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Systemic Risk in China's Insurance Industry

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AUTHOR Lin Zhang, PhD
Hunan University

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The probability of a financial crisis like the one seen in 2007–2009 has sparked concerns about systemic risk in the insurance industry. China’s insurance industry is no exception, because the fear for systemic risk has caused heated discussions in recent years. Problems in the course of the industry’s development and shocks from external risks under extreme circumstances will become risk drivers to China’s insurance industry systemic risk. In the event of that, the accomplishments that the insurance industry has achieved over decades will suffer. Therefore, controlling the systemic risk of China’s insurance industry is particularly important.

This report first comprehensively reviews the definitions of systemic risk and then chooses the China Banking and Insurance Regulatory Commission’s (CBIRC) definition of systemic risk. Based on this, the author analyzes potential sources of systemic risk in China’s insurance industry from the aspects of credit guarantees, universal life insurance, asset and liability mismatch, and alternative investment. In addition, the insurance industry’s systemic risk is not only affected by endogenous factors but will also be influenced by four other major industries: banking, real estate, securities and internet industries. As a measurement of China‘s insurance industry’s systemic risk, this paper proposes using the Systemic Risk index(SRISK)model to measure the long-run marginal capital shortfall of the listed companies’ systemic risk and matching the non-listed companies with the listed companies through the Propensity Score Matching (PSM) method. This model comprehensively measures the systemic risk capital shortfall in China’s insurance industry. The Lower Tail Dependence (LTD) method measures the dependence of systemic risk among industries. The Granger causality test is used to explain the causal relationship between the systemic risks of different industries and the insurance industry under linear and nonlinear conditions, respectively. The results show that, at present, systemic risk in China’s insurance industry is still under control. However, its growth rate has exceeded the growth rate of its business scale, and through integration with the insurance industry, other industries have potential influence on systemic risk in the insurance industry. China’s insurance industry is likely to be highly dependent with the sectors such as security, real estate, and internet, especially in the extreme situations, and it can be further trigger the systemic risk. However, there is no direct risk contagion between China’s insurance and banking industry.

Section 1: Introduction

In 2008, the global financial crisis caused the United States government to bail out U.S. financial and other institutions to help prevent a potential collapse of the world financial system. With the seizure of the American International Group (AIG), the long-standing belief that the insurance industry has almost no systemic risks instantly ended. Since that time, academia and regulatory agencies in every country have started to pay attention to the causes and the quantification of systemic risks in the insurance industry. The Geneva Association pointed out in 2010 that the insurance industry may experience systemic risk shocks if it participates in excessive derivatives transactions or when short-term financing management suffers from capital shortfalls (Geneva Association, 2010). In 2013, the Financial Stability Board (FSB) released the first list of nine global systemically important insurers, including China's Ping An Group. The global systemically important insurers, considered stabilizers in the insurance sector, will have a severe impact on the global economic and financial system in the event of a massive risk event or business failure.

At present, academic research on systemic risk in the insurance industry is still limited to theoretical modeling, most of which is to apply the systematic risk measurement method from the banking industry to the insurance industry. Although the regulatory authorities in various countries have begun to test methodologies to measure systemic risks in the insurance industry, there is still no unanimous conclusion on the quantification approach.

China's insurance industry was booming and expanding during the reform. In 2016, China's national insurance premiums totaled 3,096 billion yuan, ranking as the third largest insurance market in the world, with only a difference of 37 billion yuan from Japan, which holds the second position. In the same year, the six domestic insurance companies—including Ping An Insurance Company and China Life Insurance Company—were listed among the Fortune Global 500 companies. While in just a short few decades China's insurance industry has quickly grown to be among the world market leaders and admired internationally, it still has many challenges to address.

Although the CBIRC and related departments started limiting the size of universal life insurance in the second half of 2016, new payments of policyholders' investment accounts in life insurance companies still reached 507.654 billion yuan from January to October 2017. New payments of unit-linked insurance account in life insurance companies even reached 397.207 billion yuan (CBIRC, 2017). An increase in wealth management products undoubtedly adds to the liquidity burden on domestic insurers, making them more and more like banks. According to the China Industry Information Network, as insurers gradually become akin to banks, the possibility of a systemic risk in the insurance industry also increases, which means that nontraditional and non-core businesses increase the systemic risk of insurers (Mühlnickel and Weiß, 2015).

The industry concentration in China's insurance market is still relatively high. As of September 2017, there were 171 insurance companies (84 of which are property and casualty or P&C insurance companies, 78 life insurance companies and nine pension insurance companies) in China's insurance industry and only five listed insurance companies, of which four are listed in the Shanghai or Shenzhen Securities Exchange. From January to August 2017, the top five and top 10 P&C insurance companies' premium market share was 73.51% and 84.92%, respectively. For the life insurance industry, the top five and the top 10 life insurance companies' premium market share was 52.93% and 71.59%, respectively (China Industry Information Network, 2016). High industry concentration might have an impact on the stability of the insurance market, but so far, no scholar has thoroughly studied this issue.

At present, academics have different opinions on the influence of industry concentration on the stability of financial markets. This is not the case for concentration of the loan market. Academics believe that the concentration of the loan market will increase the interest rate of loans and the default risk of lenders, thus undermining financial market stability (Jiménez, Lopez and Saurina, 2013). This might be one of the hidden triggers of systemic risk in the Chinese insurance market and worth further study.

In addition, the stability of China's macroeconomic environment provided the prerequisite for developing other industries. The booming of the banking, real estate, securities and internet industries likewise contributed to their penetration into the insurance. However, in recent years, the bottleneck in developing the banking industry, the high real estate market prices, the imperfect system of the securities industry, and the lack of supervision in the emerging internet industry have added unknown factors to this penetration process. While businesses and channels have been diversified during the integration process, risks have also started to become more diverse. The fall of AIG during the 2007-2009 financial crisis occurred because of its involvement in writing credit default swaps on debt obligations backed by debt payments from residential and commercial mortgages, home equity loans and others. The real estate bubble burst, creating huge mortgage loan default losses and the undoing of AIG. With economic development, China's insurance industry is no longer a closed market. The continued growth of the market also means that the mixture of the insurance market with others will increase. The source of systemic risk will no longer be the internal problem of the insurance industry. Therefore, it is crucial to investigate and identify dependencies between the insurance industry and other markets especially in times of extreme events.

In summary, China's insurance industry may face the problem of spreading and expanding its regional systemic risks as a result of industry-induced factors or from the mutual penetration among sectors. It may even affect the stability of China's financial market. Therefore, it is necessary to study systemic risk of China's insurance industry.

This report is divided into six parts. Section 2 reviews the definitions of systemic risk. Section 3 discusses the existing systemic risks in China's insurance market. Section 4 analyzes the mutual penetration of the insurance industry and other industries. Section 5 determines the measurement method of systemic risk and the systemic risk dependence between the insurance industry and other industries. Section 6 is an empirical analysis, and Section 7 summarizes the report's conclusions.

Section 2: Systemic Risk Definition

Scholars and supervisors in different countries have defined systemic risk from different perspectives but have yet to reach a universally accepted definition. De Bandt and Hartmann (2000) conducted an in-depth survey of systemic and financial crises and gave the following definition, emphasizing that the core of a systemic risk definition should be contagion：

"A *systemic crisis* can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning (of an important part) of the financial system. While some particular banks play a major role, we stress that systemic risk goes beyond the traditional view of single banks guarding against vulnerability to depositor runs. At the heart of the concept is the notion of contagion, a particularly strong propagation of failures from one institution, market or system to another."

Hendricks and Mosser (2007) assume that the system is already in equilibrium and that systemic risk is defined as a process in which the economic and financial systems shift from one stable (positive) equilibrium to another stable (negative) equilibrium.

According to the FSB, International Monetary Fund and Bank of International Sentiments report (2009) to the G20 Finance Ministers and the Central Banks, systemic risk is defined as: (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy. Systemic risk in the insurance industry spreads mainly through contagion mechanisms and various financial connections and can reach a wider economy when it comes to promises to policyholders or newcomers to promote economic activity. The International Association of Insurance Supervisors (IAIS) and other regulatory agencies have adopted this definition in determining systemically important financial institutions. It also emphasizes the impact of negative externalities or market failures on the entire financial system and the real economy.

Giesecke and Kim (2011) define systemic risk as the conditional (time-varying) probability of failure of a large number of financial institutions, based on a dynamic hazard rate model with macroeconomic covariates. The European Central Bank pointed out that there is no commonly accepted definition of systemic risk at present. One approach is to describe it as the risk of experiencing a *strong* systematic event. Such an event adversely affects a number of systemically important intermediaries or markets (including potentially related infrastructures). The trigger of the event could be an *exogenous* shock (either idiosyncratic—such as limited in scope—or systematic, such as widespread), which means an event from outside the financial system. Above all, what is more internationally recognized is the systematic operation that the FSB proposed, as mentioned above.

CBIRC released the *Interim Measures for the Supervision of Domestic Systemically Important Insurance Institutions (draft)* (2016) with the definition of systematic risk as: "such that makes insurance companies difficult to maintain their business operations due to major risk events arising from internal factors of one or more insurance institutions, the insurance market, and/or uncertainties outside the insurance industry." In addition, violent fluctuations or crises in the insurance system will cause a serious adverse impact on the financial system and the real economy. Because the report intends to research the systemic risks in China's insurance market, the CBIRC's definition has been adopted.

Section 3: What Brings Systemic Risk to China's Insurers?

Before the 2008 financial crisis, due to the particularities of insurance regulation, business model and market structure, the traditional viewpoint was that the insurance industry doesn't have the conditions for systemic risks. Insurers do not face the same liquidity shortfall as banks have on run risk; on the other hand, insurers are more dependent on long-term liabilities than banks, thereby reducing liquidity risk. At the same time, Darlap and Mayr (2006) thought that the weaker interconnectedness among insurers reduced the possibility of systemic risk spreading. However, after the financial crisis in 2008, the bankruptcy crisis at AIG, the world's largest insurer, raised concerns about systemic risks in the insurance industry, realizing that insurance industry may also give rise to systemic risks.

The Geneva Association put forward in 2010 that if the insurance companies participate in too many derivative trading of noninsurance balance sheets or mismanage short-term financing, the possibility of systemic risk will increase. Cummins and Weiss (2013) tested the systemic risk factors and systemic risk activities in the U.S. insurance industry using correlation and regression analysis. They tested the statistical correlation between SRISK and the main indicators such as scale, connectedness and irreplaceability, as well as the contributing indicators such as leverage ratio, liquidity risk, complexity, duration mismatch and government management. The main conclusion is that the core business of U.S. insurance companies does not create systemic risks.

However, life insurance companies are vulnerable to intra-industry risks due to leverage and liquidity risk, and both life and property and casualty insurance are vulnerable to the reinsurance crisis resulting from the counterparty credit risk. Non-core business activities such as derivative trading have the potential to generate systemic risk, and most of the global insurance companies are exposed to the derivatives market (Cummins and Weiss, 2013). IAIS (2013) continues using the Geneva Association approach to identifying systemic risk activities and then confirming the systemically important insurers and believes that nontraditional (NT) and non-insurance (NI) financial businesses are the ones that create systemic risk in the insurance industry. NTNI activities involve financial features such as leverage, liquidity or maturity transformation; imperfect transfer of credit risks (such as shadow banking); and credit guarantees or minimum financial guarantees. They also involve products that are more financially complex than traditional insurance products in the shifting of financial market risk to insurers.

Other products of concern include those where the liabilities are significantly correlated with financial market outcomes, such as stock prices, and the economic business cycle (IAIS 2013). In 2016, IAIS also included credit and loan guarantee insurance in NT businesses. IAIS summed up the potential of systemic risk induced by NTNI businesses and its transmission mechanism (IAIS 2016).4 papers, Eling and Pankoke (2016) argue that the traditional insurance business in life, property and casualty insurance and re-insurers neither pose systemic risk nor increase insurers' vulnerability to impairments of the financial system[10]. However, non-traditional businesses may increase the vulnerability; at the same time, life insurers bear higher leverage than property and casualty insurance insurers. Table 1 combines the IAIS and Geneva Association's conclusions of NT insurance businesses.

Table 1

NONTRADITIONAL INSURANCE ACTIVITIES CLASSIFIED ACCORDING TO BUSINESS PROCESSES

	Annuities with guarantees and variable annuities	nves	Securitization of embedded value in upfront paid commissions
	Group annuities	and	Short-term funding
	Separate accounts		Securities lending
Un	Credit insurance		Credit rating utilization
	Financial guarantees	Fun	Industry-loss warranties
	CDSs/CDOs		

Source: Eling and Pankoke (2016)

The Geneva Association considers that to judge the source of systematic risk in the insurance industry is mainly to determine whether the risks posed by a specific business of the insurance institution are systematically relevant or not (Geneva Association, 2010). To make an accurate assessment of the probability of systemic risk in financial institutions, FSB believes that standards should be applied to the specific operations of financial institutions (Board of Financial Stability, 2009). Therefore, based on the identification of systemic risk sources that the Geneva Association, IAIS and other scholars have given, the author investigated the origin of systemic risk in China's insurance market from a micro perspective and believes that the main sources of systemic risk in China's insurance market are credit guarantee, minimum guarantee income of insurance contract, asset and liability mismatch, and alternative investment.

3.1 Credit guarantees

From the data of credit guarantee coverage currently disclosed by several property and casualty companies in China, the proportion of credit & guarantee insurance in total revenue in 2014–2016 had a large variation. Credit & guarantee insurance is insurance with credit risk as the subject matter of insurance. It is actually a type of insurance business in which the insurer (guarantor) provides credit guarantee for the obligor (guarantee) in the credit relationship. Some companies reached about 10%, while other companies were about 1%, and the total level was not too high. Although the credit guarantee insurance accounts for a small market share currently, the risk is huge. Problems will arise once the audit of the underwriting project is not strict, and the insurance company is likely to face huge amounts of compensation, thus generating tremendous pressure on the company's operations. Compared with institutional investors, peer-to-peer (P2P) loan platform financing from individual investors will be more likely to trigger the risk of credit guarantee insurance. According to the third-party statistics, as of the end of March 2017, 55 P2P lending platforms were cooperating with insurance companies and 33 insurers were involved in the insurance business of P2P lending industry. Some of these insurance companies have cooperated with more than five platforms, with the type of cooperative products involving guarantee insurance, credit audit liability insurance, etc. (Hexun, 2016). If insurers maintain direct or indirect contact with lenders, counterparties, investors or other market participants, their exposure of risk will be easier to spread to other financial institutions and markets, triggering macroeconomic risks.

