Does the Mobile Application Sales Channel Strengthen Insurance Inclusivity?

Abstract

Mobile insurance is gaining increasing popularity in the global insurance industry. Using a unique data of a best-selling mobile cancer insurance product from a Chinese life insurer, this paper studies the relationship between mobile technology and insurance inclusion. We find that the introduction of the mobile application channel generates higher growth for low-insured-amount policies which are closely associated with low-income population. However, this inclusion of mobile insurance is unequal – it is stronger in high-income areas than in low-income areas. Examining mechanisms, we show that reduced transaction costs help explain the inclusion of mobile insurance, while regional digital divide leads to inclusion inequality. We also provide evidence on the inclusive impacts of mobile insurance on claim compensation and insurance consumer welfare.

Keywords: Mobile Insurance; Insurance Inclusion; Digital Divide; Mobile Application

1 Introduction

Financial access inequality has long been recognized as one of the leading causes of wealth inequality (Claessens and Perotti, 2007). The high access threshold of formal finance inhibits low-income citizens from obtaining financial services, contributing to persistent poverty. Inclusive finance is an important tool to reduce this inequality of financial access (Zheng and Su, 2022). Although there is no unified and clear definition, the consensus of most studies is that inclusive finance is a financial system to provide savings, credit, insurance and other financial services for the poor who are usually neglected or excluded from formal finance (Maleika and Kuriakose, 2008; Demirgüç-Kunt and Klapper, 2012; Hasan et al., 2021; Zheng and Su, 2022). As an important component of inclusive finance, inclusive insurance is characterized by low insured amounts and easy access, protecting low-income people against specific perils in exchange for regular premium payments proportionate to the likelihood and cost of the risk involved (Churchill, 2007).

Scholastic discussion of inclusive insurance concentrates on its economic influence, including the effects on poverty reduction (Hamid et al., 2011; Schmied and Ana, 2016), economic growth (Lester, 2014; Babajide et al., 2015) and income distribution (He and Sato, 2013). With the introduction of the digital economy, there is a growing conversation that examines the potential of the insurers' adoption of digital technology (such as the mobile application) to expand the economic effects of inclusive insurance. These studies are usually carried out by constructing a composite index to measure digital insurance inclusion. For example, the digital insurance service index jointly compiled by Peking University, Shanghai Finance Institute and Ant Financial Services Group that covers three dimensions - breadth of coverage, depth of usage and digitalization (Guo et al., 2020), has been widely used to study its impact on economic growth (Ahmad et al., 2021), household consumption (Yu et al., 2022), technological innovation (Li J. and Li B., 2022), insurance purchases (Hu et al., 2022) and energy efficiency (Fu et al., 2022), etc. Overall, these studies usually directly consider the use of digital technology as a part of the insurance inclusion index in their analyses but few of them have provided rigorous empirical evidence on the relationship between digital technology and insurance inclusion. To address this gap, our paper empirically analyzes how mobile application – a typical digital technology - as a sales channel affects insurance inclusion.

Inclusive insurance focuses on low-insured-amounts or microinsurance serving low-income populations based on the same fundamentals as regular insurance. With that in mind, in this paper we empirically study the inclusion of mobile insurance by comparing the heterogeneous impacts of the mobile application (hereafter APP) channel on the demand of low- and high-insured-amount policies. This is achieved through the use of a proprietary dataset containing the purchased policy records of a cancer insurance product, provided by a large life insurer in China. This cancer insurance product was sold from 2015 to 2016 with the mobile APP channel introduced during the sales period. The dataset allows us to estimate the heterogeneous impacts of the mobile APP channel introduction at both the prefecture aggregation level and the individual policy level.

Our main results show that the introduction of the mobile APP channel prompts a 40% higher growth in low-insured-amount policies compared to the growth of high-insured-amount policies. At the individual policy level, the insured amount per policy of the APP channel is on average 7% lower than that of the non-application (hereafter non-APP) channels. Examining mechanisms, we both theoretically and empirically show that low-income people are more sensitive to transaction costs than high-income people, meaning the reduced transaction costs of mobile insurance provides a greater incentive for low-income people to mitigate risks.

