distance between regions. Earlier studies used the adjacency between regions to determine it, that is, if two regions are adjacent, the corresponding element in the spatial weight matrix is 1, otherwise it is 0. However, this adjacency matrix is not enough to reflect the objective facts between regions (Li Jing et al., 2010). For example, the weights between Shanghai and Jiangxi and Guizhou are all 0, but it is obvious that the connection between Shanghai and Jiangxi, which is geographically closer to it, is greater than the connection between Shanghai and Guizhou. Based on this, some studies use the spatial distance weight matrix to represent the spatial effect between regions. In the spatial distance weight matrix, the elements on the main diagonal are set to 0, while the elements on the non-main diagonal are set to the reciprocal of the distance between the geographical centers (or administrative centers) of the two regions or its square term (Bai Junhong et al., 2017). However, the spatial distance weight matrix cannot fully reflect the complex spatial relationship between regions. For example, the spatial distance between Hebei and Beijing, Tianjin, Henan, and Shanxi is similar, but it is obvious that Hebei has closer connections with Beijing and Tianjin. Since then, some studies have expanded on the basis of the spatial distance weight matrix, introduced "economic distance", and established an economic spatial weight matrix. In this matrix, the elements on the main diagonal are still set to 0, while the elements off the main diagonal are set to the inverse of the relative difference in the average per capita real GDP between the two regions during the sample period (Lin Guangping et al., 2005).

This paper examines the mechanism of the inter-regional mobility of population factors on insurance growth. In addition to directly bringing insurance growth to the inflow area, it may also affect insurance growth in the outflow area through the spatial spillover of insurance cognition. The connection between the inflow area and the outflow area will be more complicated than the geographical distance and economic distance. Studies have shown that in addition to the economic development gap, factors such as institutional policies, social relations and cultural background all have an impact on the direction of population mobility (Liu Yuyun et al., 2015). Therefore, this paper refers to the methods and forms of setting spatial weight matrices in previous literature, and establishes a "mobility distance" spatial weight matrix based on the differences in the scale of floating population between regions W . The matrix is set in such a way that the elements on the main diagonal are still set to 0, while the elements on the non-main diagonal are set to the inverse of the square of the average scale of population mobility between the two regions during the sample period, that is:

$$w_{ij} = \begin{cases} 0 & , \quad if \quad i = j \\ \dfrac{1}{\left(\overline{flow}_{ij} + \overline{flow}_{ji}\right)^2}, & if \quad i \neq j \end{cases} \tag{7}$$

Among them, $\overline{flow}_{ij}$ and are the average population sizes flowing from place $\overline{flow}_{ji}$ *i* to place *j* and from place *j to place i* during the sample period, respectively .

For the sake of robustness, this paper will continue to use adjacency matrix, distance matrix and economic matrix to establish spatial econometric models to test the robustness of the results.

(2)Other variable settings

As the explained variable ins_{it} , this paper selects the scale of premium income in each region as the proxy variable for the total output value of the insurance industry .

The core explanatory variable $flow_{it}$ is set as the sum of the population size flowing from area *i* to other areas and from other areas to area *i , that is:*

$$flow_{it} = \sum_{j \neq i} \left(flow_{ijt} + flow_{jit} \right) \quad (8)$$

Other explanatory variables L_{it} are set as the number of people employed in the insurance industry in each region . Due to data availability, this paper selects the amount of fixed asset investment in the financial industry in each region as a proxy variable for the fixed asset stock of the insurance industry in each region K_{it} .

As for the control variable group $X_{control}$, according to previous literature, this paper mainly selects population aging rate (*age*), urbanization rate (*city*), education level (*education*), economic development (*gdp*), industrial agglomeration (*industry*) and insurance marketization (market *)* . The setting method of each control variable is detailed in Table 1.

In addition, the premium income scale, per capita regional GDP and fixed asset investment amount of each region are deflated using the corresponding price index.