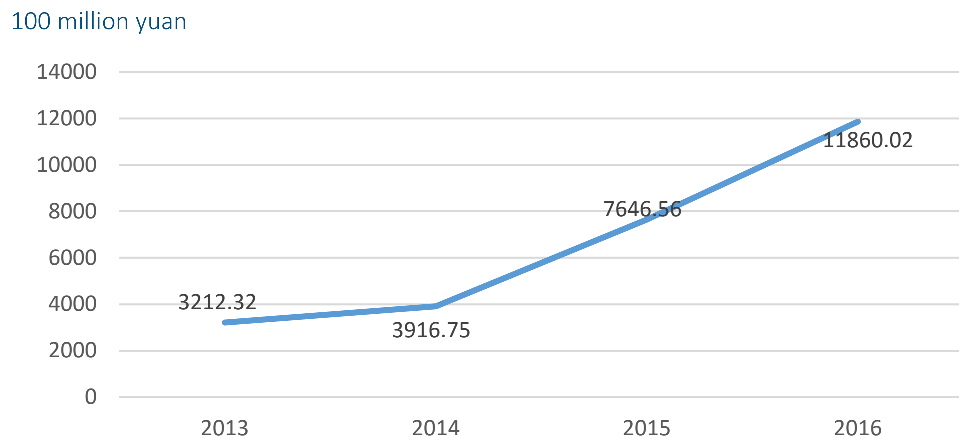
3.2 Universal life Insurance

Insurance products with financial features primarily include participating insurance, universal insurance and unit-link insurance, of which universal insurance accounted for 31.4% in China insurance market in 2016, much higher than the other two (CBIRC, 2017). With the reform of marketization of life insurance premium rate and channels opening for the use of insurance funds in recent years, financial insurance products with medium and short duration have increased dramatically, and its scale has increased faster than the original insurance premium income (as Figure 1 shows, from 2013 to 2015, new payments of policyholders' investment account[1] in the life insurance companies keep increasing, up to 1.186002 trillion yuan in 2016). Because of the lowest guaranteed benefits that universal insurance provide, regulators and scholars widely discuss the potential systemic risk posed by universal insurance. Insurers use short-term debt to roll over long-term investments, making the return of insurance products competitive compared to banks' wealth management products. When the investment yields fall sharply, an insurance company has to liquidate assets quickly to guarantee its liquidity, which will disturb the market and cause asset price fluctuations, and companies holding similar assets will suffer losses.

At the same time, the policyholder may have a run, which will have impacts on the market, the government supervision behavior, the company's reputation decline, and so forth. The payments at expiration and the surrender value of life insurance industry reached 937.9 billion yuan in 2015 and rose to 1.2 trillion yuan in 2016. In the surrender value, high-cash-value products accounted for 55%. China's insurance industry is expected to face more than 1.5 trillion yuan of maturity payment and surrender value by 2018 (Huibaoxian, 2017). Although a run on the insurance industry is rare, it cannot be ignored. Policyholders' run once occurred in smaller insurers and in a normal economic environment, although what consequences it would cause in an extreme economic environment remains unknown.

Under the pressure of low interest rates in China, along with the regulation of government, China's insurance companies will face a dilemma of both maturity payment and surrender value. It is necessary to prevent a run event; otherwise, insurance companies' liquidity will be significantly affected, which will lead to fracturing of company funds in a severe case or even a financial crisis.

Figure 1
NEW PREMIUMS AND CONTRIBUTIONS OF THE INSURANCE POLICIES OF CHINESE LIFE INSURERS IN 2013–2016



Data source: CBIRC public information data (2018)

3.3 Asset and liability mismatch

The core issue of the assets and liabilities mismatch is that insurers have mismatches in duration, yield and cash flow of assets and liabilities. At present, there are obvious mismatches in the duration of assets and liabilities in China's insurance industry. There are two types of gap in assets and liabilities: The first is large-scale insurance companies that focus on long-term guaranteed-oriented businesses. The duration of their assets and debt is long, and the average duration of the debt is greater than assets, leading to a larger

[1] According to CBIRC, the investment income part of the insurance, which did not passed the insurance risk test, is included in the new payments of policyholders' investment account.

duration gap, causing a certain mismatch between assets and liabilities.

The second category is the duration of insurance assets and liabilities, which is shorter. The data currently disclosed by a life insurance company at the end of 2016 show that the average duration of assets was 3.75 years and the average duration of liabilities was 5.79 years, both of which are short term (Securities newspaper, 2017. At present, many insurance companies in China belong to this category.

At the same time, in the low-interest-rate environment in China, premiums increased rapidly. Among them, the new annual paid policies of life insurance become the majority of total premium, indicating that the duration of the future insurance business will continue to lengthen, further increasing the investment pressure on insurance companies (see Table 2). Due to the lag in the adjustment of the assumed interest rate of insurance products, the attraction of insurance products relative to fixed deposit, bank financing and trust has been boosted in the low-interest-rate environment, which stimulates the increase in demand for insurance. However, a slowdown in economic growth, a weak stock market and a surge in bond defaults[2] have led to a decline in the rate of return on investment in nonstandard products.

Overseas investment also faces capital controls. Besides, there is a severe lack of middle-yield and medium-risk assets. Under these circumstances, the more rapid growth of a premium, the more difficult it is for insurance funds to invest, which results in a mismatch in the return on assets and liabilities and further aggravates the situation.

Table 2

CHINA'S INSURANCE PREMIUM INCOME AND THE SIZE OF INVESTMENT FUNDS (UNIT: BILLION YUAN)

	2012	2013	2014	2015	2016
Premium income	1,549	1,722	2,024	2,428	3,096
Total assets	7,355	8,289	10,159	12,360	15,117
Investments	4,510	5,423	6,800	8,745	10,906

Sources: CBIRC and China Statistics Bureau websites public data.

3.4 Alternative investment

In recent years, the proportion of alternative investments of insurance funds—including real estate, securitized assets, hedge funds, private equity funds, commodities and art—has been increasing. While alternative investments increased support for the real economy, the related hidden risks have also raised market concerns. Other investments, mainly alternative investments, keep increasing, accounting for 38.52% of the total investment as of the end of October 2017, and surpassing the scale of bonds and becoming the largest asset in insurance funds allocation (Sina Finance, 2017). The investment situation of the Chinese insurance industry in the past four years is shown in Figure 2.

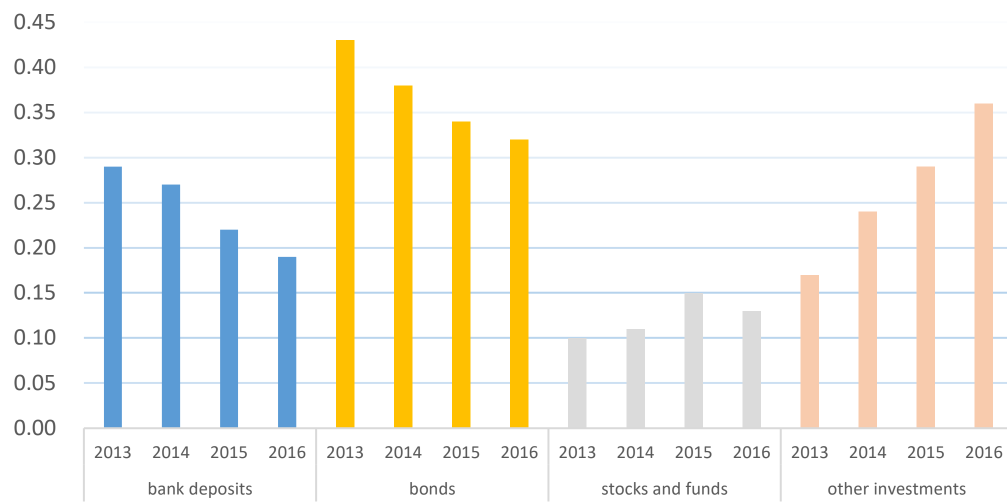
In addition, a number of small and medium-sized companies, especially platform insurance companies, that sell their products through the internet have frequently increased their alternative investments. Insurers favor alternative investments mainly because of the relatively limited return on investment in financial assets and the relatively high acquisition costs of policies, forcing companies to invest in nonstandardized assets for higher returns. However, there are potential risks in alternative investments. First, alternative

[2] Since the substantive default in the Chinese bond market in March 2014, 22 substantive noncompliance incidents occurred in 2015, involving an amount of 12 billion yuan. Breach of contract began to accelerate in 2016. In the first 11 months of 2016, a total of 54 bonds were defaulted, involving a total principal amount of 28.334 billion yuan.

investments involve additional levels of credit risk and complex trading structures and a lack of disclosure standards, making it more difficult to assess the corresponding risks and returns. In addition, the non-public markets have lower credit default costs and higher credit risk than the open market.

In the previous credit expansion period, the possibility of concentrated defaults was low. However, the credit expansion will slow down in the future, and there will be the need to guard against the risk of a concentration of defaults, since the liquidity of nonstandard products is weak. Second, compared with traditional investments, alternative investments have lower liquidity and are difficult to circulate and transfer. Because these complex, tailor-made financing structures make them hard to be resold, insurers may need to make big discounts if they want to sell those assets before they expire.

Figure 2
CHINA’S INSURANCE INVESTMENT STRUCTURE CHANGES



Source: Public information data from CBIRC.

The above four factors are the major influencing factors of systemic risk in China’s insurance industry. All of these will result in the inadequacy of the liquidity of insurers’ assets, serious solvency problems and large capital shortfalls. Owing to systemic contagion, the insolvency of one insurer is likely to lead to the bankruptcy of other insurers that have an economic connection with it directly and further spread to the whole industry. The interrelationship between financial institutions, similar to the domino effect (Helwege, 2010), exposes many financial institutions to risks simultaneously and is likely to trigger regional systemic risks. Therefore, it is an urgent task to measure the systematic risk of insurance institutions in China.

Section 4: Would Systemic Risk Spread From Other Industries to the Insurance Sector?

With the mutual penetration of the insurance industry and other industries, such as insurance companies holding shares of bank stocks and banks holding shares of insurer stocks, the systemic risk of the insurance industry will not only be affected by the internal factors of the industry but also the contagion effect of risk spillover from other industries. The impact of potential systemic risks in other industries will spread to the insurance industry in an extreme crisis event through their respective linkages and infiltration mechanisms, thus triggering systemic risks in the insurance industry. The author has defined "inter-industry systematic risk" as the systemic risk of the insurance industry triggered by other industries.

In China, the industries closely related to the insurance industry are mainly banking, securities, real estate and the internet industries. The author examined the changes in the insurance, banking, securities, real estate and internet industry indices. The author found that, during the period of 2007 to 2016, when the market was affected by emergencies, the five markets all had similar fluctuations and the price movements were essentially the same in the rest of the time. This indicates that there must be an inherent connection between the insurance industry's systemic risks and those of the other four. Therefore, the author concluded that the spread of exogenous systemic risks in the insurance industry mainly includes the industries shown in Figure 3.

Figure 3

INSURANCE, BANKING, SECURITIES, REAL ESTATE AND THE INTERNET INDUSTRY INDEX CHANGES OVER TIME

Source: WIND Database.

4.1 Banking

The complex business mode in China's financial market is becoming increasingly prevalent. A number of financial groups have their own banks and insurance companies. Many banks have their holding insurance companies. At this stage, the number of China's insurance companies controlled by the banking sector has reached 11, as shown in Table 3. Insurance groups have also made equity investments in banks. Risks are likely to spill over through this path.

Table 3
CHINA'S BANK HOLDING INSURANCE COMPANY

Bank	Holding insurance company
Bank of China	Bank of China Insurance
	BOC Samsung Life Insurance
Agricultural Bank of China	Agricultural Bank of China life
ICBC	ICBC AXA
China Construction Bank	CCB Life
	CCB P&C Insurance
Bank of Communications	BOCOMM Life
China Merchants Bank	Cigna & CMB
Bank of Beijing	BOB-CARDIF Life
Everbright Bank	Sun Life Everbright Life
Postal Savings Bank of China	China Post Life Insurance

Source: Companies' financial statements

4.2 Real Estate

As shown in Table 4, in recent years, many insurance companies have acquired stakes and/or have invested in real estate companies and have even become the largest shareholder of real estate companies. In the meantime, the real estate investment scale of insurance funds is alarming. In 2016, more than 10 insurance companies participated in real estate investment, and the total amount was 30.6 billion yuan in China (Lanjinger, 2016). As a result, the insurance industry will be affected by the real estate industry's risk.

Table 4
INSURANCE COMPANIES' EQUITY INVESTMENT IN REAL ESTATE COMPANIES

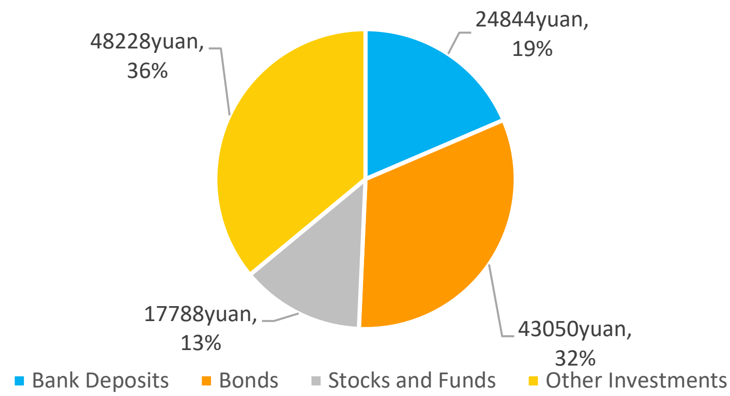
Insurance company	Investment object	Nature
Fuld life insurance	Golden Group	The largest shareholder, stake acquisition
Sunshine Insurance	Merto Land Corporation Ltd	The fourth-largest shareholder
Qianhai life	Vanke A	The fifth-largest shareholder
	CSG A	The largest shareholder, stake acquisition
	OCT A	The second-largest shareholder, stake acquisition
Guohua Life Insurance	Tianchen shares	The second-largest shareholder, stake acquisition
	New World	The third-largest shareholder, stake acquisition
Taikang life	Poly Real Estate	The second-largest shareholder, stake acquisition

Source: companies' financial statements

4.3 Securities

As large institutional investors in the securities market, insurance institutions have formed a direct connection with the securities through investment activities. Each year, the investment amount in the securities market reaches more than 1 trillion yuan. Figure 4 shows the application of China's insurance funds in 2016. Insurance funds invested in the securities market reached 60,838.38 million yuan, accounting for 45.43% of the total investment for the year. As a result, all the investments provided a channel for the risk to be introduced into the insurance industry.

Figure 4
INSURANCE FUND UTILIZATION IN 2016



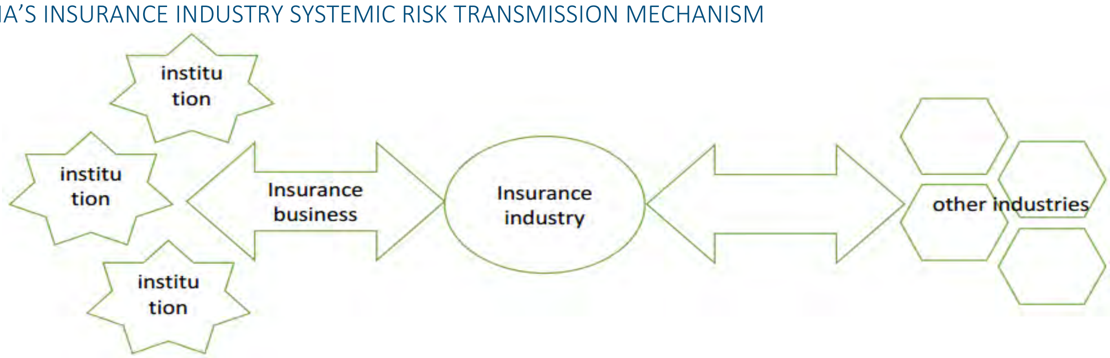
Source: CBIRC public information data(2018)

4.4 Internet

Internet giants have entered the insurance business because consumers, especially many younger individuals, like the convenience of purchasing insurance online versus traditional sales channels. Alibaba holds 16% of the stake as ZhongAn Insurance Company's largest shareholder, increased its capital to take control of Cathay Insurance, holding 51% of its stake, and set up Trust Mutual Life Insurance Company as the main sponsor. Tencent holds about a 12% stake of ZhongAn and established Hetai Life Insurance jointly with CITIC Guoan and other enterprises (Information Disclosure System of Insurance Association of China 2018). Insurance companies also enter the internet industry by using the third-party platform (such as Huize.com) for the insurance business, setting up their own internet insurance company (such as TK.cn), and other ways.

