Fintech Development and Financial Inclusion

Xun Zhang

1. Beijing Normal University
2. Institutes of Digital Finance, Peking University.

Abstract

This paper represents an early attempt to investigate whether Fintech development reduces disparity and contributes to financial inclusion and inclusive growth in China. Over the past decade, with the rapid expansion of Fintech, China has seen a transformation in the accessibility and affordability of financial services, particularly for formerly financially excluded populations. Linking the index of digital financial inclusion with China Family Panel Studies (CFPS) data, we initially find that Fintech development has a positive effect on household income, and the positive effect comes from rural households, suggesting that Fintech development helps narrow urban-rural income gap in China. We further analyze the mechanism underlying the Fintech-disparity relation and find that Fintech has significantly increased the probability that rural residents become entrepreneurs, while the effect on urban households is not significant. A decomposition of Fintech development shows that financial depth, which measures the development of the paying, lending, insurance, and investing sectors, and digital service provision, which measures the accessibility of financial services, are the two factors that contribute to entrepreneurship. Additionally, households with lower incomes or social capital have a higher probability of becoming entrepreneurs with the help of Fintech, which is also consistent with inclusiveness.

Keywords: Fintech; Disparity; Inclusiveness; Entrepreneurship; China

JEL Classification: D14, L20, R58

1. Introduction

While the development of financial technology (Fintech) has been a global phenomenon, it has particularly thrived in China. Over the past ten years, although traditional financial institutions have improved the access channels to households and significantly reduced their budget constraints, with the rapid expansion of Fintech, China has seen an even dramatic transformation in the accessibility and affordability of financial services, particularly for formerly financially excluded populations. Fintech has offered low-cost services to hundreds of millions of underserved people and thus is beneficial to China's development of financial inclusion and inclusive growth.

How does Fintech development contribute to China's inclusiveness? In this paper, we argue that Fintech makes it easier for households to borrow and significantly reduces the financing barrier faced by innovative residents. In this way, Fintech increases the probability that households are enrolled in entrepreneurship activity, especially for formally lagging groups. Previous studies show that entrepreneurship is essential to job creation (De Mel et al, 2008) and economic growth (Baumol, 1968; King and Levine, 1993; Samila and Sorenson, 2011). Factors that affect entrepreneurial activity can largely be categorized into micro factors and macro factors. Micro factors refer to entrepreneurs' individual and family characteristics, such as income and gender (Rosenthal and Strange, 2012), age (Ress and Shah, 1986), human capital (Lazear, 2005), social capital (Evan and Leighton, 1989), and risk preference (Parker, 1996). Macro factors mainly refer to the political and economic conditions, or culture and social environment where entrepreneurs are located (Djankov, 2002; Glaeser and Kerr, 2009; Han and Hare, 2013; Ghani et al, 2014). For example, Glaeser and Kerr (2009) find that entrepreneurial activities happen more frequently in areas with many small suppliers and abundant workers in relevant occupations.

Among these factors of entrepreneurship, funding available is the most important element. Because entrepreneurs need funds to start the firms, financial constraints will significantly reduce the ability to become entrepreneurs. Studies have shown that financial constraints have a negative impact on entrepreneurship (Evans and Jovanovic, 1989; Nykvist, 2008; Karaivanov, 2012). Therefore, it is widely accepted that financial development can promote entrepreneurial activity by mitigating the liquidity constraints of potential entrepreneurs (Bianchi, 2010).

However, although traditional financial institutions have improved the access channels to start-up funds that allow innovative residents to borrow and become entrepreneurs, Fintech development is still more helpful to formally lagging groups regarding their entrepreneurship activity in China. Let us suppose a case without Fintech. In this case, in order to borrow from traditional financial institutions, entrepreneurs usually must have their credit investigated by banks to determine whether they have good credit records. However, most residents in developing economies still do not have any credit record at all, due to lack of opportunity. The easiest way to establish a good credit record is to apply and use a credit card. But this is not always feasible. In China, for example, the urbanization rate passed 50% in 2011 and reached 56.1% in 2015, leaving a population of 603.5 million in lagging rural areas. According to the China Banking Association (2016), the total number of credit cards issued in China through 2015 was 530 million— even smaller than China's urban population. In other words, per capita credit card ownership in China is less than 0.5 apiece, which is only one-tenth of that in the United States. It can then be inferred that, more than half of the population in China, especially residents in rural areas where economic conditions lag, do not even have the opportunity to apply for a credit card to establish a credit record. Therefore, traditional finance methods often cannot solve the start-up funding problem for all innovative residents, especially in developing economies.

The needed solution lies in the emergence of Fintech. A simple example can help illustrate how Fintech has solved the start-up funding problem for formerly financially excluded populations and thus contributed to inclusiveness. In modern China, residents can use mobile phones to pay for most transactions, including shopping in local commercial markets or online (e.g. Alibaba, Taobao), dining in restaurants, and utilities bills, even if they do not have credit cards. More important, most mobile phone transactions could help residents gain a Fintech-defined credit record and thus facilitate residents' borrowing through Fintech channels. Therefore, Fintech can increase the probability that residents will become entrepreneurs.

This paper represents an early attempt to formally and empirically analyze whether Fintech development reduces disparity and contributes to financial inclusion and inclusive growth in China. In fact, few studies have yet investigated the impact of Fintech on income disparity, but Fintech development which relies on information, big data, cloud computing, and other innovative technologies, can further expand the scope of traditional financial services (Guo et al, 2016). Therefore, we should expect a beneficial distributive impact from Fintech.

To investigate, we link the regional index of digital financial inclusion which measures Fintech development in China, with data of the China Family Panel Studies (CFPS), which provide representative household survey data in China. The index of digital financial inclusion is a joint project by the Institute of Digital Finance, Peking University, and Ant Financial, which is one of the largest global Fintech enterprises. The index is constructed using user data from Ant Financial and shows that China's financial inclusion has been progressing rapidly with the help of Fintech and has enabled regions lagging behind in overall levels of economic development to outperform economically advanced regions. Linking the data of digital financial inclusion index with the CFPS data, and after controlling for confounding factors, we initially find that Fintech development has a positive effect on household income, and the positive effect comes from rural households, suggesting that Fintech development helps narrow urban-rural income gap in China.

We further analyze the mechanism underlying the Fintech-disparity relation and find that Fintech has significantly increased the probability that rural residents become entrepreneurs, while the effect on urban households is not significant. In fact, Fintech can only provide innovative residents with funds to start their businesses. Urban residents already have convenient financial services and thus do not benefit much from Fintech. This finding is in accord with our argument above that most residents in rural areas do not have a credit record, while urban residents can more easily establish one.

We further decompose the index of digital financial inclusion into three components to understand how Fintech development promotes entrepreneurial activity and brings in inclusiveness. We find that the two factors that contribute to entrepreneurship in rural China are financial depth, which measures the development of the paying, lending, insurance, and investing sectors, and digital service provision, which measures the accessibility of financial services. Finally, to gain a better understanding of Fintech's role in inclusiveness, we also assess which group benefits more from Fintech in rural China. We find that households with lower incomes or social capitals have a higher probability of becoming entrepreneurs with the help of Fintech, which is also consistent with inclusiveness.

This paper sheds light on the important role that Fintech plays in modern life. Based on our findings, the recent development of Fintech mostly aids the goals of inclusiveness. The rest of the paper is organized as follows. Section 2 discusses China's recent Fintech development. This is followed by providing the analytical framework, model specification, and data in Section 3. Section 4 reports baseline estimation results of Fintech development and income disparity. Section 5 explores possible transmission channels from Fintech to inclusiveness from the perspective of entrepreneurship. Finally, Section 6 concludes.

2. Fintech Development in China

Modern information technology, particularly internet-enabled technology such as mobile transactions, cloud computing, social networks, and search engines, has led to fundamental changes in the ways finance is shaped. To characterize the development of financial inclusion generated by Fintech in China, the Institute of Digital Finance, Peking University, and Ant Financial launched a joint project, which uses user data from Ant Financial to construct an index of Digital Financial inclusion.[1] Table 1 describes the measures used to construct the index. Specifically, the index covers three first-level indices: financial breadth, finance depth, and digital service provision. Financial breadth measures the number of Alipay accounts and Alipay accounts with credit cards. Financial depth measures the development of paying, lending, insurance, and investing sectors through Ant Finance. Digital service provision measures the accessibility of financial services. In other words, each first-level index is comprised of several indicators.

[Insert Table 1 approximately here]

To calculate the index of digital financial inclusion, each second-level indicator is adjusted by the dimensionless method. Then, the second-level indicators are combined into the first-level index using the variation coefficient empowerment and exponential synthesis methods. The index of digital financial inclusion is then constructed using the two methods.[2]

In Table 2, we report the constructed province indices of digital financial inclusion across provinces in 2011 and 2015. An increasing trend is easily observed in all provinces, suggesting that China's development of financial inclusion has been progressing rapidly with the help of digital finance. The data are further visualized in Figure 1, in which Panel A presents the value distribution of the index across provinces in 2011, and Panel B presents the growth rate distribution from 2011-2015. It is obvious that, although eastern China is the most advanced area in Fintech development, middle and western China are on their way to catching up, which is in accord with the principle of financial inclusion in a national perspective.

[Insert Table 2 and Figure 1 approximately here]

We further investigate the development of the three components of Fintech. Figure

[1] It is noteworthy that Ant Financial is only one of China's large digital finance firms. To better characterize China's Fintech development, Tencent with Wechat Pay should be considered. However, only data from Ant Financial are available to us. Therefore, a roughly reasonable assumption is that the index of digital financial inclusion calculated using both Alipay accounts and Wechat Pay accounts is synchronizing and has the same trend.
[2] For detailed calculations, see Guo et al. (2016).

2 reports the three indices across provinces in 2011 and 2015. We find that the indices of financial breadth and financial depth have largely the same distributions with the index of digital financial inclusion, while the index of digital service provision is significantly different and its value is largely negatively correlated with economic development. It indicates that digital service provision may play a more important role in promoting inclusive growth.

[Insert Figure 2 approximately here]

3. Specifications and Data

3.1 Specification: Fintech Development and Income Disparity

One of the conventional methods to estimate Fintech development on income to is through production function modeling, where the variable of Fintech development is included in addition to the usual input variables such as capital and labor. This is clearly inapplicable when household data are used either because of the unavailability of capital observations or due to the fact that labor input is difficult to measure at the household level. An alternative specification is to directly investigate the income impact of Fintech development by estimating the following regression model:

$$ln\left(Inc_{ijt}\right) = \gamma_0 + \gamma_1 Fintech_{j,t-1} + \gamma_2' X_{ijt} + \phi_i + \varphi_t + u_{it} \qquad (3.1)$$

In model (3.1), *i* index households, *j* index regions, and *t* index years. Moreover, Inc_{ijt} denotes household i's disposable income in region *j*, and $Fintech_{j,t-1}$ denotes the development of Fintech in region *j* where household *i* is located. To alleviate reversed causality problem, we lag the variable of Fintech development by one period. *X* denotes control variables, ϕ_i denotes household fixed effect which helps solve omitted variable bias, φ_t denotes year fixed effect, and u_{it} denotes the usual random error term. Therefore, γ_1 measures the impact of Fintech development on household income.

To precisely estimate the income impact of Fintech development, we need to control for confounding factors which will affect household income in addition to Fintech development. These covariates are classified into three categories. The first category is householder's characteristics, including gender, age, schooling years, political status, marriage status, and health condition. It is noteworthy that, since we will control household fixed effect as suggested by (3.1), the effects of time-invariant characteristics, such as gender, schooling years (as we focus on household with an adult as householder), and political status, cannot be estimated. Moreover, the age effect is also captured by the linear combination of household fixed effect and year fixed effect. To further alleviate the omitted variable bias, we control for the quadratic term of age (age^2). Another concern is that the income effect of Fintech may come from the accessibility of internet, which may bring in information that is beneficial to economic activity. Therefore, we further control the accessibility of internet and mobile, to separate the effect of information and digital finance on household income.

The second category refers to household's characteristics. Following conventional wisdom, these include family size and young dependency ratio and old dependency ratio in the family. Family size brings in economics of scale and increases household income, while a higher level of young dependency ratio or old dependency ratio lays more burden to the family and reduces household income. Whether the family has bank loan is also controlled to separate the effect of traditional finance from digital finance on household income. Finally, we control for indicators of regional economic development, including county population and economic condition.

Model (3.1) can be used to estimate the impact of Fintech on household income in general. To investigate whether Fintech development has distributive impacts, we further conduct subsample analysis. It is noteworthy that Fintech development may have heterogeneous impacts on household income. In fact, urban residents already have convenient financial services and thus may not benefit much from Fintech, while rural residents in China who are still in lack of financial services due to the *hukou* system[3]

[3] *Hukou* is a household registration system that was introduced in 1958 to control rural-to-urban migration in China. At that time, a Chinese citizen was given a rural or urban *hukou*. Newborn children inherit their *hukou* status from their mothers. The urban hukou is associated with certain privileges and entitlements (social security and public

are more likely to benefit from Fintech development. Therefore, we divide the samples into urban households and rural households to assess the distributive impacts of Fintech development. If rural households benefit more from Fintech development, the Fintech development is then considered as inclusive and contributes to financial inclusion and inclusive growth. We will also conduct quantile regression to check the robustness of the subsample empirical results.

3.2 Specification: Fintech Development and Entrepreneurship

Further, to understand the mechanism underlying the distributive impacts of Fintech development, we investigate whether Fintech development has been promoting entrepreneurship activity and whether the effect displays any heterogeneity. This impact can be examined by estimating the following discrete-choice model:

$$Entrepre_{ijt}^{*} = \beta_0 + \beta_1 Fintech_{j,t-1} + \beta_2' X_{ijt} + \theta_i + \delta_t + \mu_{ijt}$$

$$\begin{aligned} Prob\big(Entrepre_{ijt} = 1\big) &= Prob\big(Entrepre_{ijt}^{*} > 0\big) \\ &= \Phi(\beta_0 + \beta_1 Fintech_{j,t-1} + \beta_2' X_{ijt} + \theta_i + \delta_t) \end{aligned} \tag{3.2}$$

$Entrepre_{ijt}^{*}$ is the continuous latent random variable measuring the willingness of entrepreneurship, but we can only observe the entrepreneurship decision $Entrepre_{ijt}$. Other notations of (3.2) are similar to those of (3.1). Model (3.2) is estimated using Probit model. To incorporate household fixed effect, linear probability model and conditional logit model are also used for robustness check. The sign of β_1 informs if Fintech development increases or reduces the probability of becoming an entrepreneur.