However, we show that the inclusion of mobile insurance presents considerable inequality between rich and poor regions. The magnitude of the estimated growth difference between low- and high-insured-amount policies is 1.3 to 1.4 times greater in rich prefectures than in poor prefectures. This finding is consistent with prior literature on financial inclusion (Han and Melecky, 2013; Li J. and Li B., 2022; Zheng and Su, 2022).

The inequality of mobile insurance inclusion can be explained by the digital divide across prefectures. We show that digital infrastructure mediates the relationship between mobile insurance inclusion and prefecture income. On the one hand, digital infrastructure positively correlates with regional economic development; on the other hand, digital infrastructure increases access to mobile technology and thus also positively correlates with mobile insurance inclusion.

In addition to our analyses of insurance demand, we also provide evidence on the inclusive impacts of mobile insurance on post-purchase actions such as claims and indemnity. The mobile APP channel is found to present an even stronger inclusive impact on indemnity than on policy quantity because of a more relaxed risk control mechanism on low-insured-amount policies. Accordingly, the introduction of the mobile APP channel brings higher welfare improvement for the policyholders of low-insured-amount policies. We find no evidence of the inclusive impact of mobile insurance on claim rejection.

This paper makes two main contributions to the literature. First, this paper adds to the literature on insurance inclusion. On the one hand, most empirical studies of this topic rely on constructing composite indexes of insurance inclusion (Sankaramuthukumar and Alamelu, 2011; Ambarkhane et al., 2016). These indices usually have endogeneity with regional development (e.g., economic growth, population density, age structure) and lack an emphasis on the insurance access of the poor. By studying insurance inclusion through the heterogeneous effects of the mobile APP channel introduction on low- and high-insured-amount policies, our paper avoids this endogeneity problem and highlights the insurance access difference between low- and high-income people. On the other hand, this paper is the first study providing empirical evidence on the relationship between mobile technology and insurance inclusion, which complements other papers that directly use mobile internet penetration or mobile insurance as a measure of insurance inclusion (Li et al., 2020; Li J. and Li B., 2022; Sun and Tang, 2022).

Second, this paper contributes to the literature on Fintech services. A large empirical literature in this field has focused on the services of mobile banking or mobile payment (Malaquias and Hwang, 2016; Suri, 2017; Aggarwal et al., 2020; Lee et al., 2021; Suri et al., 2021), but few have paid attention to mobile insurance. To our best knowledge, in addition to a few papers empirically studying the factors of the acceptance to mobile insurance services (Lee et al., 2007; Lee et al., 2015), the most relevant piece of work is Chen et al.'s (2022) study on how the mobile internet sales strategy affects the insurer's sales performance. However, their work lacks an analysis on the inclusion of mobile insurance due to the data structure limits. In this regard, the data itself used in this paper is a contribution.

The remainder of this paper is structured as follows; the next section introduces the data with a preliminary analysis on the relationship between microinsurance and inclusion. Section 3 conducts baseline empirical specifications. Section 4 presents the baseline results and analyzes the regional inequality of mobile insurance. In Section 5, two mechanisms explaining the unequal inclusion of mobile insurance are examined. Section 6 further analyzes the inclusive impacts of mobile insurance on after-purchasing activities. The final Section 7 concludes this paper and discusses implications for the future research.

2 Background

2.1 Mobile Insurance

Our data on the purchased policies of the cancer insurance product comes from a large life insurer operating nationwide in China. This life insurer has a long operational history of over 20 years and has an established nationwide sales channel system including personal agents, call centers, Personal Computer Internet and mobile APP channels. As one of the first insurers in China to implement a mobile APP channel, this life insurer launched its mobile APP in 2014 that can be freely downloaded by users from a mobile application store. Therefore, the data is representative of the Chinese life insurance industry. The insurer's mobile APP offers a wide range of insurance products including disease, life and accident insurance. Product information such as liability, insurance period, premium, insured amount, exemption, insurance limits and clauses are easily accessed. Consumers can complete the entire purchase journey from filling in applicant information to premium payment entirely on the mobile APP.