All of these industry connections provide channels for risk transmission. In this context, if any one of the above-mentioned industries experiences an adverse risk event, the risk will transmit through the connection between industries and spill the risk into the insurance industry or even the entire financial system, seriously affecting the real economy. As a result, research of the inter-industry systematic risk is urgent.

Figure 5
CHINA'S INSURANCE INDUSTRY SYSTEMIC RISK TRANSMISSION MECHANISM



Source: Author

From the perspective of the systemic risk communication path and based on the insurance industry, the idea of measuring systematic risk is divided into two parts. The first part is a study from the inside out, starting with the insurance industry where the risk is triggered by some important insurers and then spreading to the entire industry, leading to a systemic crisis. The other part is a study from the outside-in, focusing on the impact of external shocks on the insurance system. Due to the change of the overall macroeconomic environment, systematic risks emerge in other industries and spread to the insurance industry. Figure 5 shows the transmission mechanism of systemic risk in China’s insurance industry.

Section 5: How to Measure Systemic Risk?

The 2008 financial crisis triggered a global chain reaction, and the massive bailout of AIG made scholars throughout the world research systematic risk of the insurance industry. Due to the need for macro-prudential supervision by financial supervisory authorities, a large body of literature on systematic risk measurement has been emerging in recent years.

From the perspective of the systematic risk contagion, there are two main approaches to measuring systemic risk. First, the crisis of some important insurers spreads to the entire industry and leads to a systemic crisis from the insurance industry to other industries to the entire financial sector. Thus, the key to this approach is to determine the importance of insurance institutions.

Currently, the frequently used methods based on the systemically important insurance agencies are marginal expected shortfall (MES), Conditional Value at Risk (CoVaR) (Xu et al., 2016), LTD, joint probability of danger, and so on. This approach is divided into two categories but all based on systemically important insurance agencies. One focuses on the contagion effect between risks; for instance, the CoVaR measures the intensity of a single financial institution's risk spilled over to other financial institutions (Adrian and Brunnermeier, 2011), and the methods measure the contribution of a single financial institution to systemic risk, such as quantile regression, GARCH model, Copula (Jiang et al., 2014).

The other one assumes that under the condition of a systemic risk caused by external shocks, the institution that causes the risk to spread further by exiting from the capital market is called the one that contributes the most to the risk. For example, MES calculates the marginal contribution of individual financial institutions to systemic loss of the financial system (Acharya et al, 2012b). Then there are some improvements based on it, such as, long run marginal expected shortfall (LRMES) (Engle et al, 2014); the components expected shortfall (CES) method, which considers the scale; and the systemic risk indicator SRISK (Systematic Risk Index), which measures a financial institution's liabilities, size, relevance, leverage and other factors (Acharya et al., 2012a).

Second, as a result of the overall macroeconomic change in the market economy, systemic risks have been transmitted to the insurance industry from other industries. This research approach focuses on the impact of external shocks on the insurance system and the contagion effect among industries. Before the financial crisis in 2008, to measure the impact of exogenous systemic events on their own, indicators that affect systemic risk were found mainly through the comprehensive index method, the early warning technology, and the network model and pressure scenarios tests. After the financial crisis in 2008, there are ΔCoVaR (Adrian and Brunnermeier, 2011; Xu et al., 2016); LTD (Weiß et al., 2012); BANKBETA (Chen et al., 2013); and Granger-causality (Billio et al., 2012) that measure the relationship between industries. From intra-industry and inter-industry perspectives, systemic risk in the industry is measured by calculating the capital shortfall of financial institutions through SRISK and measuring the systemic risk among industries with infectiousness and causation.

5.1 SRISK, PSM and SRISK based on PSM

Section 5.1.1 introduces the current literature on measuring systemic risk. By summarizing the literature and methods, the SRISK model was used for the study. Section 5.1.2 describes the specific methods used in this report, the SRISK model and the improvements we have made. Section 5.1.3 describes the shortcomings of this approach.

5.1.1 LITERATURE REVIEW

Through comparative analysis, Benoit et al., (2012) show that MES plays a very small role in the rankings of systemically important financial institutions and that, compared with Value at Risk (VaR), the added value of CoVaR in forecasting systematic risk is very limited. But they find that SRISK made a good compromise between the "too-big-to-fail" and the "too-interconnected-to-fail." What's more, the overall shortfall of capital that the SRISK method emphasizes can be caused by poor management of financial institutions, external macroeconomic fluctuations or monetary policies. Benoit et al. believe that SRISK has a broader space for use.

Christian Brownlees (2016) considered that the stability and sensitivity of the SRISK method are superior to those of Systemic Expected Shortfall (SES). This result is verified by data from Lehman Brothers Bank, AIG and other agencies that triggered the systemic crisis in 2008. And the results also show that SRISK has a good risk warning signal and reflects individual financial institutions' ability to resist risks and facilitate macro-level prudential supervision (Brownlees, 2017). By comparing MES, SRISK and CES methods to evaluate the validity and applicability of systematic importance of listed financial institutions in China, Wang Peihui and Yuan Wei (2017) find that under the conditions of using open market data, the MES and CES indicators are more time-efficient; that SRISK is more reliable and less time-sensitive in evaluating the scale, leverage and other information; and that SRISK and CES have better predictive ability.

Only measuring the systemic risk of listed companies won't fully reflect the current systemic risk in China's insurance industry. The measurement of systemic risk of nonlisted insurance companies is an indispensable part. But research on systemic risk of unlisted insurance companies at home and abroad is just beginning, so the measuring method of nonlisted company credit risk is used as reference. For instance, the option pricing Private Firm Model (PFM) model of Moody's KMV(Kealhofer, McQuown, and Vasicek) Company provides a way to solve the credit risk of non-listed companies. But the accuracy of the PFM model for the measurement of nonlinear sample data is poor, and the estimation results are not ideal.

Zeng et al. (2017) built the BP-KMV model of back propagation neural network combined with KMV to evaluate credit risk using the sample of 46 listed Chinese manufacturing companies and 35 non-listed manufacturing companies to calculate the default rate of non-listed companies. Liu et al. (2016) adopted the SVM regression analysis in data mining and applied it to a small, high-dimensional and nonlinear data sample to measure the credit risk of non-listed companies in China. Xie et al. (2016) used the PSM to improve PFM. By matching the market value of assets and volatility of listed companies and non-listed companies, they calculated the default distance as a measurement of credit risk. The BP neural network is not suitable for China's insurance industry, because it needs a large sample for training and test and there are only a few listed insurance companies to sample. The SVM and PSM are suitable for small sample nonlinear data, but considering the maneuverability and simplicity, the author chose the PSM method to measure the systemic risk of unlisted insurance companies.

Therefore, the author used the SRISK method that Brownless and Engel (2012) proposed to measure the capital shortfall of listed companies and used the model of propensity matching PSM to establish the connection between financial data and systemic risk, which applies financial data in the measurement of the top 18 insurance companies' systemic risk whose premium income account for 70% market share. Thus, not only can the capital shortfall in the whole insurance industry be measured more comprehensively but that can also provide a reference for macro prudential supervision.

5.1.2 METHODOLOGY

SRiSK model. Brownless and Engel (2012) propose that the objective of the SRISK model is to measure the capital shortfall that a financial firm is expected to experience conditionally on a systemic event. The SRISK calculation is analogous to the stress tests that are regularly applied to financial firms. However, it is done with publicly available information only.

The capital shortfall can be thought of as the negative impact of the company's working capital. When the capital shortfall is negative, the company has the capital surplus and can operate properly. But when the capital shortfall is positive, the enterprise will encounter financial difficulties. This is defined as the capital shortfall of firm *i* at time *t* as $CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}$, where W_{it} is the book value of equity, D_{it} is the book value of debt, A_{it} is the value of quasi-assets, and *k* is the prudential capital fraction.[3]

The author was concerned about predicting the capital shortfall that financial institutions may face under the conditions of a systemic crisis. As for different definitions of systemic crises, the author chose the definition that the rate of decline of the market falls below a threshold *C* for a period of time *h*, which Acharya et al. (2010) proposed. To generate a meaningful measure of the pressure capital shortfall, the author assumed that the system event corresponds to a sufficiently extreme scenario. The author defined the market return between period t + 1 and t + h as $R_{mt+1:t+h}$ and systemic event as $\{R_{mt+1:t+h} < C\}$. In this paper, the author set the horizon *h* to one season (that is 57 periods) and the threshold *C* to −20%. The author denoted SRISK as the expected capital shortfall conditional on a systemic risk event

$$\begin{aligned} SRISK_{it} &= E_t(CS_{it+h}|R_{mt+1:t+h} < C) \\ &= kE_t(D_{it+h}|R_{mt+1:t+h} < C) - (1-k)E_t(W_{it+h}|R_{mt+1:t+h} < C) \\ &= kD_{it} - (1-k)W_{it}(1 - LRMES_{it}) \end{aligned}$$

（1）

where the $LRMES_{it}$ is the long run marginal expected shortfall, the expectation of the firm equity multiperiod arithmetic return conditional on the systemic risk event, that is $LRMES_{it} = -E_t(R_{it+1:t+h}|R_{mt+1:t+h} < C)$, where $R_{it+1:t+h}$ is the multiperiod arithmetic firm equity return between period t + 1 and t + h. Then, the single financial institution *i* represents the capital shortfall of the financial system as a whole as

$$SRISK\%_{it} = \frac{SRISK_{it}}{\sum SRISK_{i,t}} \qquad (2)$$

The greater the value of SRISK%, the more significant the importance of financial institution *i* in the financial system.

To calculate the value of SRISK, the author first obtained the estimation of LRMES. At present, there are many ways to estimate the LRMES, and the author selected the GARCH-DCC (generalized autoregressive conditionally heteroskedasticity-dynamic conditional correlation) model (Engle, 2002, 2009). The author denoted the logarithmic returns of the firm and the market, respectively, as $\mathrm{r_{it}} = \ln(1 + \mathrm{R_{it}})$ and$\mathrm{r_{mt}} = \ln(1 + \mathrm{R_{mt}})$. The author supposed that, conditional on the information set F_{t-1} available at time t – 1, the return pair has an (unspecified) distribution *D* with zero mean and time varying covariance,

$$\begin{bmatrix} r_{it} \\ r_{mt} \end{bmatrix} | F_{t-1} \sim D\left(0, \begin{bmatrix} \sigma_{it}^2 & \rho_{it}\sigma_{it}\sigma_{mt} \\ \rho_{it}\sigma_{it}\sigma_{mt} & \sigma_{mt}^2 \end{bmatrix}\right) \qquad (3)$$

[3] Under the minimum capital adequacy requirement of Basel III, the author fixed the prudential capital fraction at 8%.

This approach required specifying equations for the evolution of the dynamics volatilities σ_{it}^2 and σ_{mt}^2 and correlation ρ_{it}. Considering the asymmetry of the financial market and the feature of high peak and heavy tail about the stock yield data, the GJR-GARCH (Glosten-Jagannathan-Runkle-GARCH) volatility model and the DCC (dynamic conditional correlation) model is choose. The GJR–GARCH model equations for the volatility dynamics are

$$\begin{aligned}\sigma_{it}^2 &= \omega_{Vi} + \alpha_{Vi} r_{i\ t-1}^2 + \gamma_{Vi} r_{i\ t-1}^2 I_{i\ t-1}^- + \beta_{Vi}\sigma_{i\ t-1}^2 \\ \sigma_{mt}^2 &= \omega_{Vm} + \alpha_{Vm} r_{m t-1}^2 + \gamma_{Vm} r_{m t-1}^2 I_{mt-1}^- + \beta_{Vm}\sigma_{mt-1}^2\end{aligned} \qquad (4)$$

where $I_{it}^- = 1$ if $r_{it} < 0$, otherwise 0 and where $I_{mt}^- = 1$ if $r_{mt} < 0$, otherwise 0. The correlation coefficient of the DCC model is calculated through the adjusted yield of the volatilities ϵ_{it} *and* ϵ_{mt}, that is $\epsilon_{it} = r_{it}/\sigma_{it}$ and $\epsilon_{mt} = r_{mt}/\sigma_{mt}$.

$$Cor\begin{pmatrix}\varepsilon_{it} \\ \varepsilon_{mt}\end{pmatrix} = R_t = \begin{bmatrix}1 & \rho_{it} \\ \rho_{it} & 1\end{bmatrix} = diag\left(Q_{it}\right)^{-1/2} Q_{it} diag\left(Q_{it}\right)^{-1/2} \qquad (5)$$

where Q_{it} is the so–called pseudo-correlation matrix. The method of DCC model for pseudo-correlation matrix Q_{it} is

$$Q_{it} = (1-\alpha_{ci}-\beta_{ci}) S_i + \alpha_{ci}\begin{bmatrix}\varepsilon_{it-1} \\ \varepsilon_{mt-1}\end{bmatrix}\begin{bmatrix}\varepsilon_{it-1} \\ \varepsilon_{mt-1}\end{bmatrix}' + \beta_{ci} Q_{it-1} \qquad (6)$$

where S_i is the unconditional correlation matrix of the firm and market adjusted returns and $S_i = E(\varepsilon_{it}\varepsilon_{it}')$. In the high DCC model, S_i can be estimated directly with the following simple average formula: $S_i = \frac{1}{n}\sum \varepsilon_{it}\varepsilon_{it}'$, which greatly reduces the complexity of the calculation. At the same time, the parameters estimated should satisfy the conditions of $\alpha_{ci} > 0, \beta_{ci} > 0, \alpha_{ci} + \beta_{ci} < 1$ to ensure that the matrix Q_{it} is positive.

For such dynamic models, LRMES are usually not available in a closed form. However, accurate LRMES prediction can be obtained based on simulation. The procedure consists of simulating a random sample of size *S* firm *i* and market arithmetic returns conditional on the information set available at time *t*,

$$\begin{Bmatrix} r_{iT+t}^s \\ r_{mT+t}^s \end{Bmatrix}_{t=1,\ldots\ldots,h} | F_T \quad s = 1, 2, \ldots, S(One\ season\ contents\ h - period) \qquad (7)$$

And then calculating the LRMES,

$$LRMES_{iT}^s = -\frac{\sum_{s=1}^S R_{i\,T+1:T+h}^s I\left\{R_{m\,T+1:T+h}^s < C\right\}}{\sum_{s=1}^S I\left\{R_{m\,T+1:T+h}^s < C\right\}} \qquad (8)$$

where $I\{\}$ is an indicative function, and, when the expression inside the bracket is true, its value is 1; otherwise it is 0. Then substituting the LRMES value into the formula (1), the SRISK value can be obtained.

PSM model. Rosenbaum and Rubin (1983) proposed the PSM method, which refers to the possibility that an individual will receive some kind of treatment under its own specific attributes (a set of established covariates). In the empirical experiment, to control the confounding variables and obtain the "net effect" between the independent variables and the dependent variables, Rosenbaum and Rubin found that if the confounding variables are included in the logit model and obtain the predicted probability of the treated sample—the probability is called the "propensity score"—then researchers can remove bias by matching individuals with similar scores. This is called the "PSM method."