Other factors that may affect entrepreneurship also come from characteristics of the householder, household and the corresponding region. Besides the determinants in (3.1), we further incorporates household income as additional determinant of household

services) that the rural citizens cannot enjoy, even today. It has been very difficult to alter one's *hukou* status. Before the early 1990s, rural citizens could not migrate to cities and towns. More recently, migration has been allowed, but the *hukou* system still discriminates against migrants in terms of educational, medical, and other welfare assistance.

entrepreneurship behavior.

3.3 Data

To estimate the models (3.1) and (3.2), we use two datasets. The first dataset is the regional index of digital financial inclusion in China as introduced in Section 3. As stated, the regional index is a joint project by the Institute of Digital Finance, Peking University, and Ant Financial and is constructed using user data from Ant Financial.

The second dataset comes from the China Family Panel Studies (CFPS), a nationally representative survey of China's communities, families, and individuals conducted in 2010, 2012, and 2014. The CFPS is funded by Peking University and carried out by the Institute of Social Science Survey of Peking University. The CFPS covers a wide range of domains for families and individuals from 162 counties in 25 provinces of China, including their economic activities, education outcomes, family dynamics and relationships, and health. Combining the two datasets and using models (3.1) and (3.2), we can estimate the effect of Fintech development on household income, income disparity, and entrepreneurship probability. It is also noteworthy that, due to availability of the data, we use the regional index of digital financial inclusion in 2011 and 2013 to predict the income and entrepreneurship in 2012 and 2014, respectively. Table 3 tabulates the summary statistics.

[Insert Table 3 approximately here]

Household Income

The data of household income are directly from the family questionnaire of CFPS database. In general, household income contains wage income, operational income, property income, transfer payment, and other income. We take the logarithm of household income as the dependent variable.

Entrepreneurship

As stated, to investigate the mechanism underlying the Fintech-disparity relation, we explore whether Fintech development has promoted entrepreneurship. We define the entrepreneurship decision at the family level, as in general, the decision is a family-based decision. The family questionnaire provides a family response on the question "Are any of your family members in charge of self-employed or private enterprises?" Whether the family is engaged in entrepreneurial activity is determined by the answer to this question. To answer the question of whether the Fintech development promotes (or increases the probability of) entrepreneurship, we define the core dependent variable in model (3.2), $Entrepre_{ijt}$, to be a binary variable, which takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and takes the value of 0 if otherwise. Table 3 shows that the proportion of residents who are engaged in entrepreneurial activity increased from 9.22% in 2012 to 9.27% in 2014, although the incremental proportion of entrepreneurial activity ($Entrepre_{ijt}$) decreased. We are interested in whether Fintech development is beneficial to this incremental proportion of entrepreneurial activity.

Fintech Development

The degree of Fintech development is directly measured by the index of digital financial inclusion developed by Peking University and Ant Financial. To investigate the transmission channels underlying the Fintech-entrepreneurship relation, we also use the sub-index of Fintech development: financial breadth, financial depth, and digital service provision. It is hypothesized that compared to financial breadth, financial depth and digital service provision are the two indices that are more related to entrepreneurship, as financial depth measures the development of the paying, lending, insurance, and investing sectors, and digital service provision measures the accessibility of financial services, both of which make it easier for residents to borrow and significantly reduce the financing barrier faced by innovative residents.

4. Fintech Development and Income Disparity

In the next two sections, we present the empirical results on the Fintech-disparity relation. This is by investigating the heterogeneity of Fintech on household income and exploring mechanism underlying the heterogeneity from the perspective of entrepreneurship.

4.1 Fintech's Role in Household Income

Firstly, we explore whether Fintech development has an effect on household income. Table 4 presents the estimation results of baseline model (3.1). In all regressions, we control for household and year fixed effects. Since income at the household level is regressed on Fintech development at the province level, the error term is likely to be serially correlated across households within a province. To address this problem, we cluster the standard error at the province level.

[Insert Table 4 approximately here]

In column (1) of Table 4, we only include the variable of Fintech development, the coefficient of which is shown to be significant. In subsequent columns, controlled variables of householder's characteristics, household's factors, regional population, and regional economic condition are added. The coefficients are consistently significant, suggesting that in general, Fintech development has contributed to the increase of household income in China. Economically, if the index of digital financial inclusion increases by one unit of its standard error, household income will increase by 3-0-3.2 percentage points.

Turning to control variables, the coefficients of householder's characteristics are mostly insignificant. Possible explanation is that the effects are almost time invariant and have largely been captured by household fixed effect. Family size is positively correlated with household income, while young and old dependency ratios play the opposite roles, as expected. It is also noteworthy that the effect of traditional finance (measured by bank loan) is insignificant, suggesting that Fintech's role in household economic activity may not be replaced by traditional finance.

4.2 Fintech Development and Income Disparity

Next, we explore the effect of Fintech development on income disparity. As stated, the role of Fintech development on household income may display heterogeneity. In fact, urban household have already enjoyed convenient financial services and thus may not benefit much from Fintech. However, rural households who are in lack of financial services are more likely to benefit from Fintech. Therefore, we expect that the positive relationship between Fintech development and household income mostly comes from Fintech's effect on rural households.

In Table 5, we divide the samples into urban and rural households and separately analyze whether Fintech development has contributed to income increase in urban and rural households. To avoid selection bias, we further limit the samples to residents who do not migrate to other areas. This reduces the sample by 11%.

[Insert Table 5 approximately here]

Columns (1)-(3) of Table 5 are the results of rural samples, and columns (4)-(6) are those of urban sample. Interestingly, Fintech only has significantly increased the household income of rural households, while the effect on urban households is not significant. On one hand, the finding indicates that the positive relationship between Fintech development on household income comes from its effect on rural households. On the other hand, the results confirm that Fintech development contributes to financial inclusion and inclusive growth by narrowing the opportunity gap and income disparity between urban and rural households. Economically, if the index of digital financial inclusion increases by one unit of its standard error, rural household income will increase by 5.5-5.8 percentage points.

To check the robustness of the empirical results, we conduct quantile regression regarding Fintech development and household income. Considering the insignificant results of urban sample, we limit the analysis within rural sample. Similar argument is expected to apply within rural households: rural households with higher income may be more capable to enjoy convenient financial services and are thus less likely to benefit much from Fintech.

In Table 6, we study the effect of Fintech development on income of household in the 25th, 50th, and 75th percentile of the income distribution. Columns (1)-(3) of Table 6 are the results of cross-sectional quantile regression model, in which we only include year fixed effect, and columns (4)-(6) are those of panel quantile regression model, which incorporates the effect of household fixed effect. However, panel quantile technique on the one hand is very sensitive to data and may not achieve converged empirical results, on the other hand changes the interpretation of the estimates (Power 2012). Therefore, we simultaneously present the estimates of cross-sectional quantile regression and panel quantile regression results for robustness check. Since we do not incorporate household fixed effect in the cross-sectional quantile regression, we further introduce the variables of householder's characteristics, including gender, age, schooling years, and political status to alleviate omitted variable bias.

[Insert Table 6 approximately here]

In columns (1)-(3), the cross-sectional evidence suggest that although Fintech increases household income for the three percentiles of households, households with lower income still benefit more from Fintech, as the coefficient of Fintech development for households in the 25th percentile is the largest, and is also significantly larger than the coefficients of Fintech development of those households in the 50th and 75th percentiles (with p-value=0.00120). In columns (4)-(6) of panel quantile regression, only the coefficient in the 25th percentile is positive and significant, confirming that Fintech development in China has been contributing to narrowing income disparity and thus contributing to financial inclusion and inclusive growth.

5. Mechanism: Fintech Development and Entrepreneurship

As we have mentioned in the introduction, Fintech has offered low-cost services to hundreds of millions of underserved people and specially makes it easier for households to borrow, significantly reduces the financing barrier faced by innovative residents, and may contribute the entrepreneurship activity, which would serve to narrow income disparity. Therefore, one mechanism underlying the Fintech-income relation may lie in

Fintech's role in entrepreneurship. In this section, we formally investigate this hypothesis.

5.1 Baseline Results

Firstly, we investigate the Fintech-entrepreneurship relation. Table 7 presents the estimation results of model (3.2) using Probit model. Province fixed effect is incorporated and therefore, we further control for householder's gender, age, schooling years, and political status to alleviate omitted variable bias. In column (1) of Table 7, we only include the variable of Fintech development, the coefficient of which is shown to be insignificant. In subsequent columns, controlled variables of householder's characteristics, household's factors, regional population, and regional economic condition are added. Different from the results of Table 4, the coefficients of Fintech development in the entrepreneurship determinant function are mostly insignificant, suggesting that in general, Fintech development does not significantly contribute to the entrepreneurial activity. The insignificant result of Fintech on entrepreneurship may also be caused by the samples of urban households, as urban households do not need Fintech to borrow and start their businesses. Thus, the Fintech-entrepreneurship relation may also display heterogeneity.

[Insert Table 7 approximately here]

To further investigate, we conduct sub-sample analysis and analyze whether Fintech development has contributed to financial inclusion and inclusive growth from the perspective of entrepreneurship. Columns (1)-(3) of Table 8 are the results of rural samples, and columns (4)-(6) are those of urban samples. As expected, Fintech has significantly increased the probability that rural residents will become entrepreneurs, while the effect on urban residents is not significant. The finding is consistent with the results of Table 5, suggesting that Fintech has contributed to China's financial inclusion and inclusive growth by narrowing the opportunity gap between urban and rural residents. Economically, if the index of financial inclusion increases by one unit of its standard error, the probability rural residents becoming entrepreneurs will increase by

4.6-4.8 percentage points[4].

[Insert Table 8 approximately here]

Turning to control variables, we find that human capital (measured by schooling years) has a significant and positive effect on entrepreneurship, which is very intuitive since human capital is the fundamental for innovative minds. The use of internet helps achieve outside information and opportunities and contributes to entrepreneurship activity.

Regarding household's factors, family size has a significant and positive effect on entrepreneurship, which is also intuitive as family often has a scale effect. A high old dependency ratio depresses the probability of entrepreneurship due to high family living burden. Different from the results of household income determinants, we find that traditional finance (measured by bank loan) also contributes to entrepreneurship activity, but given that the coefficient of Fintech development is also positive and significant, the results suggest that both Fintech and traditional finance are important for residents to start their businesses. Family income is negatively correlated with entrepreneurship activity. Intuitively, a high level of family income may reduce the incentive of the family to take on high-risk entrepreneurial activity, leaving a negative relation between them. The coefficients of county population and county economic conditions are positive and significant, as expected.

To ensure the robustness of the empirical results, we take advantage of the panel data and conduct linear probability estimation[5], as shown in columns (1)-(3) of Table 9. We also use conditional logit model to estimate (3.2) in columns (4)-(6). Conditional logit model incorporates household fixed effect and alleviates the incidental parameter problem at the same time. It is noteworthy that conditional logit model only focuses on households who change their entrepreneurship behavior in the two periods, which significantly reduces the sample size. The results using both models which incorporate household fixed effect are consistent with those in Table 8, confirming the role of

[4] The marginal effect of Fintech development is 0.00208.
[5] As Fintech is only found to benefit rural households, in what follows, we mainly focus on the rural samples.

Fintech development in financial inclusion and inclusive growth.

[Insert Table 9 approximately here]

5.2 Which Components of Financial inclusion Drive Entrepreneurship?

We have confirmed that Fintech development has contributed to inclusiveness by promoting entrepreneurial activity for rural households. However, Fintech development can be in different directions. For example, the increase of payment accounts, the development of paying, lending, insurance, and investing sectors generated by Fintech, and the accessibility of financial services, are different aspects of Fintech development, while they will not equally contribute to entrepreneurial activity and financial inclusion. Therefore, it is still essential to look into the index of digital financial inclusion to uncover why and how it drives entrepreneurship.

In this section, we analyze the relationship between the three components of digital financial inclusion—financial breadth, financial depth, and digital service provision—and entrepreneurial activity. As stated, financial breadth only measures the number of accounts that have been created at Ant Finance in the corresponding region and may not have a high relevance to entrepreneurship. Financial depth measures the development of the paying, lending, insurance, and investing sectors, and thus directly helps innovative residents with start-up funding. Digital service provision measures the accessibility of financial services and may facilitate entrepreneurs borrowing start-up funds.

In Table 10, we present the empirical results of the impacts from the three components of digital financial inclusion on entrepreneurship. In column (1)-(3), the whole sample, including urban and rural households, is analyzed and again, the coefficients of the three components are all insignificant. In column (4)-(6) where we limit the sample to rural households, as expected, we find that the coefficients of financial depth and digital service provision are positive and significant, while that of financial breadth is insignificant.

[Insert Table 10 approximately here]

5.3 Which Groups of Rural Households Benefit from Fintech?

To further investigate whether Fintech development in China brings in financial inclusion and inclusive growth, we assess which groups benefit more. This is realized by dividing the rural samples by three kinds of capital that closely correlate to entrepreneurial activity, namely, physical capital (measured by family income), human capital (measured by householder's schooling years), and social capital (measured by whether the family receives private transfer payments). The three kinds of capital are all core determinants of the entrepreneurship decision: the more capital a family has, the higher probability the family will be engaged in entrepreneurial activity (Hurst and Lusardi, 2004; Lazear, 2005). However, it is noteworthy that difference in the amount of capital has brought in inequality. Therefore, it is essential to investigate whether Fintech development can lead to inclusiveness among rural residents by alleviating the impact of these capital factors. Table 11 reports the estimation results.