The data of the cancer insurance product is used for three reasons. First, large enough sales volumes have accumulated for empirical tests. Second, the policy terms of the cancer insurance product are simple and thus there is a high standardization among insurance plans, avoiding possible bias from complex or unobservable plan settings. This product only insures cancer risk without any other optional liabilities and has a uniform fixed premium term across all policies. Third, it has been sold through the call center and offline agent channels from January 2015 to December 2016, during which the mobile APP channel was introduced on September 30th in 2016. This exogeneous mobile APP channel introduction allows us to design causal inference strategies of difference-in-difference (DD) estimates to capture the heterogeneous impacts on low- and high-insured-amount policies. The mobile cancer insurance product offers three types of optional insured amounts – 50, 100 and 200 thousand yuan. In this paper, we define low-insured-amount policies as those with a 50-thousand-yuan insured amount and define high-insured-amount policies as those with 100- or 200-thousand-yuan insured amounts.

On the mobile application, plan information such as application qualifications (e.g., insurable ages), liability, exempted liability description, insurance period, electronic insurance terms and optional plan settings (e.g., optional insured amount, additional insurance) are displayed clearly. Consumers can click on the screen to choose their preferred plan settings and see premiums. Consumers can also communicate with the 24-hour manual customer servicer for additional product information. After selecting the preferred plan, consumers have to fill in required health information details to be automatically checked for compliance with underwriting rules. Once the underwriting is approved, consumers will check and confirm the entire application form and policy plan information before paying premiums, again, via the mobile phone.

From above, it can be seen that mobile insurance has lower transaction costs compared to the traditional insurance (e.g., the insurance products sold via the offline agent channel). Three reasons account for this. The first reason is the inconvenience of offline purchases. Purchasing through an offline agent takes time and transportation overhead along with face-to-face negotiation. The second reason is the time limitations on offline channel services. For example, the bancassurance channel has fixed operation times during daytime while consumers can purchase insurance via mobile devices at any time. Moreover, health information is usually checked for compliance with underwriting rules manually by offline agents instead of automatically by machines.

2.2 Microinsurance and Inclusion

In this subsection, to underpin our empirical analysis, we preliminarily provide evidence verifying the relationship between insured amount and insurance inclusion as well as theorize the role of the mobile application channel into insurance inclusion.

2.2.1 Insured Amount and Income

Since insurance inclusion emphasizes offering insurance services to low-income population, we first provide evidence that the purchasers of low-insured-amount policies have relatively lower income. Although abundant literature has proven the positive relationship between income and insured amount (e.g., Browne and Kim, 1993; Showers and Shotick, 1994; Browne and Hoyt, 2000), it is necessary to consolidate this using our data. By averaging the insured amount across policies by prefecture and year, we regress on the log average insured amount with indicators of prefecture income (e.g., log Gross Domestic Product (hereafter GDP) per capita, log average salary of employees) as independent variables. Prefecture population (log resident population), age structure (the proportion of the 0 to 14 years old and the above 65 years old) and social insurance penetration rate (the percentage of the resident population with social insurance) are also controlled. As shown in Table 1, the average insured amount is found to present a significant and positive relationship with GDP per capita and average earnings of employees. Specifically, every 1% increase in GDP per capita and average earnings of employees leads to a 24.2% and 31.1% increase in the insured amount respectively. This evidence allies with the argument in the prior literature that "inclusive insurance mainly includes microinsurance" (Cheston, 2018; Roa et al., 2019). Therefore, the take-up of low-insured-amount policies reflects the inclusion of low-income population.

Table 1. The Relationship between Insured Amount and Income

Variables	(1) $logI$	(2) $logI$	(3) $logI$	(4) $logI$
$logGDP$	0.242**	0.311**		
	(0.108)	(0.108)		
$logSalary$			0.067***	0.228**
			(0.019)	(0.092)
Adjusted R-squared	0.533	0.618	0.521	0.706
Observations	416	416	519	486
Controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y

Note: This table shows the results of regressing average insured amount per policy on log GDP per capita and log average salary of employees. In this multivariate regression, we control also for prefecture population (log resident population), age structure (the proportion of the 0 to 14 years old and the above 65 years old) and social insurance penetration rate (the percentage of the resident population with social insurance).

2.2.2 A Simple Framework on the Inclusion of Mobile Insurance

Based on the previous empirical analysis, we next provide a simple model relating mobile insurance inclusion with transaction cost reduction. We illustrate that transaction cost reduction lowers the insurance consumption threshold to facilitate more low-income consumers buying insurance, leading to lower insurance coverage on average.