Control variable setting

Table 1

variable	symbol	Setting method
Population aging rate	*age*	The percentage of people aged 65 and above in the total population
Urbanization rate	*city*	The percentage of urban population in the total population
Education	*education*	The percentage of people with high school education or above to the population aged 6 and above
Economic Development	*gdp*	Natural logarithm of GDP per capita
Industrial Agglomeration	*industry*	Take the natural logarithm of the number of corporate legal entities
Insurance marketization	*market*	Number of insurance institutions

4. Analysis of Empirical Results

4.1Data description

This paper uses the inter-provincial panel data of 31 provinces, municipalities and autonomous regions in China from 2012 to 2015 for empirical analysis. Among the variables selected, the scale of premium income is obtained according to the premium situation table of various regions in China published on the website of the [①]China Insurance Regulatory Commission, the number of insurance institutions is obtained according to the original premium income situation table of property insurance companies and the original premium income situation table of life insurance companies of the insurance regulatory bureaus in various regions, the number of employees in the insurance industry is from the China Labor Statistical Yearbook (2013~2016), and other data including price index are all from the China Statistical Yearbook (2013~2016).

The core explanatory variables selected in this paper, namely the population mobility scale data and the mobility spatial weight matrix, are calculated based on the database of the dynamic monitoring survey of the floating population (2012-2015) conducted by the Department of Migrant Population of the National Health and Family Planning Commission (formerly the Department of Migrant Population Service and Management of the National Population and Family Planning Commission). The survey adopts a stratified, multi-stage, and size-proportional PPS sampling method. The survey covers the floating population in 31 provinces, municipalities and autonomous regions. The annual survey sample is about 200,000 people, involving a total of about 500,000 family members of the floating population. The relative error of the survey indicators is strictly controlled, which is representative of the whole country and the region. This paper marks the micro samples in the database according to the outflow and inflow places, and then classifies and sums the counts to obtain the population mobility scale matrix between 31 provinces, municipalities and autonomous regions in my country. The simple descriptive statistics of each variable data are shown in Table 2.

Data Descriptive Statistics

Table 2

variable	Observations	average value	Standard error	Minimum	Maximum
lnins	124	15.1537	1.1023	11.4311	17.0626
lnflow	124	10.2507	0.4445	8.9813	11.0771
LqCy	124	10.5789	1.2480	4.8828	12.0221
LqCy	124	3.1346	1.2408	-0.0147	5.1592
age	124	0.0945	0.0187	0.0517	0.1412
city	124	0.5502	0.1353	0.2275	0.8960
education	124	0.1260	0.0672	0.0239	0.4234
lngdp	124	10.6452	0.4027	9.8621	11.4975
lnindustry	124	12.1637	1.1578	8.0910	14.1436
market	124	50.9355	24.6823	6.0000	112.0000

4.2 Empirical Results

(1)OLS estimation results

Based on the model setting and test ideas, this paper first conducts OLS regression analysis, and the regression results are shown in Table 3. Among them, the first column in the table is the mixed regression estimation result, the second column is the fixed effect

[①] The premium income of the five independently planned cities, namely Dalian, Qingdao, Shenzhen, Ningbo and Xiamen, is uniformly included in the premium income scale of their respective provincial divisions in this article.

regression result, and the third column is the random effect regression result. The F test for choosing mixed regression or fixed effect has a statistical value of 37.88, and the P value is significantly 0 at the 1% test level, so it can be accepted that the fixed effect model is better than the mixed regression model. The LM test for choosing mixed regression or random effects has a statistical value of 92.29, and the P value is significantly 0 at the 1% test level, so it can be accepted that the random effect model is better than the mixed regression model. In the Hausman test for choosing random effects or fixed effects, the statistical value is 37.23, and the P value is significantly 0 at the 1% test level, so it can be accepted that the fixed effect model is better than the random effect model. Therefore, this paper finally chooses the fixed effect model in the OLS estimation results for the following result analysis and further testing. In the fixed effect model, the coefficient of the core explanatory variable population flow scale (*lnflow*) is significantly positive at the 10% test level, with a size of 0.0836, indicating that insurance growth is positively correlated with population flow scale. For every 1 percentage point increase in population flow scale, insurance output value will increase by 0.0836 percentage points. In addition, the number of insurance industry employees (*ln L*), fixed asset investment (*ln K*), aging rate (*age*), education level (*education*), industrial agglomeration (*ln industry*) and insurance marketization (*market*) are all significantly positive, while the urbanization rate (*city*) and economic level (*lngdp*) are positive, but not significant at the 10% test level.