[Insert Table 11 approximately here]

Physical Capital

To begin with, we investigate whether Fintech development performs differently in families with different levels of physical capital (or income). We divide the rural samples into two groups based on the median level of household income and evaluate the impact of Fintech development on entrepreneurial activity in the two samples (column 1-2). We find that households with lower incomes have a higher a probability of becoming entrepreneurs with the help of Fintech, which alleviates the negative effect from lacking start-up funds on entrepreneurial activity and is thus consistent with the principle of financial inclusion.[6]

Human Capital

Next, we turn to human capital. Human capital provides residents with knowledge and innovative minds for entrepreneurship. However, when we divide the sample based

[6] We also try dividing the samples into 5 groups based on income, the results (not reported here) remain unchanged.

on schooling years, we find that all other things remaining constant, householders with more schooling years (or equivalently, with at least a junior-school degree) benefit more from Fintech (see column 3-4), which does not accord with the principle of financial inclusion. There are two possible explanations. The first is that knowledge is the prerequisite for entrepreneurial activity, which obviously cannot be alleviated by Fintech. The second is that the use of Fintech also requires human capital and the group with low human capital is not able to grasp the benefits of Fintech.

Social Capital

Finally, we examine the role of social capital on entrepreneurship in the presence of Fintech. A family with more social capital can borrow from persons in its social network, thus reducing the financing barrier for entrepreneurial activity. Fintech, as stated, also helps residents to overcome financing barriers and thus may reduce residents' dependence on social networks. In column (5)-(6), we measure social capital by using the criteria of whether the family receives private transfer payments. If a family does, we categorize it into the group with social capital, otherwise it is categorized into the group without social capital. We find that, although marginally significant, families without social capital benefit more from Fintech. Given that social capital is an essential factor of entrepreneurship, Fintech may play a role in alleviating the effect.

6. Concluding Remarks

Whether Fintech development is inclusive remains debatable. On the one hand, financial development always benefits only residents with more physical, human, and social capitals, on the other hand, Fintech development enables China to experience transformation in the accessibility and affordability of financial services, particularly for formerly financially excluded populations.

This paper represents an early attempt to investigate whether Fintech development reduces disparity and contributes to financial inclusion and inclusive growth in China. Linking the index of digital financial inclusion with China Family Panel Studies (CFPS) data, we initially find that Fintech development has a positive effect on household income, and the positive effect comes from rural households, suggesting that Fintech development helps narrow urban-rural income gap in China. We further analyze the mechanism underlying the Fintech-disparity relation and find that Fintech has significantly increased the probability that rural residents become entrepreneurs, while the effect on urban households is not significant. A decomposition of Fintech development shows that financial depth, which measures the development of the paying, lending, insurance, and investing sectors, and digital service provision, which measures the accessibility of financial services, are the two factors that contribute to entrepreneurship. Additionally, households with lower incomes or social capital have a higher probability of becoming entrepreneurs with the help of Fintech, which is also consistent with inclusiveness.

Three policy options, based on our findings, can further promote inclusive growth with the help of Fintech. First, Fintech development should be further advocated, especially in the lagging areas such as rural China or West China. Second, special attention should be paid to the development of financial depth and digital service provision, as they could significantly alleviate financial constraints and promote entrepreneurship. Finally, public spending on education should be continued given that Fintech is more beneficial for residents with higher educational degrees.

Reference

Baumol, W. J., 1968, "Entrepreneurship in Economic Theory," *American Economic Review*, 64-71.

Bianchi, M., 2010, "Credit Constraints, Entrepreneurial Talent, and Economic Development," *Small Business Economics*, 34(1), 93-104.

China Bank Association, 2016. "Blue Book of China's Bank Card Industry Development (2016)".

De Mel, S., D. Mckenzie, and C. Woodruff, 2008, "Returns to Capital in Microenterprises: Evidence from a Field Experiment," *Quarterly Journal of Economics*, 123(4), 1329-1372.

Djankov, S., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer, 2002, "The Regulation of Entry," *Quarterly Journal of Economics*, 1-37.

Evans D. S., and B. Jovanovic, 1989, "An Estimated Model of Entrepreneurial Choice under Liquidity Constraints," *Journal of Political Economy*, 97, 808-827.

Evans, D. S. and L. S. Leighton, 1989, "Some Empirical Aspects of Entrepreneurship," *American Economic Review*, 519-535.

Ghani, E., W. Kerr, and S. O' Connell, 2014, "Spatial Determinants of Entrepreneurship in India," *Regional Studies*, 48(6), 1071-1089.

Glaeser, E. and W. Kerr, 2009, "Local Industrial Conditions and Entrepreneurship: How Much of the Spatial Distribution Can We Explain?," *Journal of Economics and Management Strategy*, 18(3), 623-663.

Guo F., T. Kong, J. Wang, X. Zhang, Z. Cheng, F. Ruan, T. Sun, and F. Wang, 2016, "The Construction of Digital Financial inclusion Index in China" (in Chinese), Institutes of Digital Finance Working Paper, Peking University.

Han, L. and D. Hare, 2013, "The Link between Credit Markets and Self-employment Choice among Households in Rural China," *Journal of Asian Economics*, 26, 52-64.

Hurst, E. and A. Lusardi, 2004, "Liquidity Constraints, Household Wealth, and Entrepreneurship," *Journal of Political Economy*, 112, 319-347.

Karaivanov A., 2012, "Financial Constraints and Occupational Choice in Thai Villages," *Journal of Development Economics*, 97(2), 201-220.

King, R. G., and R. Levine, "Finance, Entrepreneurship and Growth," *Journal of Monetary Economics*, 1993, 32(3), 513-542.

Lazear, E., 2005, "Entrepreneurship," *Journal of Labor Economics*, 23(4), 649-680.

Nykvist, J., 2008, "Entrepreneurship and Liquidity Constraints: Evidence from Sweden," *Scandinavian Journal of Economics*, 110(1), 23-43.

Parker, S., 1996, "A Time Series Model of Self-Employment under Uncertainty," *Economica*, 459-475.

Rees, H. and A. Shah, 1986, "An Empirical Analysis of Self-employment in the UK," *Journal of Applied Econometrics*, 1(1), 95-108.

Rosenthal, S. and W. Strange, 2012, "Female Entrepreneurship, Agglomeration, and a New Spatial Mismatch," *Review of Economics and Statistics*, 94(3), 764-788.

Samila, S. and O. Sorenson, 2011, "Venture Capital, Entrepreneurship, and Economic Growth," *Review of Economics & Statistics*, 93, 338-349.

Table 1. Construction of Index of Digital Financial inclusion

First Level Indicators	Second Level Indicators		Measures
Financial Breadth	Account Coverage		No. of Accounts per 10,000 persons
			Ratio of Accounts with Credit Card
			No. of Debit and Credit Cards per Alipay Account
Financial Depth	Payment		Frequency of Payment per capita
			Amount of Payment per capita
			Ratio of High Frequency Users
	Lending	Individuals	No. of Accounts with Consumer Credit per 10,000 Accounts
			Frequency of Loans per capita
			Amount of Loans per capita
		Micro Entrepreneurs	No. of Accounts with Micro Enterprise Credit per 10,000 Accounts
			Frequency of Loans per Micro Entrepreneurs
			Amount of Loans per Micro Entrepreneurs
	Insurance		No. of Accounts with Insurance per 10,000 Accounts
			Frequency of Insurance per capita
			Amount of Insurance per capita
	Investment		No. of Accounts with Investment per 10,000 Accounts
			Frequency of Investment per capita
			Amount of Investment per capita
	Credit Investigation		No. of Accounts using credit investigation per 10,000 Accounts
			Frequency of Accounts using credit investigation
	Financial Convenience		Ratio of Payment Frequency with Mobile
Digital Service Provision			Ratio of Payment Amount with Mobile over Total Payment Amount
	Cost of Financial Service		Average Loan Interest Rate of Micro Enterprise
			Average Loan Interest Rate of Consumer Credit

Note: See Guo et al. (2016).

Table 2. Development of Financial inclusion Generated by Fintech in China

Province	Index of Digital Financial inclusion		Province	Index of Digital Financial inclusion	
	2011	2015		2011	2015
China (average)	40.00	220.01	Henan	28.4	205.34
Beijing	79.41	276.38	Hubei	39.82	226.75
Tianjin	60.58	237.53	Hunan	32.68	206.38
Hebei	32.42	199.53	Guangdong	69.48	240.95
Shanxi	33.41	206.3	Guangxi	33.89	207.23
Inner Mongolia	28.89	214.55	Hainan	45.56	230.33
Liaoning	43.29	226.4	Chongqing	41.89	221.84
Jilin	24.51	208.2	Sichuan	40.16	215.48
Heilongjiang	33.58	209.93	Guizhou	18.47	193.29
Shanghai	80.19	278.11	Yunnan	24.91	203.76
Jiangsu	62.08	244.01	Tibet	16.22	186.38
Zhejiang	77.39	264.85	Shaanxi	40.96	216.12
Anhui	33.07	211.28	Gansu	18.84	199.78
Fujian	61.76	245.21	Qinghai	18.33	195.15
Jiangxi	29.74	208.35	Ningxia	31.31	214.7
Shandong	38.55	220.66	Xinjiang	20.34	205.49

Note: Data are from the Institute of Digital Finance, Peking University.

Table 3. Summary Statistics

Variable	2012			2014		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
ln (Household Income)	10964	10.0241	1.3515	10610	10.1597	1.3069
Entrepreneurship Proportion	11237	0.0922	0.2893	11577	0.0927	0.2900
Entrepreneurship	10430	0.0552	0.2284	9685	0.0386	0.1927
Fintech Development	11011	100.8067	22.0308	11338	181.1761	23.0990
Financial Breadth	11011	81.7760	28.1885	11338	171.1787	26.6921
Financial Depth	11011	117.8444	31.0368	11338	155.0006	36.0785
Digital Service Provision	11011	132.6938	15.4467	11338	261.7514	15.8017
Gender (Male=1)	11253	0.7413	0.4379	11615	0.7304	0.4438
Age	11257	51.6006	12.8531	11615	52.0503	13.6832
Schooling Years	11226	6.5500	4.7629	11321	6.6797	4.7336
Political Status (CPC Member=1)	11227	0.1195	0.3244	11584	0.1064	0.3083
Marriage Status (Married =1)	11264	0.8832	0.3212	11631	0.8655	0.3412
Health Condition (Healthy=1)	11228	0.0755	0.2642	11584	0.1180	0.3226
Internet User	10150	0.1023	0.3030	11226	0.1843	0.3877
Phone User	10150	0.7393	0.4390	11226	0.8560	0.3511
Family Size	11264	3.8561	1.7801	11631	3.7519	1.8426
Young Dependency Ratio	11264	0.1686	0.1984	11631	0.1784	0.2129
Old Dependency Ratio	11264	0.2220	0.3326	11631	0.2430	0.3478
Bank Loan (Yes=1)	11236	0.0619	0.2411	11575	0.1272	0.3332
ln (County Population)	11089	7.9134	0.9330	11180	7.9139	0.9414
ln (County Economic Condition)	11090	4.3662	1.1704	11182	4.6846	1.3597

Note: Household data are from CFPS database. Data of Fintech development are from Institute of Digital Finance, Peking University.

Table 4. Baseline Results: Fintech and Household Income

ln (Household Income)	(1)	(2)	(3)	(4)
Fintech Development	0.0017***	0.0020***	0.0014**	0.0014**
	(0.0003)	(0.0006)	(0.0006)	(0.0006)
Age^2		-0.0001	0.0003	0.0002
		(0.0003)	(0.0002)	(0.0002)
Marriage Status		-0.0585	-0.1784	-0.1759
		(0.1341)	(0.1288)	(0.1269)
Health Condition		0.0149	0.0186	0.0231
		(0.0459)	(0.0473)	(0.0482)
Internet User		0.0062	-0.0020	-0.0020
		(0.0448)	(0.0448)	(0.0456)
Mobile User		0.0113	0.0149	0.0139
		(0.0473)	(0.0447)	(0.0448)
Family Size			0.2336***	0.2347***
			(0.0253)	(0.0253)
Young Dependency Ratio			-0.4953***	-0.4932***
			(0.0820)	(0.0798)
Old Dependency Ratio			-0.2340*	-0.2307*
			(0.1218)	(0.1239)
Bank Loan			-0.0325	-0.0323
			(0.0544)	(0.0543)
ln (County Population)				-0.0723
				(0.1541)
ln (County Economic Condition)				0.0207
				(0.0203)
Household Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	21,083	19,961	19,959	19,604
R^2	0.0101	0.0107	0.0544	0.0548

Note: 1) Dependent variable is the logarithm of household income and is estimated using fixed-effect model. Independent variables include householder's characteristics (age, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5. Fintech and Urban-Rural Household Income Disparity

ln (Household Income)	Rural Household			Urban Household		
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Development	0.0012***	0.0031***	0.0025***	0.0013***	0.0013*	0.0006
	(0.0003)	(0.0008)	(0.0008)	(0.0002)	(0.0006)	(0.0006)
Age^2		-0.0009**	-0.0005		-0.0001	0.0003
		(0.0004)	(0.0004)		(0.0004)	(0.0003)
Marriage Status		0.1104	-0.0086		-0.2002	-0.3035
		(0.1493)	(0.1627)		(0.2085)	(0.2014)
Health Condition		-0.0017	0.0053		0.0731	0.0709
		(0.0539)	(0.0563)		(0.0809)	(0.0806)
Internet User		0.0187	-0.0104		-0.0057	-0.0021
		(0.0665)	(0.0665)		(0.0700)	(0.0716)
Mobile User		-0.0212	-0.0058		0.0917	0.0656
		(0.0545)	(0.0521)		(0.0616)	(0.0572)
Family Size			0.2362***			0.2335***
			(0.0292)			(0.0247)
Young Dependency Ratio			-0.3832***			-0.6843***
			(0.0908)			(0.1575)
Old Dependency Ratio			-0.3679**			-0.0150
			(0.1497)			(0.1707)
Bank Loan			-0.0985*			0.0693
			(0.0550)			(0.0888)
ln (County Population)			0.3874			-0.2347*
			(0.2712)			(0.1358)
ln (County Economic Condition)			-0.0016			0.0488
			(0.0297)			(0.0348)
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	11,245	10,603	10,502	9,675	9,238	8,997
R^2	0.0086	0.0114	0.0622	0.0144	0.0145	0.0512