The author assumed that X_i is the multidimensional vector of pre-treatment characteristics, and $\mathrm{p}(X_i)$ is the probability of individuals assigned to a treatment. The definitions are as follows:

$$\mathrm{p}(X_i) \equiv Pr(T_i = 1|X_i) = E(T_i|X_i) \qquad (9)$$

where $T_i = \{0,1\}$. Treated and control individuals with the same score $\mathrm{p}(X_i)$ will have the same X_i distribution. Therefore, an exact matching reference to $\mathrm{p}(X_i)$ can balance the X_i distribution between the treatment group and the control group. Normally,

$$T_i \perp X_i|p(X_i) \qquad (10)$$

Assuming that there is no mixture in the distribution of the treatment group, if given a propensity score, the distribution of the treatment group and the control group is independent. The detailed derivation of formula 11 is given in the appendix.

$$(Y_{i1}, Y_{i0}) \perp T_i|X_i \Rightarrow (Y_{i1}, Y_{i0}) \perp T_i|p(X_i) \qquad (11)$$

where $Y_{i1}$is the result of the variable after the individual receives the treatment (T_i =1), while Y_{i0} is the result of the same variable when the individual does not receive the treatment (T_i =0). First, if the respective probabilities of the treatment group are known or obtained through a consensus estimate, the problem of the estimating dimension is reduced to one dimension. However, in reality, the propensity score $\mathrm{p}(X_i)$ or its formula is generally not directly given, so $\mathrm{p}(X_i)$ needs to be estimated from the available data. Second, adjusting the value of X_i balances the expected value of $\mathrm{p}(X_i)$, which is the average of replicate experiments. In some special studies, X_i needs further adjusting to control the probability of unbalanced X_i. Third, an exact matching result is hard to obtain, and the range of $\mathrm{p}(X_i)$ needs to be confirmed in advance.

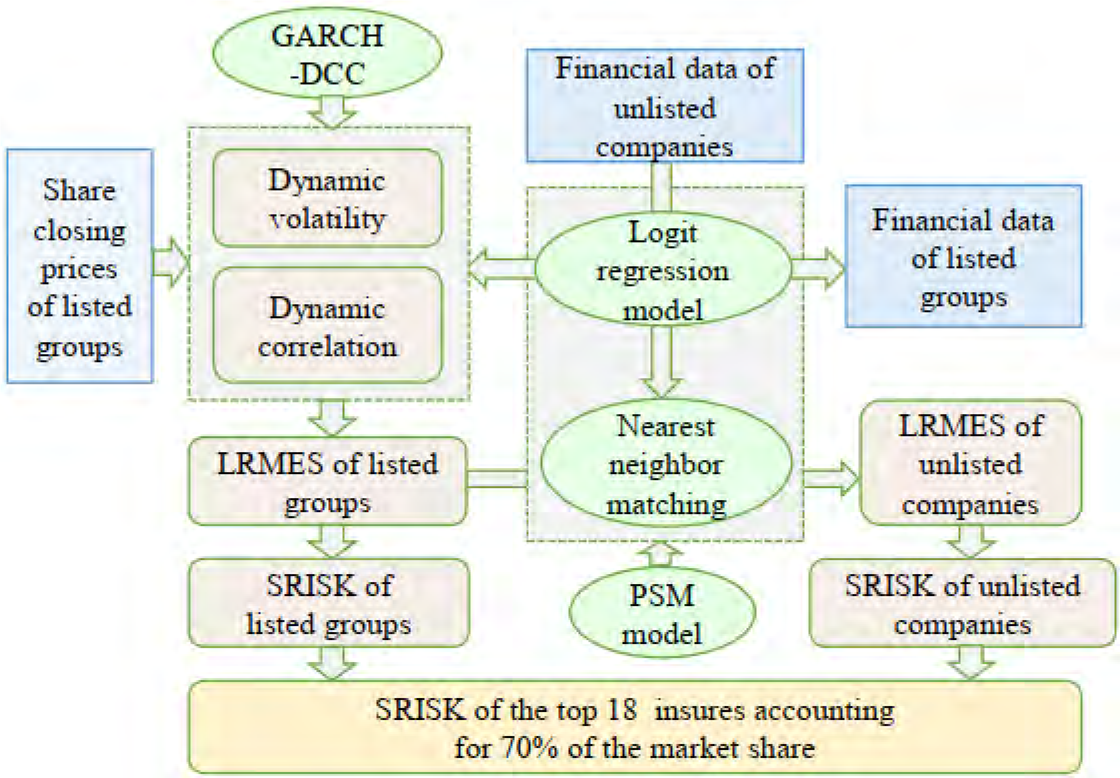
The practical application of PSM involves two steps. The first step is to establish a PSM that calculates the propensity score of a conditional probability of assignment to a treatment subject to a given a pre-trial covariate. The second step is researching the output variables. A series of analysis methods can be used, such as matched sampling, weighting, sub-classification or propensity score as a covariate for regression.

In the construction of the PSM, when there are two comparison groups, the propensity score usually needs to be obtained from a binary dependent variable regression model (Probit or Logit), which needs to include all the pretest covariates and their transformations. It is generally considered that the PSM is suitable and that the predictive probability of treated samples estimated by it is taken as the propensity score.

The matching method is a widely applied technique to find the closest propensity score in a comparison group. The selected matching units in one group can be paired with units from another group in the PSM. Nearest Neighbor Matching is one of the commonly used matching methods. The author defined P_i and P_j as the propensity score of the treated group and the control group, respectively, and I_1 and I_0 as set of the treated group and control group, respectively. When the absolute value of the difference of the propensity values is the smallest of all possible pairs of propensity values between *i* and *j*, the nearest neighbor relationship is $\mathrm{C}(P_i) = \min_j \left\| P_i - P_j \right\|, j \in I_0$. For each *i*, if only a single *j* is found that falls into $\mathrm{C}(P_i)$, then the match is nearest neighbor matching or 1-to-1 matching; but if for each *i*, there exist *n* members for *j* found to fall into $C(P_i)$, then the sub-matches are 1-to-*n* matching.

The SRISK method measures the capital shortfall from the market's perspective. That is to say, capital is measured with the market value of a financial institution's stock. Although the data access is more convenient and open, it strongly depends on the stock market's effectiveness. Figure 6 shows the working principle of the PSM-SRISK model, which is a combination of SRISK model and PSM model.

Figure 6
THE SRISK-PSM MODEL WORKING PRINCIPLE



The corresponding steps in the PSM-SRISK model's working principle are as follows. In the first step, the author collected the closing stock price data of the listed groups and got the corresponding logarithmic returns. The author used GJR-GARCH to get the dynamic volatility and DCC to get the dynamic correlation coefficient. Then through simulation, the author obtained the LRMES of the listed groups.

In the second step, the author collected the financial indicators data of the corresponding listed group and ran a Logit regression on the calculated LRMES and the financial indicators data in the first step to get the PSM, so the author got a model that links LRMES with financial data.

In the third step, the author collected the financial indicators data of non-listed companies as the input of Logit regression model and got the corresponding dynamic volatility and dynamic correlation coefficient of non-listed companies. After that, the author used the PSM method to match the LRMES of non-listed companies to the listed company's LRMES. So the author can assume that, except the difference in the variable of whether they are listed or not listed companies, the two groups of institutions after the matching are similar in the rest of the variables.

In the fourth step, the author obtained the SRISK of non-listed companies and SRISK percent of the capital shortfall relative to the whole insurance industry by substituting the LRMES data of the non-listed companies obtained in the previous step into the equity liabilities of the corresponding unlisted companies.

5.1.3 LIMITATIONS AND CONSTRAINTS

1. The calculation of LRMES of listed companies depends on the effectiveness of the stock market. LRMES is the long-term marginal capital shortfall the company faces. This parameter simulates the future results with the historical stock price. The stock market in China is generally affected by many institutional factors. The stock price does not fully reflect the value of the enterprise. In addition, investors often display panic and more obvious herding during the crisis. The performance of the stock price may not be in the normal course of the law, resulting in a decrease in the credibility of LRMES derived from the historical stock price simulation.

2. The off-balance sheet liabilities of financial institutions are not considered. The book value of liabilities is only a part of the overall liabilities of insurance institutions. The off-balance sheet operations of insurance companies mainly include commitments, guarantees and derivatives that are not reflected in the balance sheet. Off-balance sheet business is not reflected in the insurer's balance sheet, and data on this portion of the debt are harder to obtain from publicly available sources. And the SRISK model does not cover such data, which could lead to the SRISK model underestimating financial institution risk and capital shortfall.

3. Limitations of PSM. The accuracy of the PSM depends on the amount of information available to the data. If there are unobservable confounding factors in the control group, the PSM cannot reduce the resulting deviations. The proximity matching method used in the propensity score model makes only one decision at a time and does not consider the decisions that have been made in making the latter decisions. Therefore, when the model is used, difficulties are often encountered between the incomplete matching and inaccurate matching.

4. The financial statements of unlisted companies are not frequently updated. The lower frequency of the PSM-SRISK method calculation, which only uses annual data, is a slower update due to the fact that the unlisted insurer publishes only the annual financial statements. If the frequency of disclosing financial data for non-listed companies increases, the accuracy is also correspondingly improved, so insurers and regulators can make decisions faster.

5.2 Lower Tail Dependence and Granger Casualty Tests

Section 5.2.1 introduces the current literature on measuring risk between industries. By summarizing the literature and methods, LTD was used to measure tail dependence and Granger causality test was used to measure systemic risk transmitters and receivers. Section 5.2.2 describes the specific method. Section 5.2.3 describes the shortcomings of these two approaches.

5.2.1 LITERATURE REVIEW

Rodriguez (2007) used the daily returns from five East Asian stock indices during the Asian crisis and four Latin American stock indices during the Mexican crisis and concluded that the tail dependence and the asymmetry of the daily returns of stock indices in different countries would increase during periods of economic turmoil. Patro et al. (2013) investigated the correlation of financial institutions' stock returns and the validity of the stock return as an indicator of the systemic risk. Through empirical studies, the authors found that the correlation of daily stock returns is a simple, robust, predictive and timely measure of risk.

Balla et al. (2014) investigated the tail dependence of extreme losses of stock returns of large U.S.

depository institutions and identified a strong loss of dependence in extreme conditions. Motivated by the result, the authors derived extreme dependence-based systemic risk indicators and believed that the proposed indicators have the potential to inform the prudential supervision of systemic risks. In addition, Weiß and Mühlnickel (2014) used the LTD coefficients of the rates of returns of bank stocks as a measure of the degree of a bank's contribution to the systemic risk. They utilized the LTD coefficients of the rates of returns of insurance companies' stocks to capture the systematic risk effect (Weiß and Mühlnickel, 2015). And Weiß and Mühlnickel (2014), as well as Balla et al. (2014), concluded that if an individual wants to capture the influence of a particular industry or market on other industries in extreme circumstances, the tail dependence is a good measure.

Patro et al. (2013) argued that investment return data as a measure of systemic risk has the following four essential advantages: First, the information reflected in stock prices, unlike most balance sheet or corporate financial variables, is usually considered forward-looking. Second, the correlation of stock risk premiums can explain the changes in asset returns more properly than the basic variables. Third, stock returns can be an effective indicator of default risk. Fourth, compared to other potential systemic risk indicators, stock-return correlations have added advantages of being simple, robust and not subject to model or data errors. At the same time, Mühlnickel and Weiß (2015) noted that the advantage of tail dependence as a measure of systemic risk is that the LTD constitutes an asymptotic probability and, therefore, is independent of the market indices used. This allows the averaging of different financial sectors and markets. In addition, compared to other methods like MES used with moderate poor performance days of the market rather than the worst market-based performance during the real financial crisis to measure systemic risk, the measure of systemic risk based on the LTD reflects the probability of the market joint distribution at the lower tail; that is exactly the characteristic of systematic risk.

The measurement of the above correlation only represents whether an industry will affect other industries when risks occur; it cannot indicate the specific direction of risk transmission. To distinguish the role (source or victim) of an industry in the process of risk transmission, some scholars have adopted the Granger-Causality Relation Test to solve the problem. Based on the principal component analysis and the Granger Causality Relation Test, Billio et al. (2012) measured the stock return correlation among banks, insurers, hedge funds and brokerage firms. Empirical results showed that in recent years, the systemic risk of both insurers and banks are continuously increasing, and these four industries are highly correlated.

Chen et al. (2013) used spreads of Credit Default Swap (CDS) and the daily stock prices to study whether insurers are the source or victim of systemic risks. The authors argued that insurers are victims of systemic risk rather than the source by utilizing linear and nonlinear Granger-Causality Relation Tests to test the risk correlation between banks and insurers.

In view of the advantage of tail correlation in measuring systemic risk, the author of this report used it to measure inter-industry systemic risks and used the Granger Causality Test to judge the risk transmission directions among the industries.

5.2.2 METHODOLOGY

As mentioned above, for the measurement of inter-industry systemic risks, this paper calculated the LTD of the insurance industry and other four industries to define the presence of an LTD relationship between them and the magnitude of the dependence relationship so as to determine whether there is a risk contagion between industries and the degree of risk contagion that comes from different industries. After that, the author ran the Granger Causality Test to judge the transmission direction of risk of the two industries where tail dependences exist.

LTD. Tail risk is an event with small probability, whose possibility of happening is small but absolutely cannot be ignored. Once it happens, the losses are immeasurable. Tail risk is the focus of risk control theory. Relevance reflects the random change trend and the degree of correlation between two economic variables and often accounts for different interactions of financial assets in the financial field. Financial sectors are interconnected, where there are banks, insurers, real estates, securities and other different sectors. From a multivariate perspective, the overwhelming majority of financial crises in the past generally originated in one market.

For example, the U.S. subprime mortgage crisis originated mainly from the U.S. subprime real estate market and then spread to banks, stock markets and bonds and, finally, to the U.S. financial system. During the spread of risk, the correlation between different industries is stronger than at normal times. Therefore, if the returns on financial assets are divided into tail and middle, the correlation coefficient at the middle and tail distribution will be very different between different industries with the same distribution of returns. The correlation coefficient at the tail will be greater than that at the middle, and then a nonlinear correlation structure appears.

The correlation of the extreme returns occurring at the lower tail of the distribution is defined as "lower tail correlation." To some extent, LTD measures the degree of the asymptotic correlation or the asymptotic independence of different assets. When there is extreme loss risk in a particular market or industry, the need for risk diversification is urgent, but it is difficult to achieve due to the existence of tail dependence. Therefore, the lower tail correlation between different industries must be considered when measuring risks.

One commonly used measure of LTD is τ-measure (Hartmann and Vries, 2004; Longin and Solnik, 2001; Poon et al., 2004). Pairwise τ-measure is the ratio of the joint probability of a tail event to the probability of a tail event of a variable, where "tail events" only occur with a very low probability.

The lower tail dependence coefficients τ-measure of two random variables x, y—are usually defined as

$$\tau_{y|\mathrm{x}} = \frac{\lim_{\mathrm{p}\to 0} \Pr\left(\mathrm{y} < Q_y(\mathrm{p}) \text{and } \mathrm{x} < Q_x(\mathrm{p})\right)}{p} = \lim_{\mathrm{p}\to 0} \Pr\left(\mathrm{y} < Q_y(\mathrm{p}) | \, \mathrm{x} < Q_x(\mathrm{p})\right) \quad (12)$$

$Q_y(\mathrm{p}) \in (0,1)$ is one of the quantiles of the random variables *y* as a threshold of an extreme event. In the same way, $Q_x(\mathrm{p}) \in (0,1)$ is one of the quantiles of the random variables *x*. The economic meaning of $\tau_{y|\mathrm{x}}$ is the conditional probability of the tail event of *y* when a tail event occurs in *x*. To determine the thresholds in equation (12), the Hill plots are usually used. To make the Hill plot for the sequence of the sample size *n*, find the abscissa *k*, which is the starting points corresponding to the stable area of the Hill plot. Taking the value of *Q* (*k/n*) as the threshold—that is, selecting the smallest ordinal statistic that stabilizes the graph as the threshold.