OLS estimation results

Table 3

	(1) Hybrid regression	(2) Fixed effects	(3) Random Effects
lnflow	0.0161	0.0836 *	0.0804 *
	(0.25)	(1.86)	(1.80)
LqCy	0.406 ***	0.0972 ***	0.193 ***
	(10.96)	(3.58)	(7.41)
LqCy	0.0263	0.0321 *	0.0512 ***
	(1.20)	(1.81)	(2.79)
age	-3.303 ***	3.421 ***	1.716
	(-2.85)	(3.21)	(1.60)
city	-0.00857 **	0.0139	-0.000195
	(-2.02)	(1.26)	(-0.04)
education	-0.230	0.932 **	0.276
	(-0.46)	(2.18)	(0.63)
lngdp	-0.0554	0.0274	-0.340 **
	(-0.44)	(0.14)	(-2.07)
lnindusty	0.425 ***	0.246 ***	0.403 ***
	(9.17)	(4.42)	(10.97)
market	0.00953 ***	0.00969 ***	0.0133 ***
	(5.69)	(3.65)	(6.12)
_cons	6.351 ***	8.179 ***	9.975 ***
	(4.38)	(4.66)	(6.37)

N	124	124	124
R^2	0.9741	0.9163	0.9622
F or χ^2	476.4	102.2	1456.5

Note: The numbers in brackets are t values; ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. The same applies to the following charts.

(2)Spatial correlation test

As mentioned above, the mechanism of the inter-regional mobility of population factors on insurance growth, in addition to directly bringing insurance growth to the inflow area, may also affect the insurance growth of the outflow area through the spatial spillover of insurance cognition. Therefore, simply performing OLS regression may cause deviations in model setting. Therefore, this paper needs to further establish a spatial econometric model to examine the relationship between inter-regional population mobility and insurance growth. Before establishing a spatial econometric model, it is necessary to test the spatial correlation of the data. This paper selects the most widely used Moran 's I *index* to first test the spatial correlation of insurance growth in various regions under the mobility spatial weight matrix. The results show that the Moran's I index of insurance growth in various regions from 2012 to 2015 *is significant* above the 5% test level, indicating that there is significant spatial correlation.

In addition, in order to examine the robustness of the test results, referring to the practice of Bai Junhong et al. (2017), this paper introduces covariates, removes the possible trend of insurance growth through regression methods, and then performs a spatial correlation test on the residuals. According to the OLS estimation results and related test analysis in Table 1, this paper continues to select the residuals estimated by the fixed effect model for the Moran Index *I test. The test results are shown in Figure 2. The results show that the Moran Index I* of the regression residuals is significantly positive above the 1% test level, indicating that there is still a very significant spatial positive correlation. If this correlation is proven to exist, we can further infer that population mobility drives the spillover of insurance awareness from the inflow area to the outflow area, which will be conducive to the balanced growth of China's regional insurance industry. In summary, we can conclude that the estimation results obtained by OLS regression cannot fully reflect the actual situation in China. It is necessary to further establish a spatial econometric model to identify the spatial correlation of insurance growth in various regions in order to improve the accuracy of the regression results.

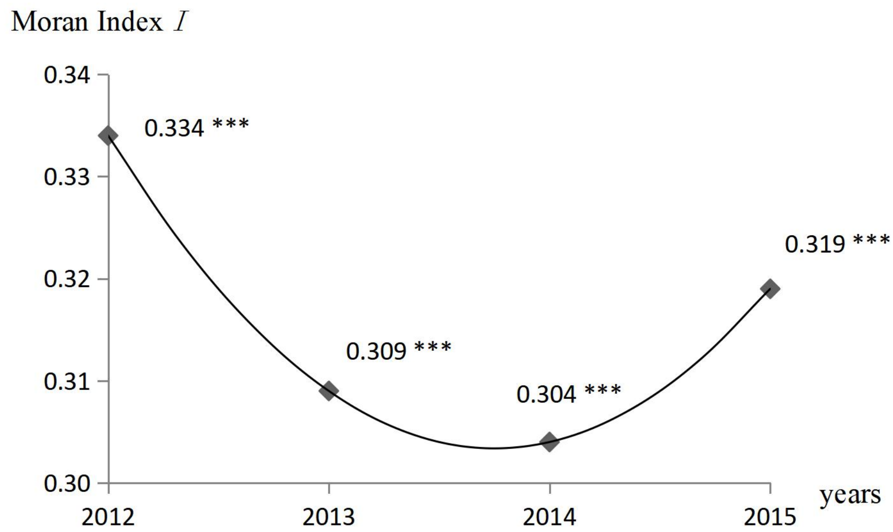

Figure 2 OLS regression residual spatial correlation test

Source: Compiled based on the results of Moran's Index *I test in Stata 13.0.*

(3)Spatial panel measurement results

This paper continues to establish spatial panel SAR model, SEM model, SAC model and SDM model, and the estimation results are detailed in Table 4. Among them, columns 1 to 3 are the estimation results of SAR model, SEM model and SAC model, and columns 4 and 5 are the estimation results of main model and interaction model of SDM model. After Hausman test, except that the SAC model must use fixed effects according to modeling requirements, the other models accept the use of random effects ①.