Note: 1) Dependent variable is the logarithm of household income and is estimated using fixed-effect model. Independent variables include householder's characteristics (age, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Fintech and Rural Household Income: Quantile Regression

ln (Household Income)	Cross-sectional Quantile Regression			Panel Quantile Regression		
	Q25	Q50	Q75	Q25	Q50	Q75
Fintech Development	0.0099***	0.0082***	0.0064***	10.0001**	-1.1405	9.7023
	(0.0011)	(0.0007)	(0.0006)	(4.4916)	(33.5937)	(68.7552)
Gender	-0.1373**	-0.1274***	-0.0915***			
	(0.0542)	(0.0267)	(0.0250)			
Age (or Age^2)	0.0029	0.0039**	0.0064***	-0.0007	8.7963	0.0151
	(0.0021)	(0.0015)	(0.0012)	(0.0165)	(115.5363)	(0.1473)
Schooling Years	0.0427***	0.0293***	0.0229***			
	(0.0047)	(0.0026)	(0.0025)			
Political Status	0.0743	0.0674*	0.1316***			
	(0.0701)	(0.0366)	(0.0387)			
Marriage Status	0.4214***	0.3200***	0.1685***	0.4230	4.1391	0.5662
	(0.0697)	(0.0479)	(0.0370)	(11.1545)	(0.0000)	(0.0000)
Health Condition	0.0374	0.0809**	0.0888***	-0.0061	-3.1431	0.2616
	(0.0569)	(0.0355)	(0.0287)	(4.9536)	(275.1719)	(13.7207)
Internet User	0.2362***	0.1663***	0.1861***	0.4123	2.6657	0.3552
	(0.0750)	(0.0473)	(0.0413)	(8.1469)	(327.2494)	(7.3715)
Mobile User	0.2777***	0.2038***	0.1606***	0.3135	-6.9602	-0.7227
	(0.0519)	(0.0354)	(0.0265)	(4.1740)	(218.7759)	(20.4667)
Family Size	0.2422***	0.2236***	0.1827***	0.2412	-0.2602	0.0376
	(0.0105)	(0.0081)	(0.0070)	(4.1540)	(67.6564)	(3.9837)
Young Dependency Ratio	-0.9519***	-0.8378***	-0.5764***	-1.0699	1.0391	-0.2634
	(0.0997)	(0.0791)	(0.0834)	(33.2225)	(652.7527)	(15.2894)
Old Dependency Ratio	-1.1288***	-1.0629***	-0.8044***	-1.1307	2.9012	-0.0025
	(0.0794)	(0.0543)	(0.0429)	(8.2867)	(1,638.2559)	(2.9065)
Bank Loan	-0.1188*	0.0468	0.0424	-0.1612	-0.1766	-0.4662
	(0.0678)	(0.0436)	(0.0335)	(4.1492)	(252.9450)	(5.0805)
ln (County Population)	0.0647***	0.0717***	0.0464***	0.0919	5.2224	0.5206
	(0.0238)	(0.0136)	(0.0139)	(23.2171)	(421.1306)	(48.0102)
ln (County Economic Condition)	0.0739***	0.0512***	0.0285***	0.0813	-8.4814	-0.5444
	(0.0167)	(0.0091)	(0.0087)	(9.2248)	(98.7638)	(6.2569)
Household Fixed Effect	N	N	N	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	10,434	10,434	10,434	10,502	10,502	10,502

Note: 1) Dependent variable is the logarithm of household income and is estimated using quantile regression model. Independent variables include householder's characteristics (gender, age, schooling years, political status, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition). The test of equality between coefficients of Fintech development in columns (1)-(3) is with a p-value of 0.00120.

2) Robust cluster standard errors are in parentheses.

3) *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 7. Fintech and Entrepreneurship

Entrepreneurship	(1)	(2)	(3)	(4)
Fintech Development	0.0066	0.0055	0.0042	0.0042
	(0.0064)	(0.0066)	(0.0069)	(0.0070)
Gender		-0.0237	-0.0484	-0.0157
		(0.0395)	(0.0419)	(0.0425)
Age		-0.0068***	0.0027	0.0021
		(0.0016)	(0.0021)	(0.0021)
Schooling Years		0.0157***	0.0207***	0.0170***
		(0.0041)	(0.0044)	(0.0044)
Political Status		-0.0775	-0.0618	-0.0626
		(0.0538)	(0.0556)	(0.0562)
Marriage Status		0.1346**	0.0468	0.0290
		(0.0591)	(0.0635)	(0.0642)
Health Condition		0.0763	0.0463	0.0297
		(0.0540)	(0.0569)	(0.0585)
Internet User		0.1786***	0.2422***	0.1867***
		(0.0499)	(0.0526)	(0.0539)
Mobile User		0.1441***	0.1489***	0.1387***
		(0.0504)	(0.0526)	(0.0528)
Family Size			0.0803***	0.0879***
			(0.0105)	(0.0107)
Young Dependency Ratio			-0.0200	-0.0286
			(0.1006)	(0.1035)
Old Dependency Ratio			-0.5223***	-0.5231***
			(0.0797)	(0.0807)
Bank Loan			0.3726***	0.3787***
			(0.0509)	(0.0516)
ln (Household Income)			-0.0800***	-0.0848***
			(0.0134)	(0.0136)
ln (County Population)				0.1003***
				(0.0225)
ln (County Economic Condition)				0.0424***
				(0.0156)
Province Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
N	19,710	18,885	18,154	18,008
Pseudo R^2	0.0197	0.0423	0.0693	0.0743

Note: 1) Dependent variable is entrepreneurship, which is a binary variable and takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and is estimated using probit model. Independent variables include householder's characteristics (gender, age, schooling years, political status, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8. Fintech and Entrepreneurship: Urban-Rural Disparity

Entrepreneurship	Rural Household			Urban Household		
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Development	0.0267***	0.0270***	0.0266**	-0.0083	-0.0122	-0.0152
	(0.0097)	(0.0100)	(0.0104)	(0.0087)	(0.0091)	(0.0098)
Gender		-0.0749	-0.0742		0.0382	0.0350
		(0.0636)	(0.0675)		(0.0517)	(0.0557)
Age		-0.0049**	0.0025		-0.0105***	0.0002
		(0.0023)	(0.0030)		(0.0022)	(0.0030)
Schooling Years		0.0282***	0.0284***		-0.0015	0.0052
		(0.0061)	(0.0064)		(0.0058)	(0.0064)
Political Status		0.0825	0.0800		-0.1887**	-0.1539**
		(0.0781)	(0.0813)		(0.0735)	(0.0776)
Marriage Status		0.0520	-0.0841		0.2020**	0.1216
		(0.0870)	(0.0929)		(0.0809)	(0.0885)
Health Condition		0.1500**	0.1180		-0.0385	-0.1166
		(0.0705)	(0.0747)		(0.0860)	(0.0933)
Internet User		0.2409***	0.2375**		0.1497**	0.2122***
		(0.0912)	(0.0972)		(0.0618)	(0.0664)
Mobile User		0.0792	0.0585		0.1689**	0.1855**
		(0.0687)	(0.0713)		(0.0772)	(0.0819)
Family Size			0.0630***			0.1206***
			(0.0145)			(0.0164)
Young Dependency Ratio			0.0599			-0.1110
			(0.1290)			(0.1517)
Old Dependency Ratio			-0.4600***			-0.5618***
			(0.1170)			(0.1128)
Bank Loan			0.3972***			0.3805***
			(0.0686)			(0.0807)
ln (Household Income)			-0.0515***			-0.1145***
			(0.0190)			(0.0195)
ln (County Population)			0.0804*			0.0885**
			(0.0429)			(0.0345)
ln (County Economic Condition)			0.0522**			0.0246
			(0.0220)			(0.0241)
Province Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	10,679	10,161	9,733	8,942	8,637	8,203
Pseudo R^2	0.0205	0.0430	0.0697	0.0295	0.0562	0.0945

Note: 1) Dependent variable is entrepreneurship, which is a binary variable and takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and is estimated using probit model. Independent variables include householder's characteristics (gender, age, schooling years, political status, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9. Linear Probability and Conditional Logit Model

Entrepreneurship	Linear Probability Model			Conditional Logit Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Fintech Development	0.0012**	0.0017***	0.0017***	0.0524*	0.0671**	0.0725**
	(0.0004)	(0.0003)	(0.0003)	(0.0282)	(0.0302)	(0.0338)
Age^2		0.0001	0.0001*		0.0078**	0.0078**
		(0.0001)	(0.0001)		(0.0035)	(0.0037)
Marriage Status		-0.0075	-0.0071		-0.2532	-0.1161
		(0.0315)	(0.0355)		(0.8550)	(0.9050)
Health Condition		0.0065	0.0014		0.2367	0.0164
		(0.0086)	(0.0086)		(0.3237)	(0.3365)
Internet User		-0.0100	-0.0080		-0.1382	-0.1457
		(0.0246)	(0.0223)		(0.4488)	(0.5148)
Mobile User		-0.0041	-0.0046		-0.2209	-0.2533
		(0.0072)	(0.0073)		(0.4003)	(0.4205)
Family Size			-0.0024			-0.0829
			(0.0029)			(0.1632)
Young Dependency Ratio			-0.0064			-0.4499
			(0.0097)			(0.9247)
Old Dependency Ratio			-0.0117			0.2391
			(0.0190)			(1.0771)
Bank Loan			0.0113			0.1072
			(0.0161)			(0.3423)
ln (Household Income)			0.0002			0.0059
			(0.0034)			(0.0935)
ln (County Population)			-0.0109			-0.3817
			(0.0189)			(1.5334)
ln (County Economic Condition)			0.0008			-0.0805
			(0.0037)			(0.2099)
Household Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	10,679	10,174	9,741	446	416	378
R^2	0.0013	0.0029	0.0039	0.0220	0.0481	0.0632

Note: 1) Dependent variable is entrepreneurship, which is a binary variable and takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and is estimated using linear probability model and conditional logit model. Independent variables include householder's characteristics (age, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10. Which Components of Fintech Drive Entrepreneurship?

Entrepreneurship	Whole Sample			Rural Household		
	Financial Breadth	Financial Depth	Digital Service Provision	Financial Breadth	Financial Depth	Digital Service Provision
Component of Fintech Development	-0.0169*	0.0035	0.0029	-0.0002	0.0176***	0.0065*
	(0.0096)	(0.0032)	(0.0024)	(0.0131)	(0.0059)	(0.0034)
Gender	-0.0162	-0.0159	-0.0155	-0.0752	-0.0777	-0.0744
	(0.0426)	(0.0425)	(0.0425)	(0.0674)	(0.0675)	(0.0675)
Age	0.0022	0.0022	0.0021	0.0025	0.0026	0.0025
	(0.0021)	(0.0021)	(0.0021)	(0.0030)	(0.0030)	(0.0030)
Schooling Years	0.0171***	0.0170***	0.0170***	0.0287***	0.0286***	0.0286***
	(0.0044)	(0.0044)	(0.0044)	(0.0064)	(0.0064)	(0.0064)
Political Status	-0.0632	-0.0623	-0.0626	0.0802	0.0813	0.0798
	(0.0562)	(0.0562)	(0.0562)	(0.0812)	(0.0813)	(0.0813)
Marriage Status	0.0295	0.0297	0.0277	-0.0849	-0.0806	-0.0863
	(0.0642)	(0.0641)	(0.0641)	(0.0927)	(0.0929)	(0.0928)
Health Condition	0.0318	0.0291	0.0309	0.1225	0.1163	0.1225
	(0.0585)	(0.0584)	(0.0585)	(0.0747)	(0.0747)	(0.0749)
Internet User	0.1876***	0.1862***	0.1867***	0.2316**	0.2430**	0.2307**
	(0.0538)	(0.0539)	(0.0539)	(0.0972)	(0.0971)	(0.0972)
Mobile User	0.1373***	0.1397***	0.1386***	0.0542	0.0594	0.0546
	(0.0529)	(0.0528)	(0.0529)	(0.0711)	(0.0714)	(0.0713)
Family Size	0.0878***	0.0878***	0.0881***	0.0627***	0.0623***	0.0633***
	(0.0108)	(0.0107)	(0.0107)	(0.0145)	(0.0146)	(0.0145)
Young Dependency Ratio	-0.0226	-0.0269	-0.0285	0.0555	0.0694	0.0581
	(0.1031)	(0.1036)	(0.1035)	(0.1288)	(0.1281)	(0.1288)
Old Dependency Ratio	-0.5245***	-0.5236***	-0.5230***	-0.4610***	-0.4604***	-0.4611***
	(0.0806)	(0.0807)	(0.0807)	(0.1167)	(0.1170)	(0.1168)
Bank Loan	0.3782***	0.3775***	0.3786***	0.3977***	0.3923***	0.3990***
	(0.0517)	(0.0517)	(0.0516)	(0.0687)	(0.0685)	(0.0687)
ln (Household Income)	-0.0852***	-0.0850***	-0.0847***	-0.0522***	-0.0523***	-0.0516***
	(0.0136)	(0.0136)	(0.0136)	(0.0191)	(0.0191)	(0.0191)
ln (County Population)	0.0987***	0.1000***	0.1006***	0.0787*	0.0788*	0.0795*
	(0.0224)	(0.0225)	(0.0225)	(0.0426)	(0.0430)	(0.0428)
ln (County Economic Condition)	0.0441***	0.0429***	0.0420***	0.0551**	0.0557**	0.0529**
	(0.0155)	(0.0156)	(0.0156)	(0.0218)	(0.0220)	(0.0219)
Province Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	18,008	18,008	18,008	9,733	9,733	9,733
Pseudo R^2	0.0747	0.0745	0.0745	0.0677	0.0705	0.0689

Note: 1) Dependent variable is entrepreneurship, which is a binary variable and takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and is estimated using probit model. Independent variables include householder's characteristics (gender, age, schooling years, political status, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11. Who Gains More from Fintech?