It is important to note that although $\tau_{y|\mathrm{x}}$ represents the conditional probability of a tail event of *y* when a tail event occurs in *x*, it does not represent a causal relationship. Similar to the correlation coefficient, the value of $\tau_{y|\mathrm{x}}$ is between 0 and 1, representing the dependent level of the tail. And $\tau_{y|\mathrm{x}}$=0 indicates the tail independence, while $\tau_{y|\mathrm{x}}$=1 indicates the complete tail dependence.

There are two estimation methods for the value of $\tau_{y|\mathrm{x}}$: copula and non-parametric estimation. Given the model risk inherent in parametric dependence modeling via copulas, the author adopted the non-parametric estimation method that Oordt and Zhou (2011) proposed, which runs a simple OLS regression coefficient as the estimate of the dependence. The specific estimation principle is as follows (Oordt and

Zhou, 2012).

For $\mathrm{x}_t, \mathrm{y}_t (t = 1,2, \dots, n)$, the non-parametric estimation of $\tau_{y|\mathrm{x}}$ can be expressed as

$$\hat{\tau}_{y|\mathrm{x}} = \frac{\sum_{t=1}^{n} I_{y\ and\ x,t}}{\sum_{t=1}^{n} I_{x,t}} \qquad (13)$$

where, $I_{y\ and\ x,t} = 1_{\left\{y_t < Q_y\left(\frac{k}{n}\right)\ and\ x_t < Q_x\left(\frac{k}{n}\right)\right\}}$, $I_{x,t} = 1_{\left\{x_t < Q_x\left(\frac{k}{n}\right)\right\}}$, $1_{\{.\}}$ indicates the indicative function. Denote $I_{y\ and\ x,t}$ as $I_{y,t} I_{x,t}$, then

$$\hat{\tau}_{y|\mathrm{x}} = \frac{\sum_{t=1}^{n} I_{y,t} I_{x,t}}{\sum_{t=1}^{n} I_{x,t} I_{x,t}} \qquad (14)$$

Therefore, the nonparametric estimator is equal to the coefficient estimated by running OLS regression of the extremum of *y* and *x* without the intercept term. That is, the nonparametric estimation of $\hat{\tau}_{y|\mathrm{x}}$ is equal to the estimated value of the OLS regression coefficient β in equation

$$I_{y,t} = \beta \times I_{x,t} + \varepsilon_t \qquad (15)$$

For a multivariate case, to estimate variable *y* and variables $x_1, x_2, \dots, x_n$, add all of the interactions of $I_{x_i,t}$ into the regression. For example, to measure the three-dimensional dependence structure of variable *y* and variables *x* and *z*, the following regression is needed.

$$I_{y,t} = \beta_x \times I_{x,t} + \beta_z \times I_{z,t} + \beta_{x,z} \times I_{x,t} I_{z,t} + \varepsilon_t \qquad (16)$$

Then under the condition that *x* and *z* are all extreme values, the estimation of the probability of *y* is the extremum $\hat{\tau}_{y|\mathrm{x,z}}$, equals to $\hat{\beta}_x + \hat{\beta}_z + \hat{\beta}_{x,z}$. The approach to calculating any other multiple dependent structure is similar to that.

This report explores the influence on the insurance industry when systemic risk occurs in banks, securities, real properties and the internet industry, so the LTD between returns data of the insurance sector and other sectors are assessed, namely the value of $\tau_{\mathrm{insurance|bank}}$, $\tau_{\mathrm{insurance|security}}$, $\tau_{\mathrm{insurance|estate}}$, $\tau_{\mathrm{insurance|internet}}$.

Linear Granger Causality Test. Considering that the LTD does not mean a causal relationship, to explore the direction of the interconnectedness between industries, the author used the Granger Causality Test to determine the causal relationship between insurance and the other four industries, thus to explore the role of the insurance industry in systemic risk contagion. Granger (1969) developed the Granger Causality Test, which is the most widely used method to verify the causal relationship between two variables. Granger Causality is a statistical concept of causality based on its predictive power. Usually the form of Granger Causality has been set as: In the prediction of the future information of a set of data, if adding another set of data to the past information is better than only using the data in the past information in the prediction results, then these two groups of data can be illustrated having a Granger causality relationship. According to whether the prediction model is linear, the Granger Causality Test can be divided into the linear and nonlinear Granger Causality Tests.

If X_t and Y_t are two stationary and ergodic time series, and assuming the mean values are both zero, then the linear internal relation can be expressed as:

$$\mathrm{X}_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t \qquad (17)$$

$$\mathrm{Y}_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t \qquad (18)$$

where, ε_t and η_t are two unrelated white noise processes and *m* is the number of pre-set maximum lag order. The parameters are a_j, b_j, c_j and d_j.

According to the definition, when b_j is not all zero, *Y* is the Granger cause of *X*; similarly, when c_j is not all zero, *X* is the Granger cause of *Y*. The lag order of the model can be selected according to the Bayesian Information Criterion. The *F* statistic is used to judge the causality relationship. And the null hypothesis can be set to be that b_j or c_j is zero according to the direction of causal relationship.

Nonlinear Granger Causality Test. After continuous development, the definition of the traditional Granger Causality Test has changed a lot. Now in statistical software, it is based on strict linear assumptions. This kind of causality test is very easy to use and reasonable in detecting the linear causality between variables. However, it cannot test the nonlinear causality between variables. Therefore, in practice, if only linear Granger causality test is used for analysis, the conclusions drawn are often unreliable, because the traditional Granger causality test may miss the significant nonlinear causal relationship between variables. Thus, it is necessary to use the nonlinear Granger Causality Test to investigate the nonlinear causal relationship.

Brock and Baek (1991) proposed a nonparametric statistical method to test nonlinear causality. The method requires that the variables is independent and identically distributed. However, the economic data usually cannot meet the requirement. Hiemstra and Jones (1994) proposed a test method based on Baek and Brock's test methods; that method does not strictly require the variables to be independent and identically distributed. The authors assumed that even if the test sequence has a short-term dependency, it is able to test the nonlinear causal relationship between variables. After making the above corrections to Brock and Baek (1991) to the nonlinear Granger Causality Test, Hiemstra and Jones proposed the Hiemstra-Jones test and tested it on the basis of the data from the U.S. stock market, and they found that the two-way nonlinear causal relationship was very obvious, which proves that the nonlinear Granger Causality Test can verify the nonlinear causal relationship between the unverifiable variables in the traditional linear causality test model.

Diks and Panchenko (2004) propose that the greater the sample size of the Hiemstra-Jones test, the more likely it is to reject the null hypothesis. When the sample size is very large, the probability of rejecting the null hypothesis approaches 1. This phenomenon comes from the deviation of the statistic caused by the change of the condition distribution (Diks and Panchenko, 2004). The authors then propose a nonparametric statistic, T_n to test for nonlinear non-Granger causality, which overcomes the drawbacks of Hiemstra-Jones statistics. For the null hypothesis (X_t is not the nonlinear Granger cause of Y_t), the statistic T_n is defined as

$$\mathrm{T}_n(\varepsilon) = \frac{(n-1)}{n(n-2)} \sum_i (\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i)\hat{f}_{Y,Z}(Y_i, Z_i)) \qquad (19)$$

where $\mathrm{Z}_t = \mathrm{Y}_{t+1}$, and ε is the bandwidth. After selecting the optimal bandwidth, T_n is the consensus estimator. The optimal bandwidth ε_n can be calculated from the coefficients of the fitted ARCH (1).

5.2.3 LIMITATIONS AND CONSTRAINT

One limitation is the lack and unreliability of data. Since China's insurance industry lacks historical event data, it is very difficult to conduct an event window analysis. In addition, both models use industry indices when they are applied. However, China's insurance market has not yet published the index of authoritative sectors, and the calculations of various industry indices available have different standards and results, which leads to some data errors in the calculation results.

Another constraint are LTD limitations. Tail dependence calculations are based on historical data and do not consider forward-looking elements, making it difficult to analyze future scenarios. With LTD, the causal relationship cannot be expressed when measuring the risk, so the direction of the specific risk transmission cannot be judged and cannot reveal the information of specific dependence structure.

Finally, Granger limitations are a constraint. Granger's method is only suitable for describing the causal relationship in the short term. It is difficult to explain the long-term causality and the false causality from the same data source cannot be distinguished.

Section 6: Results of Systemic Risk Measurement in China's Insurance Industry

6.1 Intra-industry systemic risk measurement

The data sources are analyzed in Section 6.1.1, and the results after substituting the model are described in Section 6.1.2. Section 6.1.3 provides a reasonable explanation and analysis of the final results.

6.1.1 DATA ANALYSIS

The author selected the top 18 insurers (including two listed companies and 16 non-listed companies) accounting for 70% of the market share in 2016 to calculate the size of the SRISK risk in 2014–2016 and marked them as *a-r*.

The sample data are mainly divided into two categories: The first category lists insurance group market data. The author obtained the market data of four insurance groups[4] listed in China's mainland exchanges (share price information since their listing) from Wind Database. In terms of the time dimension, due to the existence of accounting rules of fair value measurement and pro-cyclical financial supervision system, the economic cycle has upward and downward periods—that is, systematic risk has a certain periodicity (Jiang Tao, 2014; Xu Hua, 2016). The author treated each year's data of each listed group as independent samples and set them as training samples. There were 34 independent samples total: listed group A–D (2007–2016). The author obtained the closing stock price data of the industry through the weighted average of the total capital stock calculated by Wind Database.

The second category is the insurance group's financial data, which the author obtained from its annual financial statement data and solvency reports disclosed on the official website.

6.1.2 RESULTS

Solving the LRMES for the listed group using the SRISK model. The author used EViews to calculate the parameters of the GARCH-DCC model and used Matlab to calculate LRMES. The results of the parameter calculation are shown in Table 5.

Table 5

GARCH-DCC PARAMETER ESTIMATES

Variables/ Statistics	GJR-GARCH				DCC	
	w_M	α_M	γ_M	β_M	α_c	β_c
Listed Group A	0.00000537	0.054334	0.004166	0.935572	0.032892	0.894681
Listed Group B	0.00000215	0.108616	−0.04689	0.929695	0.074605	0.809632
Listed Group C	0.00000297	0.043081	0.005634	0.949816	0.008211	0.983456
Listed Group D	0.00001780	0.083963	0.051306	0.874084	0.067434	0.845015
z-Statistic of A	1.955270	3.918968	0.232192	69.87027	5.810482	57.54937
z-Statistic of B	−0.53924	3.124021	−1.67438	122.94850	8.595556	44.70530
z-Statistic of C	1.576624	3.149280	0.342602	83.43790	3.081625	143.47330
z-Statistic of D	2.132053	3.566923	1.428442	33.66375	5.576657	30.96201

Note: The figures marked red denote that they did not pass the test; the corresponding statistic values are also small.

[4] There are six listed insurance group in China, of which four are listed on the mainland and two are listed in Hong Kong. Because the mainland exchanges and Hong Kong exchanges are quite different in terms of trading rules, market practices and investor expectations, the author did not consider the insurance institutions listed in Hong Kong.

The results of the dynamic volatility and dynamic correlation are shown in Figures 7 and 8, respectively.

Figure 7
THE DYNAMIC VOLATILITY OF THE FOUR LISTED GROUPS

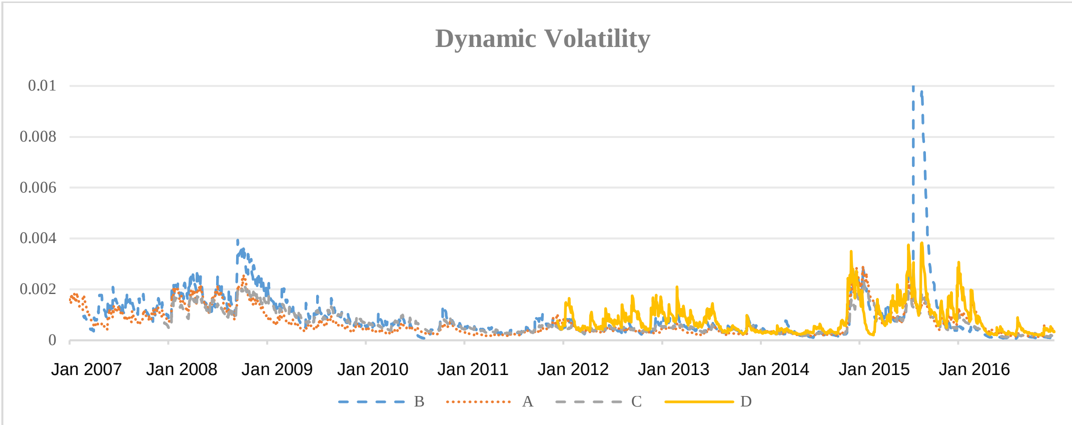
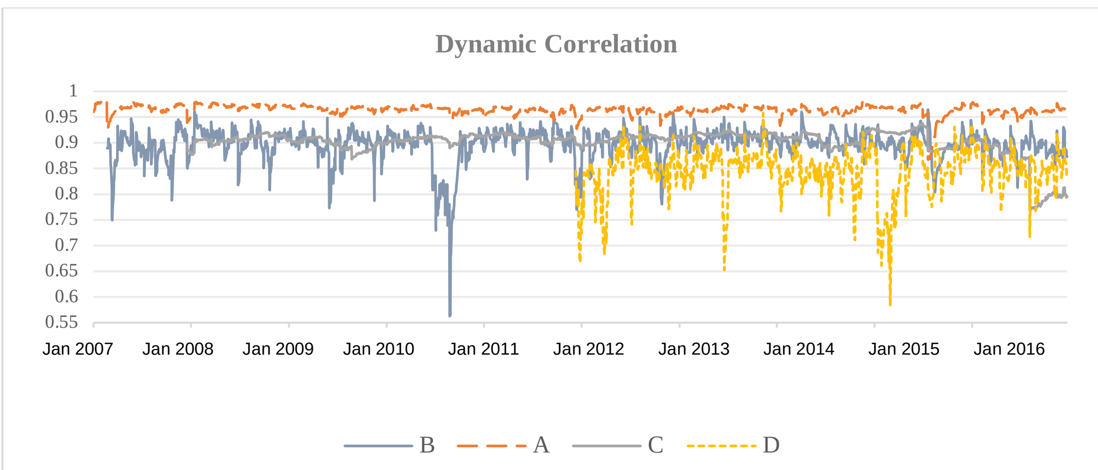


Figure 8
THE DYNAMIC CORRELATION OF THE FOUR LISTED GROUPS



Except for Listed Group B, the fluctuations of the other three listed groups are relatively stable; both are fluctuating between 0 and 0.004. Listed Group B has also performed fairly steadily except on July 24, 2015, when the share price has a sharp downturn from 80 to around 30 due to dividend payment and a share split. The outstanding shares doubled, but the total assets remained unchanged, resulting in big volatility.

Table 6 shows the yearly arithmetic average.