In a homogeneous insurance product market, a consumer has to spend a random transaction cost c in the form of hurdle to access and buy the insurance product at period 0. Let q be the loss probability at period 1 with a constant loss rate l, α be the constant subjective discount factor and y, the random income of each period. Given the loading factor λ and fair pricing principle (that is, the unit premium equals λq), a consumer would pay the premium λqI at period 0 for the coverage I at period 1[1]. We assume that consumers can be characterized along risk[2]. The q-risk type consumers share an income distribution F_y with supports $[\underline{y}, \overline{y}]$ and a transaction cost distribution F_c with supports $[\underline{c}, \overline{c}]$. F_y and F_c are uncorrelated with each other.

For a representative consumer of the q-risk type, the insurance utility gain U is made up of the difference in consumption utility $u(\cdot)$ between the insured and uninsured cases, given by

$$\mathrm{U} = u(y - \lambda qI) - u(y) + \alpha q[u(y - ly + I) - u(y - ly)] \tag{1}$$

Where $\alpha, l \in (0,1)$ and $u(\cdot)$ follows a constant relative risk aversion (CRRA) functional form. A standard optimal coverage $\hat{I}$ is derived from the following first-order condition.

$$\lambda u'\left(y - \lambda q\hat{I}\right) = \alpha u'(y - ly + \hat{I}) \tag{2}$$

By resolving Equation (2), $\hat{I}$ is endogenously determined and then the maximized insurance utility gain $\widehat{\mathrm{U}}$ is elicited. A purchase decision is made only when the insurance utility gain exceeds the disutility of transaction cost. Hence, the insurance demand

[1] The effective insurance period usually lags behind the time of the first premium payment, because most insurance products set a waiting period during which the insured cannot be compensated but can only be refunded premiums for an accident.

[2] This assumption is common in the screening theory literature, i.e., Abebe et al. (2021).

equivalent to the probability of purchasing insurance is given by

$$\text{Prob}\big(\widehat{\mathrm{U}} > c\big) \tag{3}$$

Then we can obtain the expected income and coverage of insurance purchasers

$$E(y \mid y > \widehat{\mathrm{U}}_y^{-1}(c)) \tag{4}$$

$$E\big(\hat{I} \mid y > \widehat{\mathrm{U}}_y^{-1}(c)\big) \tag{5}$$

Where $\widehat{\mathrm{U}}_y^{-1}(\cdot)$ is the reverse function of $\widehat{\mathrm{U}}$ with respect to y.

PROPOSITION: Th*e expected income and insurance coverage of insurance purchasers should both rise with an increase of transaction cost.*

PROOF: It is easy to see that $\widehat{\mathrm{U}}$ increases with y, so does $\widehat{\mathrm{U}}_y^{-1}(\cdot)$. Therefore, in Equation (4), the expected income of insurance buyers should increase with an improvement on all c. Combined with the fact that $\hat{I}$ is increasing in y from Equation (2), the expected coverage of insurance purchasers shown in Equation (5) should also increase with c.

Provided mobile insurance has a lower transaction cost than traditional insurance, our PROPOSITION demonstrates that mobile insurance is more inclusive as it encourages low-insured-amount policies by incorporating more low-income consumers who would not have been able to afford insurance.

3 Data and Empirical Strategy

3.1 The Data

We gather the anonymized data on records of all purchased policies (roughly 160 thousand in total) of the mobile cancer insurance product from the investigated life insurer. Policy characteristics include purchase time, purchase channel, insured amount, yearly premium, insurance period, premium term, policy status, hesitation period and waiting period. Policyholder characteristics can serve as control variables and include gender, age, education, profession, prefecture and the relationship with the insured person. Claim characteristics include claim record and indemnity amount. The data allows us to control for policyholder and policy characteristics in the empirical examinations.

Table 2 reports the descriptive statistics of the main variables. *Daily number of low-insured-amount policies* and *daily number of high-insured-amount policies* are at the prefecture aggregation level, counting the policies of the specific insured amount level purchased in each prefecture on each date. *APP* denotes whether the policy was purchased through the mobile APP channel. On average, the policies with the low insured amount of 10 thousand yuan account for 75% and the mobile APP channel policies account for 85% of all purchased policies.