Entrepreneurship	Physical Capital		Human Capital		Social Capital	
	Low	High	Low	High	Low	High
Fintech Development	0.0756***	-0.0002	0.0056	0.0562***	0.0233**	0.0357
	(0.0192)	(0.0133)	(0.0141)	(0.0159)	(0.0117)	(0.0245)
Gender	0.1471	-0.2204**	0.0723	-0.3399***	-0.1134	0.1364
	(0.1152)	(0.0865)	(0.0836)	(0.1147)	(0.0745)	(0.1596)
Age	-0.0012	0.0051	0.0013	0.0075	0.0048	-0.0080
	(0.0046)	(0.0042)	(0.0038)	(0.0051)	(0.0034)	(0.0067)
Schooling Years	0.0266***	0.0318***	0.0339***	0.0481**	0.0280***	0.0314**
	(0.0102)	(0.0085)	(0.0115)	(0.0224)	(0.0072)	(0.0139)
Political Status	0.2306*	-0.0001	-0.0711	0.1401	0.0104	0.3134*
	(0.1275)	(0.1069)	(0.1543)	(0.1030)	(0.0953)	(0.1668)
Marriage Status	-0.1709	0.0109	-0.1199	-0.0923	-0.0536	-0.2390
	(0.1230)	(0.1480)	(0.1080)	(0.1799)	(0.1059)	(0.1918)
Health Condition	0.0445	0.1583*	0.2123**	0.0070	0.0624	0.3810**
	(0.1283)	(0.0947)	(0.0935)	(0.1240)	(0.0833)	(0.1735)
Internet User	0.7038***	0.0115	0.2103	0.2615**	0.3007***	-0.0663
	(0.1607)	(0.1263)	(0.1810)	(0.1263)	(0.1053)	(0.2665)
Mobile User	-0.1572	0.2488**	0.0339	0.1580	0.0618	0.0555
	(0.1052)	(0.1022)	(0.0840)	(0.1373)	(0.0804)	(0.1575)
Family Size	0.1007***	0.0497***	0.0800***	0.0425*	0.0581***	0.1011***
	(0.0264)	(0.0188)	(0.0190)	(0.0240)	(0.0164)	(0.0321)
Young Dependency Ratio	-0.3786	0.4262**	-0.1253	0.4237*	0.1670	-0.4145
	(0.2526)	(0.1794)	(0.1903)	(0.2250)	(0.1508)	(0.3041)
Old Dependency Ratio	-0.4482***	-0.5633***	-0.3974***	-0.6492***	-0.4691***	-0.4703*
	(0.1587)	(0.2071)	(0.1427)	(0.2206)	(0.1360)	(0.2472)
Bank Loan	0.3585***	0.4353***	0.2531**	0.5657***	0.3986***	0.3500**
	(0.1195)	(0.0856)	(0.0996)	(0.1005)	(0.0766)	(0.1621)
ln (Household Income)	-0.0564*	-0.0405	-0.0502**	-0.0581*	-0.0537**	-0.0708
	(0.0310)	(0.0678)	(0.0245)	(0.0302)	(0.0209)	(0.0492)
ln (County Population)	0.2214***	-0.0039	0.0335	0.1800***	0.0585	0.1753*
	(0.0680)	(0.0574)	(0.0577)	(0.0689)	(0.0477)	(0.1007)
ln (County Economic	0.0482	0.0542*	0.0438	0.0735**	0.0472*	0.0623
Condition)	(0.0356)	(0.0292)	(0.0274)	(0.0368)	(0.0246)	(0.0490)
Province Fixed Effect	Y	Y	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y	Y	Y
N	4,232	5,337	6,267	3,370	7,854	1,779
Pseudo R^2	0.130	0.0667	0.0586	0.105	0.0690	0.133

Note: 1) Dependent variable is entrepreneurship, which is a binary variable and takes the value of 1 if the family was not engaged in entrepreneurial activity in the previous surveying period but is engaged in the current period, and is estimated using probit model. Independent variables include householder's characteristics (gender, age, schooling years, political status, marriage status, health condition, and usage of internet and mobile), household's factors (family size, young dependency ratio, old dependency ratio, and whether the family has bank loan), and indicators of regional development (county population and county economic condition).

2) Robust cluster standard errors are in parentheses.

3) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

How does the Quantity of Disclosed Information Provided by Insurers Affect Entity Behaviors in Internet Insurance Market?

——A Study Based on Tripartite Evolutionary Game Analysis between Government, Insurance Companies and Consumers

Shao Jie[1]

Abstract: In the first quarter of 2018, InsurTech deals reached $724 million[2], which is a record of this industry, and a 155% increase from first quarter of 2017. The emergence of internet insurance provides a new consumption pattern for insurance consumers in e-commerce era. However, without agents fulfilling duty of disclosure, many consumers realize that their own interests sometimes cannot be guaranteed. This paper will analyze the costs and benefits of three parties (i.e. government, insurance companies and consumers) and their strategies regarding information disclosure of insurance products on internet. By using evolutionary game model under bounded rationality assumption, the Nash Equilibrium (NE) and evolutionary stability strategy (ESS) of the system are explored. Then this article will analyze how entities affects each other's strategies in internet insurance market, and explain the different current situation in China and Japan. The results show that (Disclosing, not Regulating, Satisfied) is bound to be the best ESS and it is consumers' buying decision not regulation that ultimately compel insurers to disclose enough information. Finally, this article will suggest some measurements to promote the development of internet insurance market in both Japan and China.

Keywords: internet insurance; information asymmetry; information disclosure; tripartite evolutionary game analysis

1. Introduction

Since the third revolution of science and technology, digitalization has gradually transformed many industries. However, industry commentators believe that the transformation of the insurance industry has come rather late[3]. It was until 1990s, insurance products were first sold online in America. Since then, the global internet insurance market has been developing by leaps and bounds. Broadly speaking, internet insurance or digital insurance refers to when business activities that traditional insurance firms or other qualified financial institutions develop insurance products and services based on internet terminals or digital technologies[4]. Internet insurance can enhance the customer experience, improve the efficiency of insurance business process, offer new products and make insurance companies more prepared for the competition with other industries[5]. According to McKinsey's report in 2018, 43% of commercial lines of InsurTechs are about distribution and sales[6]. Therefore, some researchers

---

1 School of Commerce, Waseda University, Japan.
lincshao@asagi.waseda.jp.

2 Willis Towers Watson (2018) *Quarterly InsurTech Briefing Q1 2018*, New York, NY: Willis Towers Watson.

3 Bain & Company (2015) *Global Digital Insurance Benchmarking Report 2015*, Boston, Mass: Bain & Company.

4 Zhong and Runtao, Xu Aihuan. "Comparison of Development of Internet Insurance in US UK Japan and Inspiration to China." *South China Finance* 9 (2016): 77-82.

5 Eling, Martin, and Martin Lehmann. "The impact of digitalization on the insurance value chain and the insurability of risks." *The Geneva Papers on Risk and Insurance-Issues and Practice* 43.3 (2018): 359-396.

6 McKinsey & Company (2018) *Digital insurance in 2018: Driving real impact with digital and analytics*, New York, NY:

hold that internet insurance, in a narrow sense, mainly refers to insurance products and services that are provided through internet channel[7]. Although insurance provided through internet channel is usually simpler than traditional methods, it is still not easy for consumers to understand products or services provided by insurance firms without face-to-face communication. Concurrently, information disclosed online is much less than traditional ways. Theoretically, internet insurance firms should disclose the following information: rights and obligations of both parties in insurance contract; premium and its cost; coverage of insurance products; financial information of the firm; prediction of future situation and social responsibility[8]. However, many internet insurance firms may choose not to disclose all information, because disclosure means increasing the cost and may lead to a loss of advantages over competitors. The government may regulate the information disclosure to protect consumers, but strict mandated disclosure may inhibit innovation and enthusiasm of internet insurance firms, which in turn reduce consumers' welfare. Hence, this leads to a challenging decision problem for internet insurance market about information disclosure and its regulation.

Generally, internet insurance market has three participants, that is, insurance companies, the government and consumers. Traditional game theory solve the above three-parties decision making problem based on hypothesis that the players are intelligent rational. However, in the real world, individual rationality was restricted by the available information, cognitive limitations, and time available to make decisions[9]. Evolutionary game theory can solve this problem by relaxing assumption that each player is bounded rational, and players can learn from opposite parties to change strategies. Therefore, this paper will introduce a tripartite evolutionary game model into this information disclosure problem in internet insurance market, then build its replicated dynamic equation and analyze each player's strategy. Next, this paper will study the interaction among three parties and factors affecting their behavior. By analyzing different situations of internet insurance market in Japan and China, we will suggest some measures to promote the healthy development of internet insurance market.

The rest of this paper is organized as follows. Section 2 contains a literature review on information disclosure of internet insurance and tripartite evolutionary game theory. In Section 3, the detailed problem will be described. Also, assumptions and parameter setting will be done in this section. Then, this paper will establish and solve the evolutionary model in Section 4. Section 5 will analyze the equilibrium and discuss the stability of every entity under different circumstances. Finally, in Section 6, conclusions and suggestions will be given based on different current situation in Japan and China.

2. Literature review

2.1 Internet insurance and information disclosure

So far, there isn't any widely accepted universal definition of internet insurance. According to China Insurance Regulatory Commission (CIRC), "Internet insurance business" means the

---

McKinsey & Company.

[7] Koduka Jun. "The factors that Inhibit the Spread of Internet Life Insurance." In Proceedings of the Japan Marketing Academy Conference, Tokyo, 2016, 5. Tokyo: Waseda University.

[8] Chen Chu, "Study on the legal issues of the information disclosure obligation of Internet Insurance Subjects" (master's thesis, Nanchang University, 2017)

[9] Jiang, Zhong-Zhong, et al. "Evolutionary game analysis and regulatory strategies for online group-buying based on system dynamics." *Enterprise Information Systems* 12.6 (2018): 695-713.

business under which insurance institutions conclude insurance contracts and provide insurance services via self-operated network platforms, and third-party network platforms, among others, by relying on the Internet, mobile communications, and other technologies[10]. Internet insurance is different from traditional insurance which lack of face-to-face discussion with agents, which means the information insurers disclosed online is the only source for consumers (Chen, 2017). Meanwhile, insurance buyers cannot easily tell the value of their purchases because it depends on actuarial estimates that they do not know and cannot analyze. Nor can the quality of the insurance be ascertained until a loss materializes (B. Shahar, 2011). Therefore, two major problems of internet insurance information disclosure are: how much information is enough for consumers and how to make sure the buyers understand the products. B. Shahar (2011) held that insurers must not only disclose policy terms, they must also highlight terms that are especially important or may cause unexpected agonies. Qu (2018) also pointed out that the "I have read and understood the Terms and Conditions" button is unreasonable because consumers have to click "yes" otherwise cannot move to the next step. In addition, D. Patten (2002) examined the use of the internet for information disclosure with a sample of property and casualty insurance firms, results of the analysis indicate that financial information disclosed by the insurance firm sample is only moderate and the leaders in terms of developing web for financial gain are not balancing that leadership with respect to information disclosure. Thus, it is of great importance to study the information disclosure problem in internet insurance market. However, most of the papers are studying this problem from legal or normative perspective, few researches are about economic analysis, especially behavior strategy study based on game theory.

2.2 Evolutionary game model

Evolutionary game model was originally developed by biologists and mathematicians to address substantive questions in evolutionary biology (Maynard Smith and Price, 1973; Taylor and Jonker, 1978). D. Friedman (1991) firstly introduced evolutionary game into economics. At present, it has been widely used in industrial organization, law, economic development, international trade and policy analysis, etc. Güth (2007) analyzed buyer insurance and seller reputation in online market applying an evolutionary framework. N. Ma (2015) explored complex and dynamic game relationship among participants in forest insurance market based on tripartite evolutionary game model. Y. Gao (2017) applied the evolutionary game theory to discuss and analyze selection behavior of trans-regional hospitals and patients in Telemedicine System. Y. Yang (2019) constructed an Evolutionary Game Model under incomplete information to research what kind of role whistleblowing is playing in air pollution control campaign in China. Compared to traditional game theory, evolutionary game theory pays more attention on long term interaction process which each party can learn to acquire knowledge from the opposite parties to change their strategies (Z. Jiang, 2018), and it is also very useful for investigating the foundations of game-theoretic solution concepts, especially Nash Equilibrium (NE) and selection among multiple NE (D. Friedman, 1998). Recently, evolutionary game is widely used to analyze internet financial industry development and regulation boundary (Y. Su, 2015; Y. Zhao, 2015; H. Zhang, 2016; S. Zhou, 2016). Therefore, this article will also apply an evolutionary game model to analyze the information disclosure problem in internet insurance market, and hopefully provides some constructive suggestions

[10] CIRC, *Notice of the China Insurance Regulatory Commission on Issuing the Interim Measures for the Supervision of the Internet Insurance Business.*

for the market.

3. Problem statement and assumptions

There are three direct stakeholders in internet insurance market, each of them has two kinds of strategies when it comes to information disclosure.

Internet insurance firms provide insurance products and services online, usually they have two kinds of strategies about information disclosure. One is disclosing enough effective information for consumers to buy suitable insurance (“disclosing” strategy in brief). This may cause some direct cost like labor cost and indirect cost like giving important information away to competitors. Together, let the total cost be C_1 when insurers choose “disclosing” strategy. The other strategy is to disclose information not enough for consumers to buy suitable insurance (“not disclosing” strategy in brief). This may reduce the cost (let it be C_2, and $C_1 > C_2$), but it may jeopardize consumers’ trust and reduce the sales volume, let the revenue loss be S. For convenience sake, let the extra cost of disclosing extra information be C_i ($C_i = C_1 - C_2$). Let η, where $0 \leq \eta \leq 1$, represents the probability of internet insurers disclosing enough information.