The above four types of spatial econometric models are all estimated using the maximum likelihood method. Next, we need to select the one with better fitting effect for empirical result analysis. First, we found that the number of variables with significant coefficients in the SDM model is more than that in the SAR model, SEM model, and SAC model, and the goodness of fit is higher; secondly, we use the Wald and LR test methods to perform spatial lag test and spatial error test on the SDM model. The P values of the relevant statistics are significantly 0 at the 1% test level ②, indicating that the SDM model has better fitting effect than the other three types of spatial models; finally, we test H_0: $\delta_i = 0$ and $\delta_i = -\rho\beta_i$, that is, test whether the SDM model can be equivalently converted to the SAR model and the SEM model. The P values of the relevant statistics are significantly 0 at the 1% test level ③, that is, reject the null hypothesis, indicating that the SDM model cannot be equivalently converted to the SAR model and the SEM model. Based on the above three types of tests, this paper believes that the SDM model has the best fitting effect, so the estimation results of the SDM model are selected for empirical analysis.

① The Hausman test statistic values for the SAR model, SEM model, and SDM model are -289.66, -298.81, and -625.80, respectively.

②In the Wald test for spatial lag and spatial error, the statistical values were 5.48 and 38.12 , respectively; in the LR test for spatial lag and spatial error , the statistical values were 22.96 and 22.81, respectively.

③ The Wald test statistic values of $\delta_i = 0$ and $\delta_i = -\rho\beta_i$ are 25.52 and 25.26 respectively.

In addition, referring to previous literature, this paper constructs the adjacency spatial weight matrix, geographic distance spatial weight matrix and economic distance spatial weight matrix to re-conduct spatial panel econometric regression to test the robustness of the estimation results. The results show that after using the other three spatial weight matrices, the fitting effect of the SDM model is still the best. Moreover, although these three types of spatial weight matrices are not as good as the mobility spatial weight matrix constructed in this paper in representing the complex connections between regions in terms of geographic distance, economic development and cultural background, resulting in changes in the size of the coefficients in the estimation results, the direction and significance level have not changed substantially. It can be concluded that the estimation results of this paper are robust.

From the estimation results of the SDM model in Table 4, the coefficients of the horizontal term and spatial interaction term of the population flow scale (*lnflow*) are significantly positive at the 10% test level, indicating that the flow of population factors will not only have a direct impact on local insurance growth, but also have an effect on insurance growth in other regions through inter-regional spatial relations. However, it should be pointed out that the regression coefficient of the SDM model in Table 4 is not an accurate measure of the direct and indirect impact of factors such as the scale of population flow on insurance growth, but needs to be calculated separately. The calculation results are detailed in further analysis.

We found that after adding spatial lag and interaction terms, the direct effects of other explanatory variables and control variables on insurance growth also changed to varying degrees. In addition to the number of insurance employees (*lnL*), industrial agglomeration (*lnindusty*) and insurance marketization (market *)* , which are still significantly positive at the 1% test level, and the urbanization rate (*city*), which is positive but still insignificant at the 10% test level, the significance of fixed asset investment (*lnK) has increased, the aging rate (age*) and education level (*education*) are no longer significant, and the economic level (*lngdp*), although not significant at the 10% test level, has changed from positive to negative. In general, the external environmental factors affecting insurance growth did not play a significant role as expected by theory, especially economic development and population structure factors did not become the driving force of insurance development, which is consistent with the conclusions of Sun Xiuqing (2009) and other studies. In addition, in the spatial interaction model, the aging rate (*age*) and urbanization rate (*city*) are significantly negative, indicating that changes in the population age structure and urban-rural structure between regions have a certain negative impact on insurance growth. This is related to the fact that large-scale population mobility has a short-term impact on the population structure of the two places, while the insurance industry adjustment is relatively lagging. This conclusion is similar to the empirical results of Guo Jinlong and Zhang Lei (2014) . The coefficient of the interaction term of industrial agglomeration (*lnindusty*) is significantly positive, indicating that industrial migration and agglomeration between regions can drive insurance growth.