Table 6
THE ANNUAL LRMES OF LISTED INSURANCE GROUP

Year	Listed group	Volatility	Correlation	LRMES	Year	Listed group	Volatility	Correlation	LRMES
2007	A	0.00103	0.9675	0.2573	2007	B	0.00120	0.8865	0.2811
2008		0.00155	0.9710	0.2922	2008		0.00202	0.9043	0.3331
2009		0.00064	0.9661	0.2426	2009		0.00110	0.8951	0.3027
2010		0.00042	0.9652	0.2507	2010		0.00056	0.8727	0.2411
2011		0.00033	0.9614	0.2438	2011		0.00046	0.9059	0.2753
2012		0.00042	0.9614	0.2608	2012		0.00046	0.8952	0.2543
2013		0.00037	0.9660	0.2441	2013		0.00054	0.9088	0.2661
2014		0.00043	0.9632	0.2614	2014		0.00046	0.9040	0.2664
2015		0.00119	0.9574	0.2693	2015		0.00344	0.8947	0.3931
2016		0.00047	0.9613	0.2871	2016		0.00021	0.8920	0.2072
2007	C	0.00067	0.8890	0.2574	2011	D	0.00059	0.7948	0.2648
2008		0.00141	0.9066	0.2819	2012		0.00079	0.8402	0.2615
2009		0.00098	0.8964	0.2882	2013		0.00073	0.8568	0.2711
2010		0.00061	0.9078	0.2785	2014		0.00059	0.8442	0.2712
2011		0.00041	0.9093	0.2517	2015		0.00137	0.8326	0.2269
2012		0.00042	0.9072	0.2331	2016		0.00062	0.8527	0.3392
2013		0.00046	0.9165	0.2412	2015	C	0.00111	0.9098	0.2576
2014		0.00037	0.9054	0.2223	2016		0.00031	0.8484	0.2251

Solving the non-listed company's LRMES using the PSM model. Two PSM are constructed, which are P_1 and P_2. P_1 represents the dynamic volatility of the company, and P_2 represents the company correlation coefficient. The author used the Logit model to calculate the propensity scores:

$$\mathrm{Logit}P_1 = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n + \varepsilon_1 \qquad (20)$$

$$\mathrm{Logit}P_2 = \beta_0 + \beta_1 Y_1 + \beta_2 Y_2 + \cdots + \beta_m Y_m + \varepsilon_2 \qquad (21)$$

where X_i and Y_i are the control variables; n and m are the number of covariates and ε_1 is a random error term.

The selection of variables directly determines the accuracy of the matching. Alex Z Fu (2008) believes that regardless of whether they are related to treatment assignment and estimation results, all variables should be considered. When choosing the variables of the Logit regression model, variables that can distinguish the listed companies and non-listed company and those affect the company's dynamic volatility and correlation should all be included. Generally speaking, compared to the unlisted insurance companies, the listed ones have more financing channels, underwriting ability and solvency.

In China, due to the lack of research on unlisted insurance company's systematic risk based on PSM and in view to the characteristics of China's insurance industry and the availability of data, the author selected 12 business indicators[5] that may have an impact on the insurance institution's dynamic volatility and dynamic correlation. Then, the author repeated screening the variables according to the nonlinearity and significance of the variables and the goodness of fit of the model, and the author eventually got the final six variables, which are included in the Logit regression model P_1 and P_2.

[5] All contain total assets profit rate, underwriting potential, assets operating income growth rate, retention ratio, asset profit growth, market share, separation rate, comprehensive loss rate, capital utilization rate, full surrender rate, asset liability ratio and the rate of return on investment.

Table 7

VARIABLE DESCRIPTION

Variable		Definition	Calculation formula
Volatility P1	X1	Underwriting Potential	(insurance business income − the ceded-out premium)/ (share capital or paid-in capital + surplus reserve + capital reserve)
	X2	Surrender rate	surrender value/insurance business income
	X3	Asset-liability ratio	Liabilities/Assets
Correlation P2	Y1	Total Assets Profit Margin	Net Profit/Total Assets (Return on Investment)
	Y2	Market share	the company's original premium income/total industry premium income
	Y3	Combined ratio	(claims paid − Reimbursement expenditure + Extraction of outstanding compensation reserves − Repay the outstanding claims reserves)/Earned Premium

The results of the parameter estimation of the Logit regression model are shown in Table 8.

Table 8

PROPENSITY SCORE REGRESSION MODEL COEFFICIENT ESTIMATION RESULTS

Coefficient		Estimated Value	P(>|t|)
P_1	α_0	−7.1711	<2e-16***
	α_1	0.3161	0.1918
	α_2	0.5260	0.0232*
	α_3	−0.4445	0.0803
P_2	β_0	2.35182	< 2e-16***
	β_1	0.15828	0.03096*
	β_2	0.34642	0.00043***
	β_3	0.16899	0.033297*

Note: ***, **, *, and . indicate 0.1%, 1%, 5%, and 10%, respectively

After substituting the index values for each company into the model to get the propensity scores P_1 and P_2, the author used the nearest neighbor 1-to-*n* matching method to match the unlisted insurance companies with the listed insurance companies.[6]

The insurance company SRISK and SRISK%. Based on the matching results from Table 8, the author simulated the LRMES of 18 insurers and substituted the corresponding debt and equity data to obtain the SRISK and SRISK% for each insurer. The calculation results are shown in Table 9.

[6]The matching results are shown in Appendix A.

Table 9

THE SRISK AND SRISK% OF 18 INSURERS IN 2014–2016 (UNIT: MILLION YUAN)

2014/insurer	SRISK	SRISK%	2015/insurer	SRISK	SRISK%	2016/insurer	SRISK	SRISK%
c	40889	46%	c	63218	46%	C	61424	28%
m	19438	22%	f	21119	15%	F	50526	23%
g	15197	17%	m	18580	13%	M	27430	12%
j	5200	6%	j	13432	10%	G	22145	10%
e	4462	5%	p	8324	6%	J	19038	9%
l	2957	3%	g	7075	5%	P	18053	8%
p	247	0%	e	6752	5%	E	15142	7%
i	163	0%	i	47	0%	H	6696	3%
o	0	0%	l	0	0%	O	2902	1%
d	0	0%	o	0	0%	L	0	0%
a	0	0%	h	0	0%	I	0	0%
n	0	0%	d	0	0%	D	0	0%
k	0	0%	a	0	0%	A	0	0%
f	0	0%	n	0	0%	N	0	0%
h	0	0%	k	0	0%	K	0	0%
b	0	0%	b	0	0%	B	0	0%
q	0	0%	q	0	0%	Q	0	0%
r	0	0%	r	0	0%	R	0	0%
Total SRISK	88,553	100%	Total SRISK	138,547	100%	Total SRISK	223,356	100%
Original insurance premium income	202,348	–	Original insurance premium income	242,825	–	Original insurance premium income	309,591	–

6.1.3 EMPIRICAL ANALYSIS

Table 9 suggests the following conclusions.

SRISK increased significantly. The total SRISK for the insurance industry in 2014, 2015 and 2016 was 88,553, 138,547 and 223,356 million yuan, respectively, an increase of 56.46% in 2015 and an increase of 61.21% from 2015 to 2016, which far exceeded the industry growth rate of 23.69%. As the size of the industry grew, SRISK increased faster.

Robert Engle[7] (2015) pointed out that both the United States and Europe showed a decline in SRISK size after the 2008 financial crisis and the 2011 European sovereign debt crisis, while in Asia, especially China, the SRISK size rose from 0 to about 3,653 billion yuan and showed strong volatility. As of December 2017, SRISK in China ranked first in the world with about 5513 billion yuan, and Japan ranked the second with about 5048 billion yuan, followed by France, the United Kingdom and the United States (Engel's research team, 2018). Based on that, from a macro perspective, the systemic risk of China’s financial sector significantly increased. As a result, the capital shortfall of the insurance industry, which is a part of financial system, also increased year by year.

Unlisted insurers performed outstandingly. Calculations show that the average systematic contribution of listed companies in 2014 was 8.5%, while the average contribution of non-listed insurance companies in 2014 was 5.2%, rising to 5.9% in 2015 and slightly decreasing to 5.6% in 2016. Thus, the contribution of non-listed companies to systemic risk is an important part. Although non-listed companies have less financing channels than listed companies, their disclosure requirements are not as strict as listed ones, and their decision power of the management are relatively more centralized. Listed companies generally have

[7] Robert Engle is a Nobel laureate, and he is the director of the Volatility Institute at New York University Stern.

better credit and will not easily get involved in bank-run-like surrender risk. Therefore, systemic risk in China's insurance industry should consider unlisted insurers' contribution.

The risk contribution to life and property and casualty insurers. Academia generally believes that life insurance companies have more risks than property and casualty insurers. However, there is always a lack of concrete measures. Based on Table 9, there is an extreme result in China's insurance market. From 2014 to 2016, none of the property and casualty insurance companies faced a capital shortfall when the crisis event happened, while life insurance companies were more vulnerable to systemic risks, because the contribution is 100%.

Among the 18 insurers, which make up 70% of the entire market, five were property and casualty insurance companies, accounting for 27.8% of them. However, the five contribute 0% to the systematic risk of capital shortfall. On the one hand, life insurers are more vulnerable to intra-industry crises because Mortgage-Backed Security (MBS) and leverage are more vulnerable than mortgage-backed companies. On the other hand, due to the business model and business characteristics, life insurance companies are more at risk.

In terms of liability management, the long-term liability of life insurance companies leads to the problem of long-term mismatch between their assets and liabilities and the increase in liquidity risk. As for the use of funds, life insurance companies have more investments. In recent years, as insurance investment channels have expanded, the credit risk and exchange rate risk have been increasing. With respect to NT products, the investment guarantee products, and the universal insurance are all systematic trigger factors. However, due to the large difference between the proportion of investment products of life insurers and the proportion of credit guarantee products of property and casualty insurance companies, there is a big difference in life insurers' and property and casualty insurance companies' contributions to systemic risk.

Concentration–Vulnerability effect. In 2014, the *f* insurance company had a capital shortfall of 0. However, in 2015, it became the second largest contributor to the total SRISK, accounting for 15% and rising to 23% in 2016. The SRISK of *h* insurance company in 2014 and 2015 was zero. In 2016, the SRISK of company *h* is 6,696 million yuan, contributing about 3% to the total SRISK. Both *f* and *h* belong to the same insurance group.

On the one hand, an insurer cannot exert a significant influence on an investment when its investment share does not reach 20%; and at the same time, if the investment targets of *f* and *h* coincide with other subsidiaries in the group, financial accounting changes from available-for-sale financial assets to long-term equity investment and will thus increase the book value of the company and amplify the asset bubble.

Weiß and Neumann (2014) proposed the hypothesis of "concentration–vulnerability"—that is, the group makes the risk aggregate; the higher the concentration, the greater the possibility of systemic risk. On the other hand, in terms of the composition of premiums, some companies are short-term financial insurance-based companies, and the substantial increases in their debt-side businesses were due to their high-return yet low-liquidity investments.

6.2 Inter-industry dependence measurement

Section 6.2.1 provides a simple descriptive statistical analysis of the data source, and Section 6.2.2 describes the results after substituting the model. Section 6.2.3 provides a reasonable explanation and analysis of the final results.

6.2.1 DATA SOURCE

The author used daily closing price data from Wind Database, which consisted of the Shenwan industry classification standard index for insurers, real estates, banks, securities and internets from Jan. 9, 2007, to Jan. 6, 2017, totally 2,434 trading days. For convenience, the rate of return for each industry is expressed as the logarithmic return $\mathrm{R_{i,t}} = 100 \times \ln(\mathrm{P_{i,t}}/\mathrm{P_{i,t-1}})$, where $\mathrm{R_{i,t}}$ represents the return rate of the ith industry index at time t; $\mathrm{P_{i,t}}$ and $\mathrm{P_{i,t-1}}$ represent the stock closing prices of the ith industry in period *t* and *t-1*, respectively. To avoid that the real rate of return or rate of change is too small, which would reduce the data's accuracy, the real rate will be increased by 100 times. Let v, w, x, y and z denote the index returns for the insurance, banking, securities, real estate and internet industries, respectively. Table 10 shows the descriptive statistics for index returns.

Table 10
DESCRIPTIVE STATISTICS FOR INDEX RETURNS

	Insurance (v)	Banks (W)	Securities (x)	Real estates (y)	Internet (z)
Mean	−0.011969	−0.005245	−0.009904	0.005212	0.048565
Median	−0.0466	0.000000	0.000000	0.113800	0.249700
Maximum	9.568100	9.646000	9.487300	9.853900	11.89260
Minimum	−26.5551	−13.3531	−24.1162	−9.4341	−9.7232
Std. Dev.	2.524570	1.840860	2.991066	2.384264	2.447330
Skewness	−0.402628	−0.208854	−0.355293	−0.515201	−0.466274
Kurtosis	9.949282	8.652343	6.235800	4.938305	4.406971
Observations[8]	2433	2433	2433	2433	2433

6.2.2 RESULTS

In accordance with the method described above, the author made the Hill plots to select the 74th order statistics as the threshold—that is, $\mathrm{u} = 87/2433 \approx 0.035758$. Table 11 shows the 74th order statistics of the logarithmic returns as the corresponding threshold in each industry.

Table 11
THE THRESHOLD OF LOGARITHMIC RATE OF RETURN FOR EACH INDUSTRY

Variable	Threshold
Insurance (v)	−4.8394
Banks (w)	−3.6790
Securities (x)	−6.3071
Real estates (y)	−5.4067
Internet (z)	−5.4067

Regression models $I_{v,t} = \beta_w \times I_{w,t} + \varepsilon_t$, $I_{v,t} = \beta_x \times I_{x,t} + \varepsilon_t$, $I_{v,t} = \beta_y \times I_{y,t} + \varepsilon_t$and $I_{v,t} = \beta_z \times I_{z,t} + \varepsilon_t$ are constructed for v and w, x, y, z according to Equation (18), and the regression coefficient β_w, β_x, β_y and β_z are determined as the non-parametric estimations of pairwise τ-measures $\tau_{v|w}$, $\tau_{v|x}$, $\tau_{v|y}$ and $\tau_{v|z}$. The value of pairwise τ-measure represents that the conditional possibility of insurers being at risk given only one of other industries is at risk. The pairwise τ-measures results are shown in Table 12.

The author constructed a multivariate regression model that included all possible interactions among w, x,

[8] Because of the differential calculation for returns, there is one observation loss in each series.

y and z. Because of the multicollinearity and the statistically insignificance of the model coefficients, the author eliminated the insignificant variables continuously and finally obtained the results, as shown in Table 13, which indicate the probability of crisis in the insurance sector conditional on crisis in all or any of the other four sectors.

Table 12
PAIRWISE $\boldsymbol{\tau}$-MEASURE BETWEEN INSURERS AND THE OTHER FOUR INDUSTRIES

	Probability	Std. Error	T value	Pr(>|t|)
$\tau_{v\|w}$	0.61644	0.01597	38.61	0.0000 ***
$\tau_{v\|x}$	0.54795	0.01696	32.30	0.0000 ***
$\tau_{v\|y}$	0.47940	0.01780	26.94	0.0000 ***
$\tau_{v\|z}$	0.35616	0.01895	18.80	0.0000 ***

Note： *** indicates significance at 1% level. When the original hypothesis is rejected and a systemic risk is identified in an industry, the insurance industry will be at risk.

Table 13
MULTIDIMENSIONAL $\boldsymbol{\tau}$-MEASURE BETWEEN INSURERS AND OTHER FOUR INDUSTRIES

	Probability	Std error	T value	P value
$\tau_{v\|w,\bar{x},\bar{y},\bar{z}}$ (1)	0.452	0.02348	19.266	0.0000 ***
$\tau_{v\|\bar{w},x,\bar{y},\bar{z}}$ (2)	0.325	0.02519	12.883	0.0000 ***
$\tau_{v\|\bar{w},\bar{x},y,\bar{z}}$ (3)	0.084	0.02855	2.954	0.0032**
$\tau_{v\|\bar{w},\bar{x},\bar{y},z}$ (4)	0.045	0.02166	2.069	0.0387*
$\tau_{v\|w,\bar{x},y,\bar{z}}$ (5)	0.718	0.05394	3.36	0.0008***
$\tau_{v\|w,\bar{x},\bar{y},z}$ (6)	0.119	0.04654	-8.123	0.0000***
$\tau_{v\|\bar{w},x,\bar{y},z}$ (7)	0.535	0.04656	3.557	0.0004***
$\tau_{v\|\bar{w},x,y,\bar{z}}$ (8)	0.229	0.05366	-3.35	0.0008***
$\tau_{v\|w,x,y,\bar{z}}$ (9)	1.000	0.07973	2.647	0.0082**

Note: The absence of the bar denotes no systemic risk in that particular industry. *** indicates significance at 1% level. When the original hypothesis is rejected and a systemic risk is identified in an industry, the insurance industry will be at risk. * indicates significance at 5% level. When the original hypothesis is rejected and a systemic risk is identified in an industry, the insurance industry will be at risk.