The government acts as the supervisor of internet insurance market, and accordingly has two strategies: “regulating” and “not regulating” information disclosure of insurers. When government regulate the information disclosure of internet insurance firms, there is some direct cost like labor cost, and if the mandated disclosure requirement is too much, it may jeopardize the competition in this market (indirect cost). Together, let the total cost be C_g. Also, government can impose a penalty on insurers if they fail to fulfil government’s requirement (let it be F_c). When insurers disclose enough information, the market is perfect with welfare V_g. Meanwhile, if insurers don’t disclose enough information, the government may suffer from a market efficiency loss L_1, and a loss of reputation and trust from consumers (L_2) when government choose “not regulating” strategy. Let μ, where $0 \leq \mu \leq 1$, represents the probability of government choosing “regulating” strategy.

Let V_m represents the consumers’ welfare when insurance companies disclose enough information, and V'_m be the consumers’ welfare when insurance companies do not disclose enough information. Consumers might buy the unsuitable insurance because of lack of information, therefore V'_m is smaller than V_m ($V_m > V'_m$). Consumers can express their dissatisfaction by complaining about insurers. This may cause consumers cost of complaining (C_m), but may also bring them compensation (F_m) if the insurers don’t disclose enough information. Let σ, where $0 \leq \sigma \leq 1$, represents the probability of consumers choosing “satisfied” strategy.

Based on the statement above, the game strategies of three parties and corresponding parameters are shown in Table 1.

Table 1. Variables setting and meaning

Variables	Meaning of the variables
V_g	Public welfare of government when insurers disclose enough information
C_g	Cost of government regulating the disclosure of internet insurance products
L_1	Market efficiency loss of government when insurers don't disclose enough information
L_2	Reputation and trust loss when government choose not-regulating and insurers choose not-disclosing enough information

V_c	Revenue of internet insurers
C_i	Cost of internet insurers when they disclose extra information
S	Revenue loss of reduced sale volume when internet insurance firms don't disclose enough information
F_c	Penalty on internet insurers if the government thinks they don't disclose enough information
F_m	Compensation to the consumers by the internet insurers if they are sued by consumers because of not disclosing enough information
V_m	Welfare of consumers when insurers disclose enough information
V_m'	Welfare of consumers when insurers do not disclose enough information
C_m	Cost of complaining when the consumers are not satisfied with products
μ	Probability of government regulating the disclosure of internet insurance products
η	Probability of internet insurers disclosing enough information
σ	Probability of consumers being satisfied and don't complain internet insurance firms

For the sake of convenience, some other assumptions are made as below.

(1) Each player is bounded rational to decide whether to change their strategies, and they are all self-interest when entering the system.

(2) Each player can adjust their behavior in the long-term equilibrium.

(3) Government has the motivation to regulate the market when insurance companies don't disclose enough information ($F_c - C_g > 0$).

(4) Consumers can get compensation from insurance companies only if government regulate the market.

And then the payoff matrix is shown as in Table 2.

Table 2. Payoff matrix of three parties

		Government			
		Regulating		Not regulating	
		Insurance company		Insurance company	
		Disclosing	Not disclosing	Disclosing	Not disclosing
Consumer	Satisfied	$\begin{pmatrix} V_g - C_g \\ V_c - C_i \\ V_m \end{pmatrix}$	$\begin{pmatrix} V_g - C_g - L_1 + F_c \\ V_c - F_c - S \\ V_m' \end{pmatrix}$	$\begin{pmatrix} V_g \\ V_c - C_i \\ V_m \end{pmatrix}$	$\begin{pmatrix} V_g - L_1 \\ V_c - S \\ V_m' \end{pmatrix}$
	Complaining	$\begin{pmatrix} V_g - C_g \\ V_c - C_i \\ V_m - C_m \end{pmatrix}$	$\begin{pmatrix} V_g - C_g - L_1 + F_c \\ V_c - F_c - F_m - S \\ V_m' + F_m - C_m \end{pmatrix}$	$\begin{pmatrix} V_g \\ V_c - C_i \\ V_m - C_m \end{pmatrix}$	$\begin{pmatrix} V_g - L_1 - L_2 \\ V_c - S \\ V_m' - C_m \end{pmatrix}$

Noting: each combination is shown as $(\text{government}, \text{insurers}, \text{consumers})^T$

4. Evolutionary game model and solution

Based on payoffs matrix above, the expected payoff of each parties can be expressed as below:

4.1 Internet insurance firms

The payoff equation of internet insurance firms choosing "disclosing" strategy is:

$$U_\eta = V_c - C_i \tag{1}$$

The equation of internet insurance firms choosing "not disclosing" strategy is:

$$
\begin{aligned}
U_{1-\eta} &= \mu\sigma(V_c - S - F_c) + \mu(1-\sigma)(V_c - S - F_c - F_m) \\
&+(1-\mu)\sigma(V_c - S) + (1-\mu)(1-\sigma)(V_c - S) \\
&= V_c - S - \mu(F_c + F_m - \sigma F_m)
\end{aligned} \tag{2}
$$

The equation of average expected payoff of internet insurance firms is:

$$U_{\eta,1-\eta} = \eta U_\eta + (1-\eta)U_{1-\eta} \tag{3}$$

According to the method raised by Taylor and Jonker (1978)[11], replicator dynamics equation is used to represent the learning and evolution mechanism, that is, the change rate of η is:

$$
\begin{aligned}
F(\eta) = \frac{d\eta}{dt} &= \eta\left(U_\eta - U_{\eta,1-\eta}\right) \\
&= \eta(1-\eta)[S - C_i + \mu F_c + \mu(1-\sigma)F_m]
\end{aligned} \tag{4}
$$

4.2 Government

Likewise, the equations of government choosing “regulating” and “not regulating” strategies are:

$$
\begin{aligned}
U_\mu &= \eta\left(V_g - C_g\right) + (1-\eta)\left(V_g - L_1 + F_c - C_g\right) \\
&= V_g - C_g + (1-\eta)(F_c - L_1)
\end{aligned} \tag{5}
$$

$$
\begin{aligned}
U_{1-\mu} &= \eta V_g + (1-\eta)\left[\sigma\left(V_g - L_1\right) + (1-\sigma)\left(V_g - L_1 - L_2\right)\right] \\
&= V_g - (1-\eta)(L_1 + L_2 - \sigma L_2)
\end{aligned} \tag{6}
$$

The equation of average expected payoff and corresponding replicator dynamics equation are:

$$U_{\mu,1-\mu} = \mu U_\mu + (1-\mu)U_{1-\mu} \tag{7}$$

$$
\begin{aligned}
F(\mu) = \frac{d\mu}{dt} &= \mu\left(U_\mu - U_{\mu,1-\mu}\right) \\
&= \mu(1-\mu)[(1-\eta)(L_2 - \sigma L_2 + F_c) - C_g]
\end{aligned} \tag{8}
$$

4.3 Consumers

The equations of consumers choosing “satisfied” and “complaining” strategies are:

$$U_\sigma = \eta V_m + (1-\eta)V'_m \tag{9}$$

$$
\begin{aligned}
U_{1-\sigma} &= \mu\eta(V_m - C_m) + \mu(1-\eta)\left(V'_m + F_m - C_m\right) \\
&+(1-\mu)\eta(V_m - C_m) + (1-\mu)(1-\eta)\left(V'_m - C_m\right) \\
&= \eta V_m + (1-\eta)V'_m + \mu(1-\eta)F_m - C_m
\end{aligned} \tag{10}
$$

Average expected payoff and replicator dynamics equations are:

$$U_{\sigma,1-\sigma} = \sigma U_\sigma + (1-\sigma)U_{1-\sigma} \tag{11}$$

$$
\begin{aligned}
F(\sigma) = \frac{d\sigma}{dt} &= \sigma\left(U_\sigma - U_{\sigma,1-\sigma}\right) \\
&= \sigma(1-\sigma)[C_m - \mu(1-\eta)F_m]
\end{aligned} \tag{12}
$$

Ultimately, the population dynamic of the evolutionary game can be represented as:

---

[11] Taylor, Peter D., and Leo B. Jonker. "Evolutionary stable strategies and game dynamics." *Mathematical biosciences* 40.1-2 (1978): 145-156.

$$\begin{cases} F(\eta) = \eta(1-\eta)(S - C_i + \mu F_c + \mu F_m - \mu\sigma F_m) \\ F(\mu) = \mu(1-\mu)\{(1-\eta)[(1-\sigma)L_2 + F_c] - C_g\} \\ F(\sigma) = \sigma(1-\sigma)[C_m - \mu(1-\eta)F_m] \end{cases} \tag{13}$$

Now, set equations in (13) equal to zero, then we can get 11 equilibrium solutions in system as follows $X_1 \sim X_{12}$:

$X_1(0,0,0), X_2(1,0,0), X_3(0,1,0), X_4(0,0,1), X_5(0,1,1), X_6(1,0,1), X_7(1,1,0), X_8(1,1,1),$

$X_9\left(1 - \frac{C_m}{F_m}, 1, \frac{S - C_i + F_c + F_m}{F_m}\right), X_{10}\left(1 - \frac{C_g}{F_c}, \frac{C_i - S}{F_c}, 1\right),$

$X_{11}\left(1 - \frac{C_g}{L_2 + F_c}, \frac{C_i - S}{F_c + F_m}, 0\right)$

5. Equilibrium analysis and discussion

5.1 Stability analysis

The stability of equilibrium points can be derived by analyzing the part stability of Jacobian matrix (Friedman 1991). Jacobian matrix can be presented as following $\mathbb{J}$:

$$\mathbb{J} = \begin{bmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{bmatrix} = \begin{bmatrix} \frac{\partial F(\eta)}{\partial \eta} & \frac{\partial F(\eta)}{\partial \mu} & \frac{\partial F(\eta)}{\partial \sigma} \\ \frac{\partial F(\mu)}{\partial \eta} & \frac{\partial F(\mu)}{\partial \mu} & \frac{\partial F(\mu)}{\partial \sigma} \\ \frac{\partial F(\sigma)}{\partial \eta} & \frac{\partial F(\sigma)}{\partial \mu} & \frac{\partial F(\sigma)}{\partial \sigma} \end{bmatrix} \tag{14}$$

Where, $a_1 = \frac{\partial F(\eta)}{\partial \eta} = (1 - 2\eta)(S - C_i + \mu F_c + \mu F_m - \mu\sigma F_m)$

$a_2 = \frac{\partial F(\eta)}{\partial \mu} = \eta(1-\eta)(F_c + F_m - \sigma F_m)$

$a_3 = \frac{\partial F(\eta)}{\partial \sigma} = -\mu\eta(1-\eta)F_m$

$b_1 = \frac{\partial F(\mu)}{\partial \eta} = \mu(1-\mu)(\sigma L_2 - F_c - L_2)$

$b_2 = \frac{\partial F(\mu)}{\partial \mu} = (1 - 2\mu)\{(1-\eta)[(1-\sigma)L_2 + F_c] - C_g\}$

$b_3 = \frac{\partial F(\mu)}{\partial \sigma} = -\mu(1-\mu)(1-\eta)L_2$

$c_1 = \frac{\partial F(\sigma)}{\partial \eta} = \sigma(1-\sigma)\mu\eta F_m$

$c_2 = \frac{\partial F(\sigma)}{\partial \mu} = \sigma(1-\sigma)(\eta - 1)F_m$

$c_3 = \frac{\partial F(\sigma)}{\partial \sigma} = (1 - 2\sigma)[C_m - \mu(1-\eta)F_m]$

According to Lyapunov's indirect method, when all eigenvalues (λ) of Jacobian matrix are real and have the same sign, the equilibrium point is called Node. The node is stable (unstable) when the eigenvalues are negative (positive). Otherwise, when all eigenvalues are real and at least one of them is positive and at least one is negative, the equilibrium point is called Saddle. Saddles are always unstable.[12]

For equilibrium point $X_1(0,0,0)$,

[12] Eugene M. Izhikevich. "Equilibrium." Scholarpedia, 2(10):2014. http://www.scholarpedia.org/article/Equilibrium#fig:Equilibria_nonhyperbolic.gif

$$\mathbb{J}_1 = \begin{bmatrix} S - C_i & 0 & 0 \\ 0 & L_2 + F_c - C_g & 0 \\ 0 & 0 & C_m \end{bmatrix}$$

$\lambda_1 = S - C_i$

$\lambda_2 = L_2 + F_c - C_g$

$\lambda_3 = C_m$

According to the parameter setting and model assumptions, $\lambda_2 > 0$ and $\lambda_3 > 0$. Therefore, X_1 is unstable.

Similarly, the stability of rest 10 equilibrium points are analyzed using the same method. The stabilities of eight pure strategy equilibriums are shown in Table 3.

Table 3. Result of analyses of stabilities of pure strategy equilibriums

Balancing point	λ_1	λ_2	λ_3	Stability
X_1	$S - C_i$	$L_2 + F_c - C_g > 0$	$C_m>0$	If $S < C_i$, saddle; otherwise unstable node
X_2	$C_i - S$	$-C_g<0$	$C_m>0$	Saddle
X_3	$S - C_i + F_c + F_m$	$C_g - L_2 - F_c$	$C_m - F_m$	If $C_g - L_2 < F_c$, $C_m < F_m$, $F_c + F_m < C_i - S$, stable; otherwise unstable
X_4	$S - C_i$	$F_c - C_g>0$	$-C_m < 0$	Saddle
X_5	$S - C_i + F_c$	$C_g - F_c<0$	F_m-C_m	If $F_m < C_m$, $F_c < C_i - S$, stable; otherwise unstable
X_6	$C_i - S$	$-C_g<0$	$-C_m < 0$	If $C_i < S$, stable; otherwise saddle
X_7	$C_i - S - F_c - F_m$	$C_g>0$	$C_m>0$	If $F_c + F_m < C_i - S$, unstable node; otherwise saddle
X_8	$C_i - S - F_c$	$C_g>0$	$-C_m < 0$	Saddle

As for the mixed strategy equilibriums ($X_9 \sim X_{12}$), their existence ($\eta, \mu, \sigma \in [0,1]$) relies on the model variables.