Spatial panel estimation results

Table 4

variable	SAR	SEM	SAC	SDM	
	(1)	(2)	(3)	(4)	(5)
lnflow	0.0903 **	0.0890 **	0.0169	0.0805 *	0.180 *
	(2.06)	(2.25)	(0.71)	(1.78)	(1.86)
l	0.171 ***	0.165 ***	0.0253	0.170 ***	0.0476
	(6.08)	(5.81)	(1.58)	(6.41)	(1.09)
l K	0.0499 ***	0.0519 ***	0.0130	0.0495 ***	0.00360
	(2.95)	(3.12)	(1.40)	(3.12)	(0.08)
age	2.230 **	2.254 **	-0.0399	0.817	-8.954 ***
	(2.06)	(2.19)	(-0.06)	(0.72)	(-2.60)
city	-0.000332	-0.00205	0.00150	-0.00874	-0.0326 *
	(-0.05)	(-0.34)	(0.21)	(-1.30)	(-1.91)
education	0.434	0.559	0.0467	0.281	0.503
	(1.01)	(1.34)	(0.20)	(0.69)	(0.57)
lngdp	-0.309 *	-0.287 *	-0.0710	-0.114	0.00773
	(-1.86)	(-1.76)	(-0.67)	(-0.66)	(0.02)
ln industry	0.384 ***	0.386 ***	0.0850 ***	0.354 ***	0.193 **
	(8.44)	(11.09)	(2.96)	(7.50)	(2.36)
market	0.0132 ***	0.0140 ***	0.000282	0.0152 ***	0.00590
	(6.12)	(6.50)	(0.17)	(6.60)	(0.65)
_cons	10.07 ***	9.810 ***	——	6.697	——
	(6.68)	(6.56)	——	(1.29)	——
λ or δ	-2.013 ***	-0.209	-0.743 ***	-1.937 ***	——
	(-8.57)	(-1.38)	(-6.17)	(-6.46)	——
N	124	124	124	124	
R^2	0.9583	0.9567	0.9487	0.9652	

4.3Further analysis

The regression coefficient of the SDM model in Table 4 is not an accurate measure of the impact of factors such as population mobility on insurance growth. Based on the model setting principle (LeSage and Pace, 2008), this paper further calculates the direct effect, indirect effect and total effect of each factor on insurance growth using the partial differential method. Among them, the direct effect reflects the average impact of each factor on local insurance growth, the indirect effect reflects the average impact of each factor on insurance growth in other regions, and the total effect reflects the average impact of each factor on national insurance growth. The calculation results are shown in Table 5.

As can be seen from Table 5, the direct and indirect effects of population mobility scale (*lnflow*) are significantly positive, indicating that inter-regional population mobility not only promotes insurance growth in the region, but also promotes insurance growth in other regions through the spillover effect of insurance cognition. Among them, for every 1 percentage point increase in population mobility scale, the local insurance industry will grow by 0.0794 percentage points, and the insurance industry in other regions will grow by 0.184 percentage points, which will lead to an overall growth of 0.264 percentage points in the national insurance industry. Further analysis shows that compared with the OLS fixed effect estimation results, the direct effect of inter-regional population mobility in the SDM model is smaller, which to a certain extent shows that if the spatial correlation of insurance growth and influencing factors in various regions is not considered, the role of inter-regional population mobility in promoting local insurance growth will be overestimated. The insurance cognition spillover with inter-regional population mobility, its indirect promotion effect on insurance growth in other regions accounts for more than two-thirds of the overall growth effect, indicating that the role of inter-regional population mobility on insurance growth is more reflected in the spatial spillover effect of insurance cognition, but it is ignored by the OLS measurement results. The direct and indirect effects of other explanatory variables and control variables are basically similar to the above analysis, and will not be repeated here.