Table 12 shows that the LTD of the insurance industry and the other four industries are all non-zero, which demonstrates that, even if systemic risks do not occur in the insurance industry, the insurance industry is also subject to the risks of other industries, which may still induce systematic risks in the insurance industry. Among the four LTD coefficients, the insurance industry has the highest LTD of the banks. The probability of systemic risk in the insurance industry is 0.61644 in the case of systematic risk in the banking industry, followed by the LTD coefficient between insurers and securities of 0.54795. The third is the LTD coefficient with real estate, which is 0.47940; and the smallest is the LTD coefficient with the internet industry, which is 0.35616.

Based on that conclusion, the systemic risk of the insurance industry is as high as about 62% in the case of systemic risks in the banking industry. Therefore, there is a very close relationship between the systemic risks of the insurance industry and the banking industry and another relatively close relationship is between the securities industry and the real estate.

The mixed financial services offered by entities in a group has become more and more frequent in the financial system in recent years. It is very common for financial corporations to combine insurance and banking. Relatively speaking, the number of insurance group companies carrying out securities business is smaller, which partly explains that the LTD between the insurance industry and the banking industry is greater than that between the insurance industry and the securities industry. In addition, the risk of securities firms is less affected by systemic financial risks of the banks.

One reason is that the securities companies and banks have different ways of handling capital investments. Security companies have sound firewall systems. Customers' and their own funds are completely separated from each other when they invest. Even if the self-owned funds suffer serious losses in the investment, that will not have too much impact on customers'. This separation mechanism fundamentally reduces the possibility of securities companies' credit risk.

Second, the debt structure of a securities company is different from that of a bank. Its liabilities are not the customer's own funds but some regular commercial paper and secured loans. Such a liability structure makes it less risky to run like banks when the liquidity is reduced. Therefore, from the perspective of the securities firm's own development and the amount of funds or the tightness of the connection between the securities industry, the risk accumulation in the securities industry is not as serious as that in the banking industry, and the impact of risk spillovers is also relatively smaller than the banking industry.

Generally speaking, the connection between the real estate sector and the insurance sector is only an investment relationship, rather than such a close link as exists between insurance and banking and securities within the financial conglomerate. Therefore, the LTD of the real estate industry is smaller than that of banks and securities. The interconnection between the systemic risk of the internet industry and the insurance industry is the smallest among the four; the main reason is that insurers' investment in the internet industry is small and there is still much room for growth in the online insurance business. However, a tail coefficient of 36% still deserves insurers' and regulators' attention. At present, the penetration between China's insurance industry and the internet industry is becoming stronger and stronger. The interconnection between the two industries will deepen gradually in the future.

Table 13 shows that the rank of closeness is consistent with the result of pairwise matching, when the systemic risk of only one specific industry (the first four rows) occurs, which proves the robustness of the results. If and only if crisis occurs in one industry, banking is most closely linked with the insurance industry, followed by the securities industry. If only one of the real estate and internet industries has systemic risks, there is little chance that the insurance industry will be at risk. This shows that insurers need to be vigilant about the systemic risks of the banking and securities industries. When only one of these two industries is individually exposed to risks, there is a higher probability of transmitting the risk to the insurance industry.

Given an extreme event in the banking sector, the link of the insurance sector with the real estate sector is much stronger than the link with the internet sector (comparing row 5 and row 6). Similarly, given an extreme event in the real estate sector, the link of insurance sector with the banking sector is much stronger than the link with the security sector (comparing row 5 and row 8). In addition, when systemic risks happen simultaneously in the banking, securities and real estate industries, the probability that systemic risks happen in the insurance industry is very high. It means that even if an industry is at risk, it does not necessarily spread to the insurance industry; but when several industries are simultaneously at risk, the entire financial market is facing systemic risk and the insurance industry cannot escape.

In spite of the tail dependence between the insurance industry and the other four industries, the conditional probability characterized by the LTD does not represent a causal relationship. The author used the Granger Causality Test to determine the causal relationship between the insurance industry's returns and the other four industries' returns to determine the direction of the risk contagion.

Linear Granger Causality Tests. Since Granger Causality Tests require the stationarity of sequences, the author first tested the stationarity of the index return series of the insurance, banking, securities, real estate and internet industries. The author used the Augmented Dickey–Fuller (ADF) statistic to test; the results are shown in Table 14. The null hypothesis of the ADF test is that the sequence is nonstationary and contains one-unit root. All the sequences rejected the null hypothesis at 1% level according to the *p* value of the ADF test. It can be concluded from Table 14 that the five industries index returns are all stationary series.

Table 14
RESULTS OF STATIONARY TESTS

Variable	ADF statistics	*P* value
Insurance (V)	−9.32493	0.0000***
Banks (W)	−11.18847	0.0000***
Securities (X)	−12.64044	0.0000***
Real estates (Y)	−20.31403	0.0000***
Internet (Z)	−15.89831	0.0000***

Note: *** indicates significant at 1% level.

To explore the causality between the systemic risk of the insurance industry and the other four industries, Linear Granger Causality tests between the index of the insurance industry and one of the other four industries is carried out.[9] The results are shown in Table 15.

Table 15
LINEAR GRANGER CAUSALITY TESTS

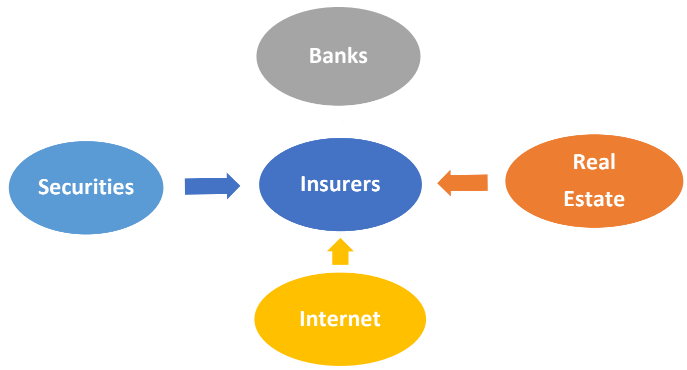
Null hypothesis	*P* value
V does not linear Granger cause X	0.6688
V does not linear Granger cause Y	0.4851
V does not linear Granger cause W	0.7055
V does not linear Granger cause Z	0.8208
X does not linear Granger cause V	0.2749
Y does not linear Granger cause V	0.0016***
W does not linear Granger cause V	0.0002***
Z does not Linear Granger cause V	0.0014***

Note： *** indicates significant at 1% level and the null hypothesis was rejected.

As can be seen in Table 15, the insurance industry is not the linear Granger cause of the other four industries at 1% significance level, while the other three sectors except the banking industry are the linear Granger causality of the insurance industry. Figure 9 is a linear Granger-causality diagram; the direction of the arrows represent the causal relationship. The figure shows that the insurance industry was directly affected by the securities, real estate and internet industries, and the insurance industry did not have a significant direct impact on other industries.

[9] The author considered only pairwise Granger Causality due to the significant multicollinearity among the returns.

Figure 9
LINEAR GRANGER-CAUSALITY RELATIONSHIP



Source: according to the empirical results

The other three industries have the direct impact on the insurance industry mainly due to the investment of insurance funds in other industries. In recent years, the amount of insurance investment has risen sharply, while there has been no major change in the funds invested in bank deposits, which led to a year-on-year decline in bank deposits as a proportion of total investment, down to 18.55% in 2016, far less than the amount invest in bonds, equity and securities investment funds (45.43%) and other investments (36.02%). From this perspective, the insurance industry is more susceptible to the direct infection of risks from other relevant industries than the banking industry.

As for the reason that the insurance industry will not directly cause risks to other industries, the author believes that the main source of funding for insurance companies come from the insurance policy, which is more decentralized and is able to provide sustained and stable premium income. As such, there is no need to obtain large-scale capital access to financial markets. This means a lower liquidity risk.

Although the insurance industry will not directly cause risks to other industries, other industries may cause risks into the insurance industry. This means that the insurance industry is a systemic risk receiver, not a transmitter. The insurers need to do a good job of internal risk prevention and improve the profitability, while ensuring the safety of investments in insurance funds. When other industries suffer extreme risk losses, insurers need to suspend cooperative agency business with banks and internet companies in a timely manner so as to weaken the risk spillover effects from other industries.

Brock-Dechert-Scheinkman (BDS) Tests. Research shows that a large number of time series exist nonlinear dynamic characteristics. Before studying the nonlinear causal relationship between the returns of insurance industry and the returns of the other four industries, it is necessary to perform a nonlinear dependence test to see whether the series are characterized by nonlinearities.

The author first constructed VAR models for the insurance's and other industries' index returns to filter out the linear relationships, then apply the nonlinear dependence tests to the VAR residuals to determine whether there is a nonlinear relationship between the residual series. The author used BDS tests (Brock et al., 1996) and results are reported in Table 16. The results show that all the BDS test statistics significantly reject the null hypothesis that the residual series is independent and identically distributed at 1% significance level. Therefore, it can be concluded that there are significant nonlinear dynamic characteristics between the insurance industry's returns and the other four industries' returns, and it is not enough to determine the relationship between the two simply using the traditional linear Granger causality test.

Table 16
BDS TESTS FOR NONLINEARITY[10]

Dimension	Banking		Security		Real estate		Internet	
	BDS statistic	*P* value	BDS Statistic	*P* value	BDS statistic	*P* value	BDS statistic	*P* value
m=2	0.023458	0.0000	0.014588	0.0000	0.014395	0.0000	0.013886	0.0000
m=3	0.046587	0.0000	0.024808	0.0000	0.028126	0.0000	0.021883	0.0000
m=4	0.061923	0.0000	0.029543	0.0000	0.033096	0.0000	0.024243	0.0000
m=5	0.069937	0.0000	0.029583	0.0000	0.032537	0.0000	0.023549	0.0000
m=6	0.070196	0.0000	0.026331	0.0000	0.028960	0.0000	0.020556	0.0000

Results of Nonlinear Granger Causality Tests. In this paper, the author used the methodology that Diks and Panchenko (2004) proposed to do the nonlinear Granger Causality Test to the normalized residuals in which linear relationships are filtered out by VAR model. After calculating the bandwidth, ε_w, ε_x, ε_y and ε_z is 0.9814, 1.1374, 1.1653 and 1.2067, respectively. For lags L_x=L_y=1, 2, …, 8, the results of tests are shown in Tables 17–20.[11] The overall nonlinear Granger-causality diagram is shown in Figure 10.

Table 17
NONLINEAR GRANGER CAUSALITY TESTS ON INSURANCE AND BANKING INDUSTRIES

L_x=L_y	H_0: V does not nonlinear Granger cause X		H_0: X does not nonlinear Granger Cause V	
	T_n	*P* value	T_n	*P* value
1	5.386***	0.00000	5.857***	0.00000
2	4.933***	0.00000	4.705***	0.00000
3	4.009***	0.00003	4.472***	0.00000
4	3.301***	0.00048	3.380***	0.00036
5	2.742***	0.00305	2.982***	0.00143
6	2.657***	0.00394	2.460***	0.00694
7	1.994**	0.02308	1.871**	0.03069
8	2.016**	0.02191	1.427*	0.07674

[10] The value of threshold of BDS tests equals the standard deviation of VAR residuals.
[11] Lx = Ly indicates that the variables take the same number of lags. * (**, or ***) donates significance at the 10% (5% or 1%) level.

Table 18

NONLINEAR GRANGER CAUSALITY TESTS ON INSURANCE AND SECURITIES INDUSTRIES

L_x=L_y	H_0: V does not nonlinear Granger cause Y		H_0: Y does not nonlinear Granger cause V	
	T_n	*P* value	T_n	*P* value
1	5.228***	0.00000	5.144***	0.00000
2	5.246***	0.00000	4.429***	0.00000
3	4.646***	0.00000	3.776***	0.00008
4	3.961***	0.00004	2.661***	0.00389
5	3.258***	0.00056	2.650***	0.00402
6	3.132***	0.00087	2.655***	0.00396
7	2.499***	0.00623	2.306**	0.01056
8	2.274**	0.01149	2.236**	0.01267

Table 19

NONLINEAR GRANGER CAUSALITY TESTS ON INSURANCE AND REAL ESTATE INDUSTRIES

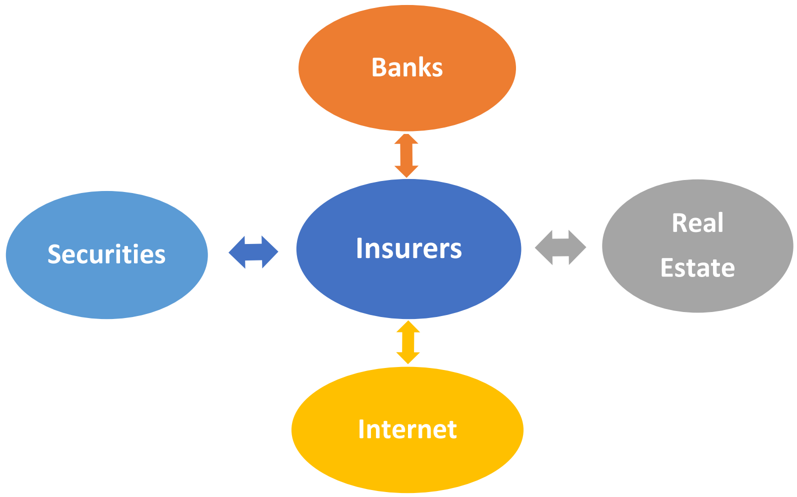
L_x=L_y	H_0: V does not nonlinear Granger cause of W		H_0: W does not nonlinear Granger cause V	
	T_n	*P* value	T_n	*P* value
1	4.992***	0.00000	6.068***	0.00000
2	5.246***	0.00000	5.625***	0.00000
3	4.192***	0.00001	5.118***	0.00000
4	3.484***	0.00025	4.017***	0.00003
5	2.816***	0.00243	3.468***	0.00026
6	3.067***	0.00108	3.333***	0.00043
7	2.707***	0.00340	3.043***	0.00117
8	2.489***	0.00641	2.905***	0.00184

Table 20

NONLINEAR GRANGER CAUSALITY TESTS ON INSURANCE AND INTERNET INDUSTRIES

L_x=L_y	H_0: V does not nonlinear Granger cause Z		H_0: Z does not Nonlinear Granger cause V	
	T_n	*P* value	T_n	*P* value
1	3.505***	0.00023	3.128***	0.00088
2	3.252***	0.00057	3.587***	0.00017
3	3.055***	0.00113	2.960***	0.00154
4	1.906**	0.02831	2.580***	0.00495
5	2.350***	0.00938	2.274**	0.01148
6	2.066**	0.01942	2.662***	0.00388
7	1.771**	0.03831	2.346***	0.00949
8	1.980**	0.02387	2.197**	0.01401

Figure 10
NONLINEAR GRANGER-CAUSALITY RELATIONSHIP



Source: according to the empirical results

Tables 17–20 show that tests strongly rejected the two-null hypothesis that the insurance industry's returns are not a nonlinear Granger cause of the returns of the other four industries, and the returns of the other four industries are not a nonlinear Granger cause of the returns of the insurance industry. Hence, the author observed that there is a significant bi-directional nonlinear Granger causal relationship between the insurance industry and the other four industries, so the risk may transmit between the insurance and the other four industries.