For X_9: $L_m + C_m < F_m$ and $F_c < C_i - S < F_c + F_m$;

for X_{10}: $C_i > S$, $C_i - S < F_c$;

for X_{11}: $C_i > S$, $C_i - S < F_c + F_m$.

Then, their stabilities are discussed as below.

Table 4. Eigenvalues of Jacobian matrix of mixed strategy equilibriums

	$\lvert\lambda E - A\rvert$	λ
X_9	$\begin{bmatrix} \lambda & a_2 & a_3 \\ 0 & \lambda - b_2 & 0 \\ c_1 & c_2 & \lambda \end{bmatrix}$	$\lambda_1 = b_2 = C_g - \frac{C_m}{F_m}(\frac{C_i - S - F_c}{F_m} L_2 + F_c)$ $\lambda_2 = \pm\sqrt{a_3 c_1} = \frac{F_m - C_m}{F_m}\sqrt{\frac{(S - C_i + F_c + F_m)(C_i - S - F_c)}{F_m}}$ $\lambda_3 = -\sqrt{a_3 c_1} = -\frac{F_m - C_m}{F_m}\sqrt{\frac{(S - C_i + F_c + F_m)(C_i - S - F_c)}{F_m}}$

X_{10}	$\begin{bmatrix} \lambda & a_2 & a_3 \\ b_1 & \lambda & b_3 \\ 0 & 0 & \lambda - c_3 \end{bmatrix}$	$\lambda_1 = \sqrt{a_2 b_1} = \frac{\sqrt{(F_c - C_g)C_g(C_i - S)(C_i - S - F_c)}}{F_c}$ $\lambda_2 = -\sqrt{a_2 b_1} = -\frac{\sqrt{(F_c - C_g)C_g(C_i - S)(C_i - S - F_c)}}{F_c}$ $\lambda_3 = c_3 = \frac{(C_i - S)}{F_c} * \frac{C_g}{F_c} * F_m - C_m$
X_{11}	$\begin{bmatrix} \lambda & a_2 & a_3 \\ b_1 & \lambda & b_3 \\ 0 & 0 & \lambda - c_3 \end{bmatrix}$	$\lambda_1 = \sqrt{a_2 b_1} = \sqrt{\frac{(L_2 + F_c - C_g)(C_i - S)(C_i - S - F_c - F_m)C_g}{(L_2 + F_c)(F_m + F_c)}}$ $\lambda_2 = -\sqrt{a_2 b_1} = -\sqrt{\frac{(L_2 + F_c - C_g)(C_i - S)(C_i - S - F_c - F_m)C_g}{(L_2 + F_c)(F_m + F_c)}}$ $\lambda_3 = c_3 = C_m - \frac{C_i - S}{F_c + F_m} * \frac{C_g}{L_2 + F_c} * F_m$

As shown in Table 4, each of three equilibriums has one real eigenvalue and a pair of complex-conjugate eigenvalues with zero real part. That means these mixed strategy equilibriums are not stable.

5.2 ESS discussion

The evolutionary stability can be analyzed to conclude an evolutionarily stable strategy (ESS) justification under different circumstances, as detailed below. In each scenario, no party would have the motivation to change current behavior, the system will stay stable.

Scenario 1: $C_m < F_m$, $F_c + F_m + S < C_i$

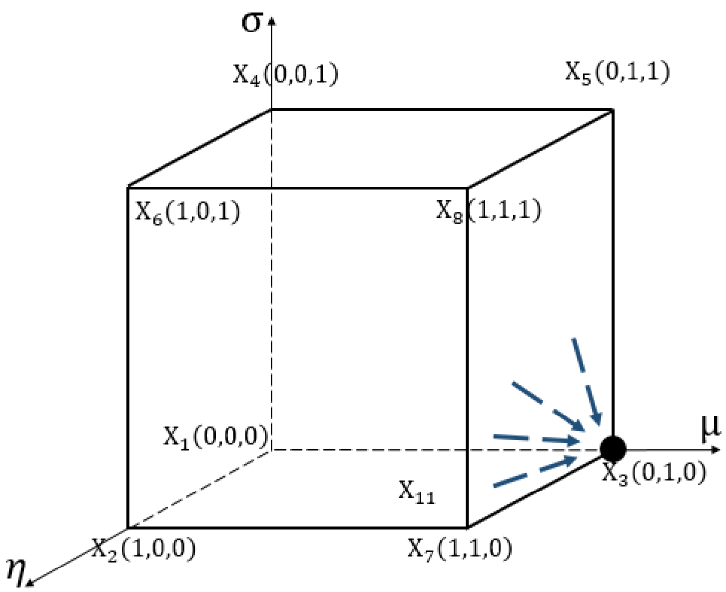

Figure 1 Phase diagram of scenario 1

In this case, based on Table 3 and Table 4, $X_3(0,1,0)$ is the only asymptotic stable point. The phase diagram is shown as Figure 1. This means, internet insurance firms would choose not to disclose enough information to the consumers, while even though government choose to regulate information disclosure of insurers, consumers are still not satisfied and choose to complain about it. This situation occurs because even if the penalty government charges from internet insurers is more than its regulating cost ($C_g < F_c$), and the compensation consumers get from insurers is more than complaining cost ($C_m < F_m$), but the summation of total amercement paid by the insurers and revenue loss is less than the cost of disclosing enough information ($F_c + F_m + S < C_i$). That is to say, this situation is caused by insufficiency of regulation or low information sensitivity of consumers or information disclosure cost being too high.

Scenario 2: $F_m < C_m$, $F_c < C_i - S < F_c + F_m$

Scenario 3: $F_m < C_m$, $F_c + F_m < C_i - S$

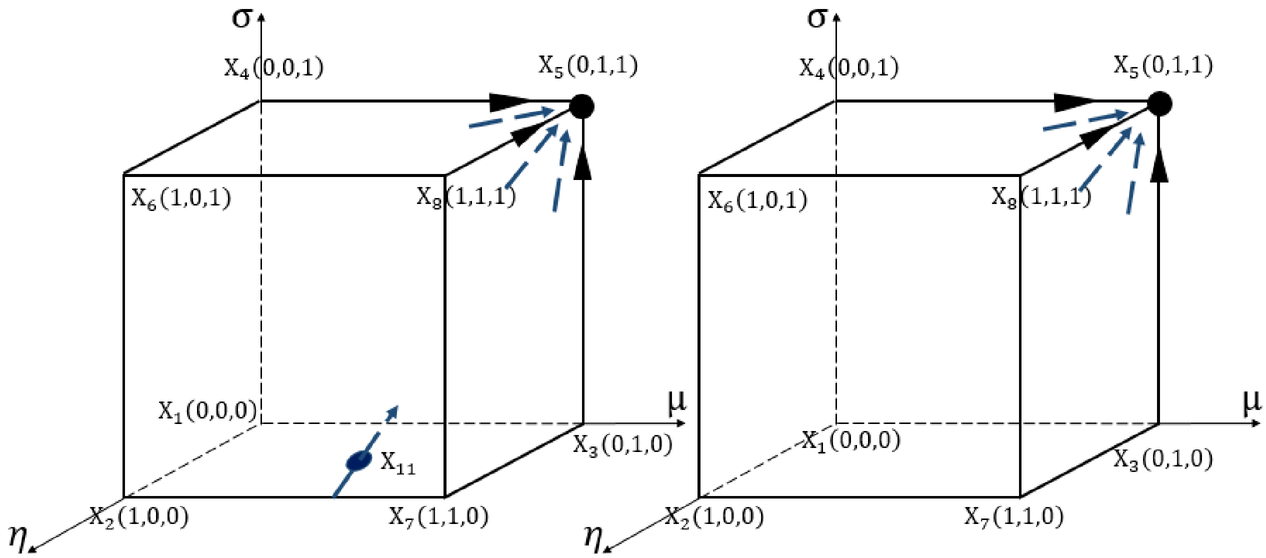

Figure 2 Phase diagram of scenario 2 (left) and scenario 3 (right)

In both scenario 2 and scenario 3, $X_5(0,1,1)$ is the only asymptotic stable point. The phase diagram is shown as Figure 2. That means, the system will be stable with (not Disclosing, Regulating, Satisfied) strategy under these circumstances. The insurers choose not to disclose enough information because the cost of disclosing enough information is larger than the summation of penalty paid to government and revenue loss caused by reduced sales volume ($C_i > F_c + S$). The government has the motivation to regulate the market because the penalty government charges from internet insurers is more than its regulating cost ($C_g < F_c$). However, consumers would choose "satisfied" strategy because the compensation they can get is less than their complaining cost ($F_m < C_m$). That is to say, even though the government is regulating the market, but the supervision is not enough to push insurers to disclose enough information. Meanwhile, the supervision from consumers is not enough either (S is not big enough), and it might also be the case that the consumers are easily satisfied under these circumstances. Therefore, it is not a good stable state because insurers tend to not disclose enough information and consumers' rights are not well protected.

Scenario 4: $C_i < S$

$X_6(1,0,1)$ is the only asymptotic stable point in this scenario. The system would be stable with (Disclosing, not Regulating, Satisfied) strategy. The phase diagram is shown as Figure 3. In this case, the insurers would choose to disclose enough information to the consumers, because the revenue loss caused by sales volume decreasing is larger than the cost of disclosing enough information ($C_i < S$). And if the insurers choose not to disclose enough information, they might even have to pay other penalty, the loss will become unbearable. Considering insurers are initiatively disclosing enough information, the government don't have the motivation to regulate anymore, thus the government would choose "not regulating" strategy. On the other hand, the consumers perform as the supervisor by not buying insurance product without enough information. Once the insurers choose to disclose enough information, the consumers would tend to be satisfied. This is a relatively good stable state because the market is regulating itself, the government doesn't need to spend extra money on supervising the information disclosure.

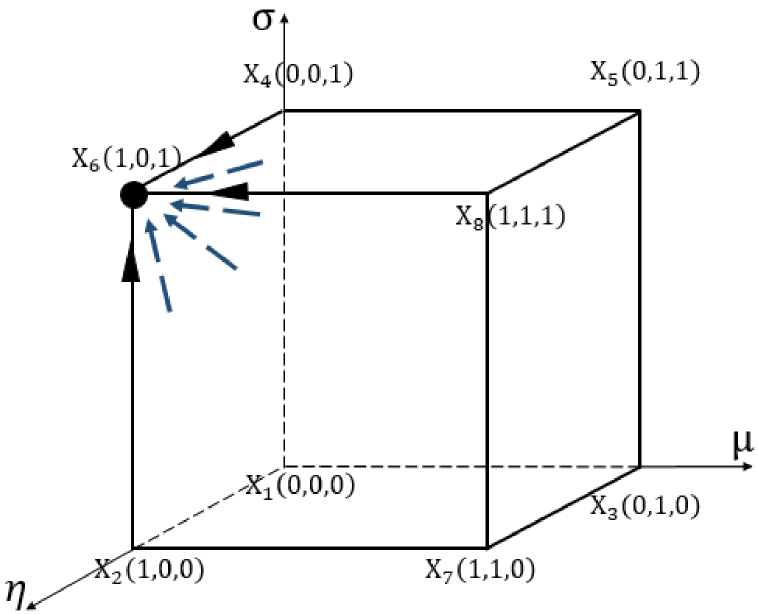

Figure 3 Phase diagram of scenario 4

5.3 Entity behavior discussion

In this section, we will analyze how the variables affect the equilibrium of the proposed three parties in this model.

The internet insurance firms can choose to disclose enough information or not. There are five variables that may affect their behavior: the amercement paid to the government or consumers (F_c, F_m), consumers' complaining cost (C_m), revenue loss caused by sales volume decreasing (S), and the cost of disclosing extra information (C_i). Of which, C_i is the only variable that can be controlled by insurers. As shown in Table 5, if $C_i > F_c + F_m + S$, insurers always tend to choose not to disclose enough information in spite of the size of F_m. While if $F_c + S < C_i < F_c + F_m + S$, insurers would choose not to disclose enough information when $F_m < C_m$; if $F_m > C_m$ or $S < C_i < F_c + S$, there is no stable point in this system, every equilibrium is a saddle point, the system will become chaotic and insurers would choose to disclose enough information with a random possibility. However, if $C_i < S$, insurers would choose to disclose enough information.

Table 5. Stabilities of equilibriums with C_i of different size

Balancing point	Numeric size of C_i			
	(-∞,S)	[S,F_c+S)	[F_c+S,F_c+F_m+S)	[F_c+F_m+S,+∞)
X_1	Unstable	Saddle	Saddle	Saddle
X_2	Saddle	Saddle	Saddle	Saddle
X_3	Saddle	Saddle	Saddle	$C_m<F_m$, stable; $C_m>F_m$, saddle
X_4	Saddle	Saddle	Saddle	Saddle
X_5	Saddle	Saddle	$C_m>F_m$, stable; $C_m<F_m$, saddle	$C_m>F_m$, stable; $C_m<F_m$, saddle
X_6	Stable	Saddle	Saddle	Saddle

X_7	Saddle	Saddle	Saddle	Unstable
X_8	Saddle	Saddle	Saddle	Saddle
X_9	Not exist	Saddle	Saddle	Not exist
X_{10}	Not exist	Saddle	Not exist	Not exist
X_{11}	Not exist	Saddle	Saddle	Not exist

The government can control three variables to affect other parties' behavior: the amercement paid by insurers (F_c, F_m) and cost of consumer complaining (C_m). As stated above, if F_c and F_m are too small compare to C_i, insurers would choose not to disclose enough information in the long run. But when $F_c+S<C_i<F_c+F_m+S$, if government makes $F_m>C_m$, although the system would be chaotic, there is a possibility that the insurers will choose to disclose enough information. Besides, C_m and F_m can also affect consumers' behavior: if $C_m>F_m$, there is no benefit of complaining, so the consumers would choose "satisfied" strategy. On the other hand, there are also three variables that may affect government's decision: penalty on internet insurers (F_c), cost of government regulating the market (C_g) and reputation and trust loss from consumers (L_2). The government only has the motivation to regulate the market when the penalty government charges from internet insurers is more than its regulating cost ($C_g<F_c$). C_g might be too big to bear when there is a serious information asymmetry problem between supervision department and insurers. L_2 functions similarly with F_c, it guarantees that the government has motivation to regulate the market.