Table 2. Description on the Data of 2015 to 2016 Observations

	Variables	Observations	Mean	Std. Dev
Prefecture Aggregation Level	Daily Number of low-insured-amount policies	21,066	5.695	16.980
	Daily Number of high-insured-amount policies	13,231	2.997	6.183
Individual Policy Level	Insured amount	159,638	11.648	3.096
	APP	159,638	0.854	0.353
	Age	159,638	38.678	9.035
	Gender	159,638	0.614	0.487
	Advanced education	159,638	0.185	0.388
	Financial employee	159,638	0.168	0.374
	Insurance period	159,638	11.535	5.175
	Unit premium	159,638	0.011	0.010
	Self-insured relation	159,638	0.111	0.315
	Policy cancellation	159,638	0.084	0.278
	Policy claim	159,638	0.032	0.176
	Indemnity	5,128	7.664	6.058

Note: The data description uses all the policies purchased in 2015 and 2016. *Daily number of low-insured-amount policies* and daily *number of high-insured-amount policies* are variables at the prefecture aggregation level, counting the policies purchased in each prefecture on each date. *Insured amount* is in 10 thousand Yuan. *APP* denotes whether the policy was purchased through the mobile APP channel. *Gender* denotes female policyholder. *Advanced education* denotes a bachelor degree or above of the policyholder. *Financial employee* indicates that policyholder was employed in the financial industry. *Unit premium* calculates the premium per yuan of insured amount per year. *Self-insured relation* indicates that the policyholder is the insured. *Policy claim* is the dummy indicating whether the policy has claimed. *Indemnity* is the amount of indemnity of compensated policies (the statistical description is based on compensated policies).

We also compare the plan settings between the policies of mobile APP and non-APP channels, as shown in Table A1 of the Appendix. The ranges of plan settings[3] such as waiting period, hesitation period and insurance period are very similar indicating no differences between the plan settings offered by the mobile APP and non-APP channels. Insurers are usually reluctant to vary any plan properties for the same product across different channels, because variations would intensify channel benefit conflicts (Geyskens et al. 2002). The consistency of the investigated products across digital and offline distribution channels is a crucial advantage of our data, as it avoids potential

[3]Each investigated insurance product shares the same premium rate table across different distribution channels.

bias from unobservable product differences evident in other literature (Brown and Goolsbee 2002).

3.2 Identification Strategy

We study the inclusion of mobile insurance by identifying the difference in the impacts of the mobile APP channel on the quantities of low- and high-insured-amount policies. The identification strategies are performed at both the prefecture aggregation level and individual policy level.

Prefecture Aggregation Level Estimators

The prefecture aggregation level estimates capture the heterogeneous effects of introducing the mobile APP channel on the quantities of low- and high-insured-amount policies. At this level, we adopt both a standard Difference-in-Difference (hereafter DD) estimator and an Event Study estimator as specified in equations (6) and (7) respectively:

$$logY_{i,t,r} = \alpha + \beta Post_t \times LC_r + LC_r + RISK + \mu_i + \upsilon_t + \varepsilon_{i,t,r} \tag{6}$$

$$logY_{i,t,r} = \alpha + \sum_{k=0}^{273} \beta_{-k} Post_{-k} \times LC_r + \sum_{m=1}^{94} \beta_{+m} Post_{+m} \times LC_r + LC_r + RISK + \mu_i + \upsilon_t + \varepsilon_{i,t,r} \tag{7}$$

For the insured amount level r, prefecture i and date t, LC is an dummy taking value 1 if the policy has a high-insured-amount level otherwise taking value 0; $logY_{i,t,r}$ is the logarithmic number of purchased policies; $Post_t$ is a dummy defined as 1 after

September 30th in 2016 otherwise 0; $Post_{-k}$ and $Post_{+m}$ are both dummies denoting k days before and m days post September 30th respectively; μ_i denotes the prefecture fixed effect and υ_t, the date fixed effect. $\varepsilon_{i,t,r}$ denotes the error term. We cluster the robust standard errors at the prefecture level. The event study estimator essentially identifies the daily dynamic effects of the mobile APP channel introduction and therefore can also serve as a parallel trend test to examine whether the growth difference between low- and high-insured-amount policies exist before the introduction date. To construct the regression sample for both estimators, we group all the policies sold in 2016 by low- and high-insured-amount and then aggregate them into the policy quantity separately by prefecture and date.