In addition, the smaller the lags, the stronger the significance, which means the impact between the two industries in a short period of time is even greater. The result of the nonlinear Granger causality test does not contradict the results of the linear one, because the linear Granger causality test provides a causal relationship based only on the mean, whereas the nonlinear Granger causality test also considers the connection between the variations of different industries. In the absence of a linear causal relationship, there are many indirect effects that can connect the insurance to the four other industries, such as business convergence, herding and so forth.

6.2.3 EMPIRICAL ANALYSIS

For the Granger causality between the insurance and other industries, the author considered the risk infection mechanisms among industries.

Direct Infection Mechanisms—Asset Management. Insurers invest a lot of money. In 2016, the insurance funds invested 2.484421 trillion yuan in bank deposits, 6.083838 trillion yuan in the securities market and 4.822808 trillion yuan in other investments. When one of the other industries encounters a systemic risk or the price of assets falls sharply, insurance companies' return on investment will be directly affected, resulting in the insufficiency of liquidity and insolvency of the insurers, leading to risk loss finally.

Compared to the amount and proportion of insurance funds invested in the securities market and other markets, the amount invested in bank deposits is relatively small and the proportion is relatively low. Therefore, if the banking industry is in crisis and cannot honor its liabilities, the impact on the solvency of the insurance industry is relatively small and is difficult to cause a direct systemic risk in the insurance sector from this channel. Relatively speaking, the huge amount and high proportion of investments in other industries besides bank deposits now represent a disaster for the investment returns of insurers in the event of asset impairment. The insurance company's main source of funding is premium income from policyholders. Insurance policies are more dispersed and able to provide sustained and stable premiums; insurers do not have the need for large-scale capital from financial markets and have lower liquidity risk. Therefore, it is less likely to transmit risk through the asset management channel directly to other industries.

Direct Infection Mechanisms—Capital Market. The systemic risk that transmit to the insurance industry is mainly from the securities industry. With the continuous development of financial markets, a variety of financial innovation products including CDS, Collateralized Debt Obligation (CDO), MBS and ABS are devised in the financial market. As an institutional investor, insurance companies will buy these securities in the capital market to bear the risk.

For example, a subsidiary of AIG and a number of investment banks on Wall Street and commercial banks conducted a large number of transactions involving credit derivatives such as CDS, which made them take on the credit risk in the securities market. Such products are designed to disperse and package the risk. Resale and packaging of these risks make it difficult to identify the underlying assets and more difficult to assess their risks. In addition, the leverage of such products is extremely high, and losses can be quite substantial once the risks get out of control.

Once the systemic risk occurs in the securities industry, the insurance companies involved in these products will become a victim, difficult to escape. As a result, the former AIG incurred significant asset impairment and faced a business failure. This example fully demonstrates that the credit risk can be transmitted to the insurance sector through asset securitization. This also explains why the insurance industry, as a victim, will be directly infected by the securities industry through capital markets.

Direct Infection Mechanisms—Credit and Guarantee Insurance. Risk transmission channels are mainly reflected in the insurance companies when they provide credit guarantee insurance products to the real estate, internet and other industries. Through the credit and guarantee insurance business, insurance companies guarantee the lending behavior of other industries and institutions. When the institutions in this industry are in crisis and unable to repay their borrowings, they can only choose to default, and the insurance companies need to pay back the loans.

If the majority of policies encounter large claims at the same time, which will make insurer's solvency insufficient, so the risk transmits into the insurance industry. At present, China's real estate enterprises are characterized by a high level of indebtedness with a total loan amount of nearly 36 trillion yuan (Eastmoney, 2017). At the same time, with the rapid development of the internet finance, the net loan made through the internet has reached 5 trillion yuan (Sohu, 2017).

In this context, when the real estate or the internet industry is in crisis and the collective default occurs, the large compensation payouts of insurance companies are likely to make them insolvent, which will lead to risks. In other words, when there is a systemic risk in the real estate industry or the internet industry, it is possible that the risk will spread to the insurance industry.

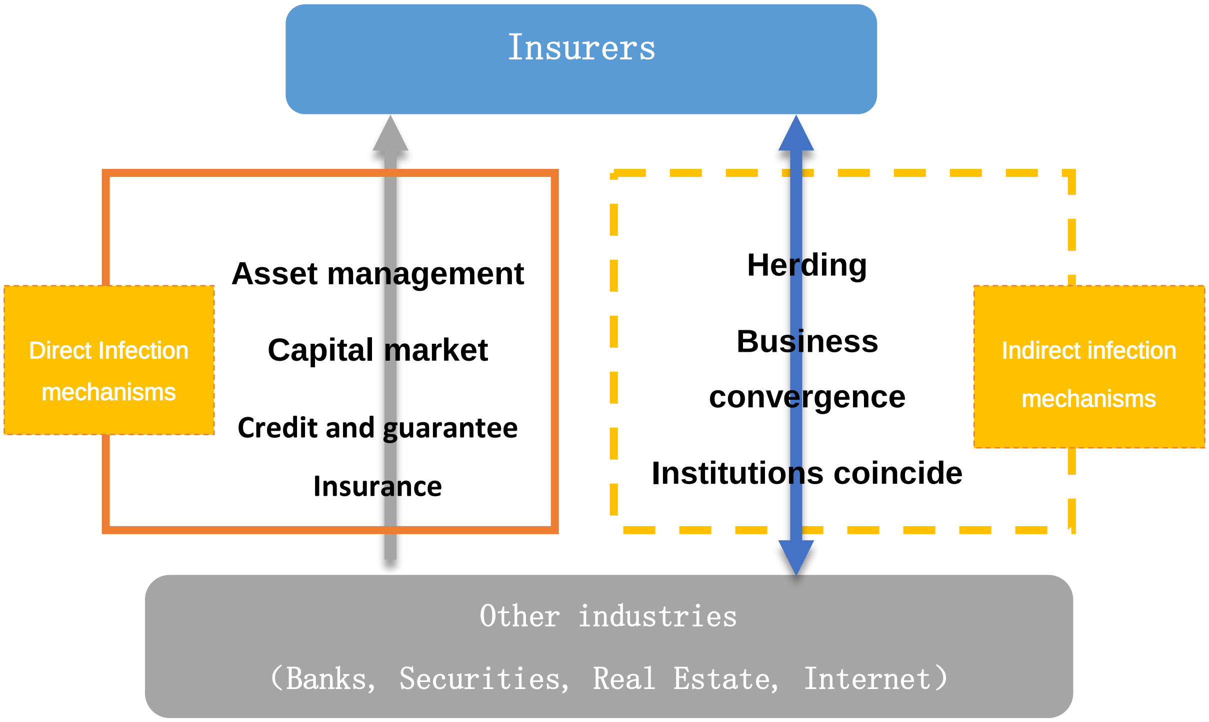
Indirect Infection Mechanism—Herding. In economics, the herding effect refers to the fact that some investors in the market do not have the exact investment information or do not reach their own expectations, and they will change their behavior according to the behavior of others. When an agency in a business goes bankrupt or simply sends out bad news, which results in a loss of confidence on the public's part, people's behavior can deviate greatly. This will have an impact on this enterprise or even on this industry. There will be panic redemptions and result in insufficient market liquidity and capital shortage.

When the public expects a risk in a financial market, it will expand its role in other industries and worsen the operating environment of the entire financial system, causing a systemic risk to the entire system. The impact of the U.S. AIG incident on market confidence is evident. Therefore, when the insurance industry suffers extreme risks, it can cause panic in the entire financial market. It is easier for the public to spread this panic to its closely linked industries including the banking, securities, real estates and internet industries and influence these sectors through indirect channels. Similarly, when the banking, securities, real estate or internet industries are in distress, investors could not be rational with the insurance industry and then risk transmits to the insurance industry due to investors' herding behavior. In general, the insurance industry and other industries will be affected through cross-infection due to herding behavior and loss of public confidence.

Indirect Infection Mechanism—Business Homogeneity and Risk Exposure Increase. Within the financial markets, businesses of different sectors are getting increasingly homogeneous. The banking and the insurance industries have gradually developed various financial derivatives within the NT investment model. The insurance and the securities sectors have launched capital preservation products like banks. Banking institutions have also carried out the insurance business. In addition, insurance companies and Internet companies have operated Internet insurance business. This mutual penetration of businesses has raised the leverage of the entire market. When the risk hits, it will exacerbate the evolution of systemic risk. Specifically, insurers are unable to pay compensation if there is a systemic risk in the insurance industry. A large part of banks and internet companies that carry out insurance business are insurance agent vendors, which can easily pass the systemic risk of the insurance industry to the banking and internet industries in this way. Conversely, this channel has created a two-way contagion between the insurance industry and other industries.

Indirect Infection Mechanism—Institutions Coincide. The formation of a large financial conglomerate allows subsidiaries within a single group to cover a wide range of industries. When there is a risk in a certain industry and it affects the same industry subsidiaries in the group, the capital level of the group will be affected and then spread to the insurance subsidiaries. In addition, when there is a significant risk in a subsidiary of the group, investors will continue to withdraw their funds to avoid risks due to the distrust of the subsidiary. As a result, the liquidity of the subsidiary will deteriorate, and eventually the entire group will be affected. The status of large financial groups in the market cannot be underestimated, since a group that is too big to fail in risk will bring crisis to the entire market. The mechanism of systematic risk transmission among industries is shown in Figure 11.

Figure 11
MECHANISM OF SYSTEMATIC RISK TRANSMISSION AMONG INDUSTRIES



Source: Based on the empirical results of the report.

Section 7: Conclusion

Starting from risk factors within an industry and mutual penetration between industries, the author has measured the systematic risk capital shortfall of China's insurance industry and the risk contagion with other industries. At the same time, the author has identified the direction of risk contagion and assessed the overall systematic risk in China's insurance industry.

The author has improved the PSM method on the basis of the SRISK model and proposed a suitable method to measure the systematic risk of China's insurance companies in general. Based on the LRMES model, the SRISK model not only contains static financial information that reflects listed companies' operation conditions but also dynamic information that reflects the market fluctuation. The improved model also makes full use of the financial information of nonlisted companies and improves the estimation accuracy of their long-term marginal expectation loss, thus expanding the scope of application in the current situation of China's insurance market, whose development is unbalanced and have fewer listed companies.

The demonstration result shows that SRISK has an average annual growth rate of more than 50%, which surpasses the growth rate of premium income. The growth rate of systemic risk is much higher than the growth of business scale. On average, the contribution to systemic risk SRISK% of nonlisted insurance companies was about 5.2%, which was slightly lower than the 8.5% of listed companies in 2014, and it increased to about 5.9% in 2015 and slightly decreased to 5.6% in 2016. The result means that the supervision of systematic risk in nonlisted companies should be considered.

In addition, the market share of property and casualty insurance companies is about 27.8%, while the contribution to systemic risk was 0. Different business models and characteristics may lead to the great difference of concentration of systemic risk levels. Among the risk factors within the industry, four significant factors have a tremendous impact on the liquidity of the of insurance companies' assets, including the increase of credit guarantee insurance business, the large sale of long-term guaranteed insurance products, the diversification of alternative investment types of assets, and the aggravation of the mismatch of assets and liabilities. China's insurance industry should pay attention to the four factors to avoid insufficient solvency and large capital shortfall.

In addition to enhancing the internal optimization of the insurance market, the risk of infection to the insurance industry from other sectors can't be ignored. The author used the LTD method to measure the probability of risk occurrence in the insurance industry in the case that extreme risk emerges in other industries so as to analyze the contagion of insurance and other industries under extreme conditions. The author used the Granger Causality Test to analyze the direction of risk transmission among industries; it explores the mechanism of risk transmission. The results show that China's insurance industry is highly linear and dependent on securities, real estate and internet industries in extreme situations and is highly vulnerable in the event of systemic risk in the other three industries.

However, there is no direct risk-transmission relationship with banking. And in the direction of risk contagion, the insurance industry only plays a role in absorbing the direct transfer of systemic risk from other industries and does not transmit to other industries. However, the nonlinear relationship exists between the insurance industry and the banking, securities, real estate and internet industries, which means that in the extreme situation, the insurance industry and other industries will infect each other at a high probability. At present, the penetration of direct business in China's insurance industry and other industries hasn't been thoroughly explored yet. As a result, the infection of systemic risk is mainly through the market fluctuation and the integration of institutions. The above industries are actively seeking a chance to penetrate into the insurance industry. Especially in the emerging industry of the internet, the trend of entering the financial sector is increasing. Big data and retail features of products make the internet more accessible to the insurance industry. With the closer convergence between the two industries and the insufficiency of internet regulation over the development of the industry, unknown risk will increase.

Section 8: Acknowledgments

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Project Oversight Group Members:

Haifei Chen, FSA

Victor Chen, FSA, CERA, FCIA

Lynn Lin, FSA

Prof. Xiaojun Wang

Society of Actuaries Staff:

Jessie Li, FSA, Lead China Representative

Ronora Stryker, ASA, MAAA, Senior Practice Research Actuary

Jan Schuh, Senior Research Administrator

Appendix A: Propensity Score Matching Results of Non-listed Companies

PROPENSITY SCORE MATCHING RESULTS OF NON-LISTED COMPANIES

Year	Non-listed companies	Matching results	Year	Non-listed companies	Matching results	Year	Non-listed companies	Matching results
2014	i	2011 D	2015	i	2011 D	2016	i	2016 C
	f	2012 A		f	2015 C		f	2014 C
	h	2011 B		h	2014 C		h	2013 D
	b	2013 A		b	2015 D		b	2014 C
	j	2011 A		j	2009 C		j	2014 C
	l	2008 C		l	2013 D		l	2015 C
	m	2010 B		m	2014 D		m	2015 C
	o	2011 D		o	2014 B		o	2015 C
	p	2013 A		p	2016 C		p	2013 D
	q	2011 D		q	2014 B		q	2016 D
	r	2014 B		r	2012 A		r	2014 D

Appendix B: Proof to the Formula (11)

Proof to the formula (11) is as follows:

$$\begin{aligned}\mathrm{E}\big(T_i|Y_1,Y_0,p(X)\big) &= E_X[E(T_i|Y_1,Y_0,X)|Y_1,Y_0,p(X)]\\ &= E_X[E(T_i|X)|Y_1,Y_0,p(X)]\\ &= E_X[p(X)|Y_1,Y_0,p(X)]\\ &= p(X)\end{aligned}$$

Therefore, if the propensity score $\mathrm{p}(X_i)$ is known the average effect of treatment, it can be estimated as follows:

$$\begin{aligned}\mathrm{t}|_{T=1} &= E(Y_{i1}|T_i=1) - E(Y_{i0}|T_i=1)\\ &= E(Y_{i1}-Y_{i0}|T_i=1)\\ &= E\{E[Y_{i1}-Y_{i0}|T_i=1,p(X_i)]\}\\ &= E\{E[Y_{i1}|T_i=1,p(X_i)] - E[Y_{i0}|T_i=0,p(X_i)]|T_i=1\}\end{aligned}$$

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Society of Actuaries
475 N. Martingale Road, Suite 600
Schaumburg, Illinois 60173
www.SOA.org