Direct effects, indirect effects and total effects based on the SDM model

Table 5

variable	Direct Effect		Indirect effects		Total Effect	
Inflow	0.0794 **	(2.04)	0.184 *	(1.67)	0.264 **	(2.33)
I	0.172 ***	(5.99)	0.0434	(1.19)	0.215 ***	(4.88)
I K	0.0503 ***	(2.83)	-0.00167	(-0.04)	0.0486	(1.10)
age	1.044	(0.88)	-9.468 **	(-2.26)	-8.423 *	(-1.77)
city	-0.00750	(-1.10)	-0.0312	(-1.64)	-0.0387 *	(-1.79)
education	0.267	(0.63)	0.357	(0.40)	0.623	(0.69)
lngdp	-0.138	(-0.74)	0.0219	(0.05)	-0.116	(-0.25)
ln industry	0.354 ***	(7.76)	0.180 **	(2.33)	0.534 ***	(6.96)
market	0.0148 ***	(7.29)	0.00674	(0.93)	0.0216 ***	(3.04)

5.Conclusion and Implications

With the accelerated reform of the household registration system and the close exchanges and cooperation between regions, China is gradually entering an open society with free flow of population factors. The inter-regional flow of population factors has become an important factor affecting the transformation and development of various economic activities such as the insurance industry. However, due to the limitations of research perspectives and data methods, the regional insurance industry interactions brought about by the inter-regional flow of population factors have been ignored for a long time. Based on the traditional insurance growth theory, this paper focuses on the intrinsic mechanism of the inter-regional flow of population factors on insurance growth, and uses provincial panel data from 2012 to 2015 to construct a flow spatial weight matrix based on the scale of inter-regional population flow. According to the modeling order and test rules of OLS →SEM and SAR →SAC SDM, →a spatial econometric empirical analysis is conducted . The main research conclusions of this paper and its policy implications mainly include:

Population mobility between regions not only promotes insurance growth in the region, but also has a promoting effect on insurance growth in other regions through the spillover effect of insurance cognition. By calculating the direct, indirect and total effects of the scale of population mobility between regions on insurance growth, we further concluded that for every 1 percentage point increase in the scale of population mobility, the local insurance industry will grow by 0.0794 percentage points, and the insurance industry in other regions will grow by 0.184 percentage points, thus making the national insurance industry grow by 0.264 percentage points overall. The indirect promoting effect of insurance cognition spillover with population mobility between regions on insurance growth in other regions accounts for more than two-thirds of the total growth effect. The policy implication of this conclusion is that since inter-regional population mobility has a significant spatial spillover effect on insurance cognition and is the main contribution to promoting insurance growth, on the basis of deepening the reform of the household registration system and improving the social insurance collection and settlement mechanism to encourage the free flow of population factors between regions, the inflowing regions should strengthen safety and health, employment, learning exchanges and skills training to promote the social integration of the floating population, the outflowing regions should change their development concepts, do a good job in industrial acceptance and adjustment, improve regional productivity, and use employment and entrepreneurship policies to actively guide the return of active population, so as to achieve benign interaction between regions and balanced development of the insurance industry (Zhang Wei et al., 2005).

Population inter-regional mobility links various factors that affect insurance growth between regions, forming a complex linkage network that acts together on insurance growth. Insurance growth in each region does not exist independently. It is not only affected by factors such as local insurance factor input, population structure, and economic level, but also by insurance growth in other regions and the above factors through population inter-regional mobility. In general, the external environmental factors in the region that affect insurance growth did not play a significant role as expected by theory, especially economic development and population structure factors did not turn into driving forces for insurance development. Changes in the age structure of the population and the urban-rural structure between regions have a certain negative impact on insurance growth, which is related to the fact that large-scale population mobility has impacted the population structure of the two places in the short term, while the adjustment of the insurance industry has lagged behind. In addition, industrial migration and agglomeration between regions can drive insurance growth. The policy implications of this conclusion are: on the one hand, each region should not only pay attention to the external environment for the development of the insurance industry in its own region, but also strengthen exchanges and cooperation with other regions, make full use of the resources and conditions of other regions, avoid vicious competition, and make overall plans to promote the coordinated development of China's insurance industry (Zheng Wei and Liu Yongdong, 2008); on the other hand, insurance institutions should still focus on strengthening internal governance and product innovation, improve their sensitivity to the insurance market and consumer demand, adjust product structure and marketing strategy in a timely manner in the face of the impact of floating population on regional development, and introduce differentiated insurance products suitable for floating population in a timely manner (Zou Hong et al., 2011). This is also an inherent requirement of "supply-side reform" and "improving quality and efficiency" in the insurance industry.

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