Consumers' strategy is affected by C_m and F_m. If $C_m>F_m$, there is no benefit of complaining, so the consumers would prefer "satisfied" strategy. On the other hand, consumers can affect other parties' behavior by changing their confidence level in government (L_2) and buying decision online (S). That means, if insurers don't disclose enough information, the consumers can choose not to buy insurance products and services on internet. It will push insurers to disclose enough information (like Scenario 4) when S is too large for insurers. L_2 functions similarly to S, when the penalty charged by government F_c is not good enough to motivate the government regulating the market, L_2 can work as a supplement and push government to regulate (like Scenario 1).

6. Conclusions and suggestions

This paper focuses on information asymmetry problem in internet insurance market. Compared to traditional insurance, insurance provided through internet channel is usually simpler and modularized. That means, different with traditional insurance, it is the insurers instead of consumers who have the information advantage. Without agents fulfilling information duty, consumer protection could be more difficult than traditional insurance. Therefore, this paper employs three-party evolutionary game theory to study how the quantity of disclosed information provided by insurers affects the behaviors of the government and consumers, and how insurers react to their strategies. On the basis of research above, conclusions are given as follows.

(1) There are only three possible stable strategy combination from long-term perspective (as shown in Figure 4). That is, X_6 (Disclosing, not Regulating, Satisfied), X_3 (not Disclosing, Regulating, Complaining) and X_5 (not Disclosing, Regulating, Satisfied). That means, under these three circumstances, nobody would have motivation to change their strategies, new comers of this market would also follow these strategies. Amongst, X_6 (Disclosing, not

Regulating, Satisfied) would be the best for healthy development of internet insurance industry.

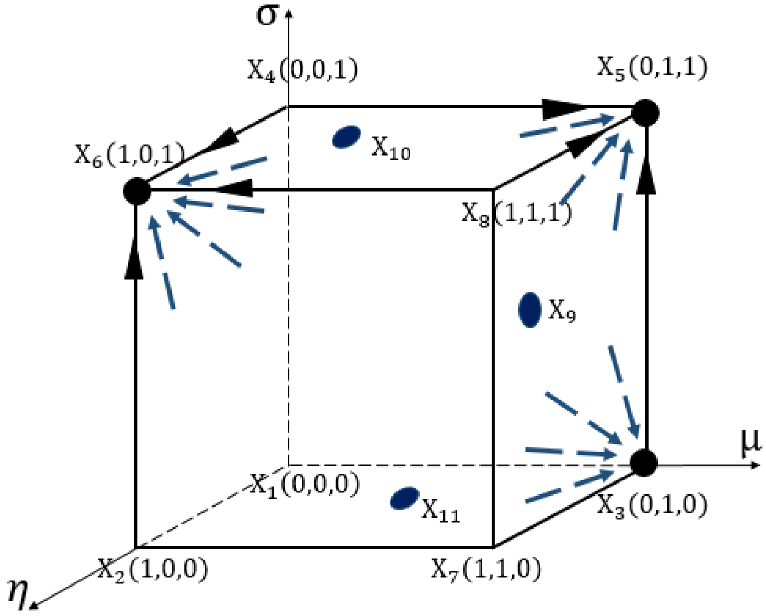

Figure 4 Phase diagram of all stable points

(2) When insurers do not disclose enough information, the government always tends to choose to regulate the market. However, when the government regulates insurers' disclosure, no matter how strictly the government regulates, there would always be occasions that insurers choosing "not disclosing" strategy.

(3) The quantity of information insurers disclose mainly depends on the cost (or profit) of disclosing. The penalty from the government would motivate insurers to disclose more information. But it is consumers' buying decision (S) that ultimately compel insurers to disclose enough information to consumers.

These conclusions may be adopted to explain different situations in different countries. For instance, China has become one of the most advanced internet insurance market because of its developed mobile payment, and it is still developing very rapidly. According to INZURER's report[13], 10 of the top 100 InsurTech firms in 2018 are located in China, while that number of Japan is zero. However, in the year of 2017, dispute number of every billion dollar premium in China was 175.61, while that number of Japan was 18.83,[14] which may indicate that consumers in Japan are more easily satisfied than in China. Governments in both Japan and China tend to regulate the market due to their East Asia culture background. But in China, because of the rather short history of insurance industry and its overgrowth of internet insurance industry, regulation is less sufficient than Japan, and the internet insurers are inclined to not disclose enough information. However, Japan's insurance industry has a very long history, and FSA (Financial Services Agency) of Japan is one of the strictest supervisor in the world, the internet insurers are inclined to disclose enough information. Therefore, the current situation in China is more similar to X_3 (not Disclosing, Regulating, Complaining) and situation in Japan is more similar to X_8 (Disclosing, Regulating, Satisfied).

According to the previous research, the current situation in China is stable in the long run,

---

[13] INZURER (2008) *top 100 InsurTech firms 2018*, Hong Kong, HK: INZURER.

[14] Dispute numbers are from website of CIRC (http://bxjg.circ.gov.cn/web/site0/tab5175/info4104507.htm) and FSA (https://www.fsa.go.jp/soudan/2017soudan10-12/2017_10-12.html); premiums derive from Swiss Re (2018) Sigma No 3/2018.

as shown in Figure 4. That means, the participants in the current market do not have the motivation to change their behavior, and the new comers do not have the ability to change the situation but to follow others' strategy (e.g. new internet insurers would choose not to disclose enough information). The reason of this situation is mainly because of the insufficient regulation under overgrowth of internet insurance market. The regulator in China cannot change policies in such rapidly changing industry, and also unwilling to regulate too harshly in order to protect the vitality in this industry. Besides, consumers in China do not trust agents as much as themselves [15], and they are more high-tech savvy, price sensitive and brand independent. Both insurers and consumers are more willing to take risks.

Although the situation in China is stable, with insurers not disclosing and consumers being unsatisfied, it is not a good occasion for future development of internet insurance market. Therefore changes from each party are necessary. This paper proposes the following suggestions.

(1) Lower cost of disclosing information would make insurers more willing to disclose enough information to consumers. Insurers could lower the cost by simplifying and modularizing services and products.

(2) Although the government is regulating the market, the supervision of information disclosure is still insufficient. The government can enhance the regulation by raising the standard of "enough" information and increasing the penalty of insurers violating.

(3) Enhance the consumers' education. The consumers should make their buying decisions not based on price only, but also their needs. The consumers need to be able to interpret information provided by insurers and lean to only buy those with enough information.

On the other hand, in Japan, the current situation is unstable, as shown in Figure 4. Any disturbance would change the situation into unpredictable direction. The market might stop developing and shrink until it disappears. There are two main possible reasons that lead to this situation. One is that the regulation is too strict. The standard of "enough" disclosure is too high, and the amercement is unbearable. The other reason might be consumers being too conservative. In Japan, agents have a long history and high acceptance. According to Lifenet's investigation[16], 52.3% of the interviewees believe that buying insurance without talking with agents is the biggest demerit of internet insurance. Compared to cheap price, consumers care more about companies' brand. They are also risk averters, 51.7% of the interviewees are worried about their personal information security online, and 51.5% of the interviewees are worried that their insurance knowledge is not enough to make decision by themselves. Therefore, proper guidance of this market is necessary. For the healthier development of internet insurance market in Japan, this paper proposes the following suggestions.

(1) The government should appropriately loose regulation and encourage innovation of internet insurance. For example, lowering the standard of traditional insurance companies entering internet insurance market, or giving internet companies more access to insurance market.

(2) The regulation of information disclosure should not only focus on the quantity, but also the quality. The information of internet insurance and traditional insurance should be

[15] According to China Internet Insurance Development Report 2017, 28.9% of the interviewees believe that buying insurance without agents is actually the merit of internet insurance.

[16] Lifenet (2011) *Investigation of Life Insurance through Internet Channel in 2011*, Tokyo: Lifenet. https://www.lifenet-seimei.co.jp/shared/pdf/2011-3601.pdf

comparable. The insurance companies should also try to simplify and modularize their products, make it easy to understand. That will also lower the cost of disclosing information and make internet insurance business more appealing.

(3) Enhance the consumers' education. That will give consumers more confidence of making their own decisions. Their rational decisions would benefit the development of this market.

However, this paper still has two limitations. Firstly, this paper puts more consideration on the information advantage of insurers, the information advantage of consumers or moral hazard is not involved. Another limitation is that this study only considers the effect of quantity of information. The quality of information is not involved. Future extensions of this research could be developed to several directions. Firstly, the effect of quality of information might be incorporated into this model. Furthermore, some empirical analysis could be done on the basis of this model.

Acknowledgements

Deepest gratitude goes to Professor Nakaide, for his constant encouragement and guidance. The author is also deeply indebted to Professor Takase, Professor Kataoka and Professor Watanabe from Waseda University, for their instructive advice and kind help.

Funding

The author would like to thank the China Scholarship Council under No. 201806980008.

References

Willis Towers Watson (2018) *Quarterly InsurTech Briefing Q1 2018*, New York, NY: Willis Towers Watson.

Bain & Company (2015) *Global Digital Insurance Benchmarking Report 2015*, Boston, Mass: Bain & Company.

Zhong Runtao, Xu Aihuan. "Comparison of Development of Internet Insurance in US UK Japan and Inspiration to China." *South China Finance* 9 (2016): 77-82.

Eling, Martin, and Martin Lehmann. "The impact of digitalization on the insurance value chain and the insurability of risks." *The Geneva Papers on Risk and Insurance-Issues and Practice* 43.3 (2018): 359-396.

McKinsey & Company (2018) *Digital insurance in 2018: Driving real impact with digital and analytics*, New York, NY: McKinsey & Company.

Koduka Jun. "The factors that Inhibit the Spread of Internet Life Insurance." In Proceedings of the Japan Marketing Academy Conference, Tokyo, 2016, 5. Tokyo: Waseda University.

Chen Chu, "Study on the legal issues of the information disclosure obligation of Internet Insurance Subjects" (master's thesis, Nanchang University, 2017)

Jiang, Zhong-Zhong, et al. "Evolutionary game analysis and regulatory strategies for online group-buying based on system dynamics." *Enterprise Information Systems* 12.6 (2018): 695-713.

CIRC, *Notice of the China Insurance Regulatory Commission on Issuing the Interim Measures for the Supervision of the Internet Insurance Business*.

Taylor, Peter D., and Leo B. Jonker. "Evolutionary stable strategies and game dynamics." *Mathematical biosciences* 40.1-2 (1978): 145-156.7. D. Friedman (1991)

Eugene M. Izhikevich. "Equilibrium." Scholarpedia, 2(10):2014. http://www.scholarpedia.org/article/Equilibrium#fig:Equilibria_nonhyperbolic.gif

INZURER, "top 100 InsurTech firms 2018", (Apr. 2018), p.28-31. http://www.inzurer.com/Insurance_Post_April_2018.pdf

Ben-Shahar, Omri, and Carl E. Schneider. "The failure of mandated disclosure." *University of*

Pennsylvania Law Review Feb. 2011: 647+. Business Insights: Global.
Qu Guanjun, “Research on Internet Insurance Consumer Protection”, (master’s thesis, Lanzhou University, 2018)
Maynard Smith J, Price G. “The logic of animal conflict”. *Nature* 246 (1973): 15–18
Güth, Werner, Friederike Mengel, and Axel Ockenfels. "An evolutionary analysis of buyer insurance and seller reputation in online markets." *Theory and Decision* 63.3 (2007): 265-282.
Ma, Ning, et al. "Forest insurance market participants' game behavior in China: An analysis based on tripartite dynamic game model." *Journal of Industrial Engineering and Management (JIEM)* 8.5 (2015): 1533-1546.
Zhao, Yi, Dong Li, and Liqiang Pan. "Cooperation or competition: An evolutionary game study between commercial banks and big Data-based e-Commerce financial institutions in China." *Discrete Dynamics in Nature and Society* 2015 (2015).
Friedman, Daniel. "Evolutionary games in economics." *Econometrica* 59.3 (1991): 637-666.
ZHAO Dao-zhi, HAO Jia-qiny, YANG Jie, HAN Hong-shuai. “Evolutionary Game Analysis of the Three Parties in the Sharing Economy Considering the Network Externality of the Platform”, *Control and Decision* (2019): 1-10
Yunpeng Yang, Weixin Yang. “Does Whistleblowing Work for Air Pollution Control in China? A Study Based on Three-party Evolutionary Game Model under Incomplete Information”, *Sustainability*, 11 (2019): 324
Friedman, Daniel. "On economic applications of evolutionary game theory." *Journal of evolutionary economics* 8.1 (1998): 15-43.
Dennis M. Patte. “Give of Take on the Internet: An Examination of the Disclosure Practices of Insurance Firm Web Innovators”, *Journal of Business Ethics*, Vol. 36, No. 3 (2002): 247-259
Yuxuan Gao , Yueping Du, Bingzhen Sun, Rui Wang, Chaoying Jiang. “Tripartite Evolutionary Game Analysis on Selection Behavior of Trans-Regional Hospitals and Patients in Telemedicine System”, *International Journal of Computational Intelligence Systems*, Vol. 10 (2017): 1132–1148.
WEI, Fang-fang, and Fu-ji CHEN. "Evolutionary Game Analysis Between Governments, Enterprises and Citizens in Network False Information." *Operations Research and Management Science* 6 (2012).
Zhang Hongwei, Xu Yifei. “An Analysis of Internet Financial Regulation through Dynamic Game Model”, *Financial Economics Research*, Vol. 31, No. 5 (2016).
Su Ying, Rui Zhengyun. “The Development and Supervision of Internet Financial-Based on the Perspective of Evolutionary Game”, *Communication of Finance and Accounting*, 11 (2015):19-22+129.
Zhou Siqing, Guo Qin. “The Evolutionary Game Analysis of Internet Financial Innovation and Regulation Boundaries”, *Journal of Quantitative Economics*, Vol. 33, No. 5 (2016).