To avoid the potential influence of consumer risk difference between the APP and non-APP channels on the quantity growth of purchased policies, $RISK$, a vector including the averages of predicted policy risk and unit premium at the prefecture aggregate level, is added as a necessary control of policy risk. Unit premium based on actuary pricing reflects the average risk of the population with similar risk characteristics including age and gender. Predicted policy risk serves as a control of adverse selection, obtained by the prediction from an individual policy level logit regression on policy claim. This logit regression uses a dummy of whether the policy has claimed as the dependent variable while a series of policyholder and policy characteristics[4] (not only including age and gender) as independent variables, with a high R-squared of 93%. In the prefecture aggregate level estimators, we average the predicted policy risk and unit premium across the policies for each date and prefecture[5].

Individual Policy Level Estimator

The individual policy level estimate captures the average difference in the insured amount per policy between the mobile APP and non-APP channels. At this level, the estimator essentially compares the insured amount choice between the policies of the mobile APP and the non-APP channel, as shown in Equation (8).

$$logI_{i,j,t} = \alpha + \beta APP_{i,j,t} + risk + Controls + \mu_i + v_t + \varepsilon_{i,j,t} \tag{8}$$

Where for the individual policy j purchased in prefecture i on date t, $logI_{i,j,t}$ is the logarithmic insured amount; APP is a dummy of whether the policy was purchased via the mobile APP channel; Similar to the prefecture aggregation level estimator, $risk$ is a vector including the predicted policy risk and unit premium of the individual policy; $Controls$ is a vector including a series of policy and policyholder

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[4] The policyholder and policy characteristics include age and age squared of the policyholder, a dummy of policyholder gender, dummies of policyholder education, a dummy of policyholder as a financial employee, dummies of the relationship between the policyholder and the insured, insurance period (in years), unit premium, a dummy of policy status (cancellation), dummies of the policyholder prefecture and purchase date. The use of the characteristics other than age and gender can capture the risk not adjusted into the unit premium which partly causes adverse selection.

[5] Taking *unit premium* for example, for the policies 1,…j…,J purchased in prefecture r and date t, we calculate the average the unit premium by $\frac{\sum unit\ premium_{i,j,t}}{J}$.

characteristics: age and age squared of the policyholder, a dummy of policyholder gender, dummies of policyholder education, a dummy of policyholder as a financial employee, dummies of the relationship between the policyholder and the insured, insurance period (in years), unit premium and a dummy of policy status (cancellation). Robust standard errors are clustered at the prefecture level. The regression sample for Equation (8) consists of the policies sold after the introduction of the mobile APP channel (from September 30th, 2016 to December 31st, 2016).

4 Results

4.1 Pre-Trends

Our prefecture aggregation level DD estimate relies on an important assumption of parallel pre-trends, that there is no difference in the daily change of the quantity of purchased policies between low- and high-insured-amount policies for 2016 observations. That is, the daily changes of the policy quantity are similar for low- and high-insured-amount policies. If this assumption is violated, the estimated effects could be non-causal because they may still exist even without introducing the mobile APP channel.

To validate this assumption, we first graph the daily quantity of purchased policies by low- and high-insured-amount in 2016, presented in Figure 1. Visual evidence shows that overall low- and high-insured-amount policies maintain very similar daily quantity trends before September 30th. However, the difference in daily policy quantity abruptly increases after the introduction date with low-insured-amount policies exhibiting higher growth than high-insured-amount policies. Figure 2 plots the results of estimated coefficients and 95% confidence intervals of the event study estimator (Equation 7). It shows that before the introduction date, the pivots of the estimated growth differences between low- and high-insured-amount policies are always around zero; while a significant drop in the growth difference occurs once the mobile APP channel was launched. After that introduction date, the estimated dynamic effects remain significantly negative, demonstrating that the introduction of the mobile APP channel prompts higher growth for low-insured-amount policies than for high-insured-amount policies.

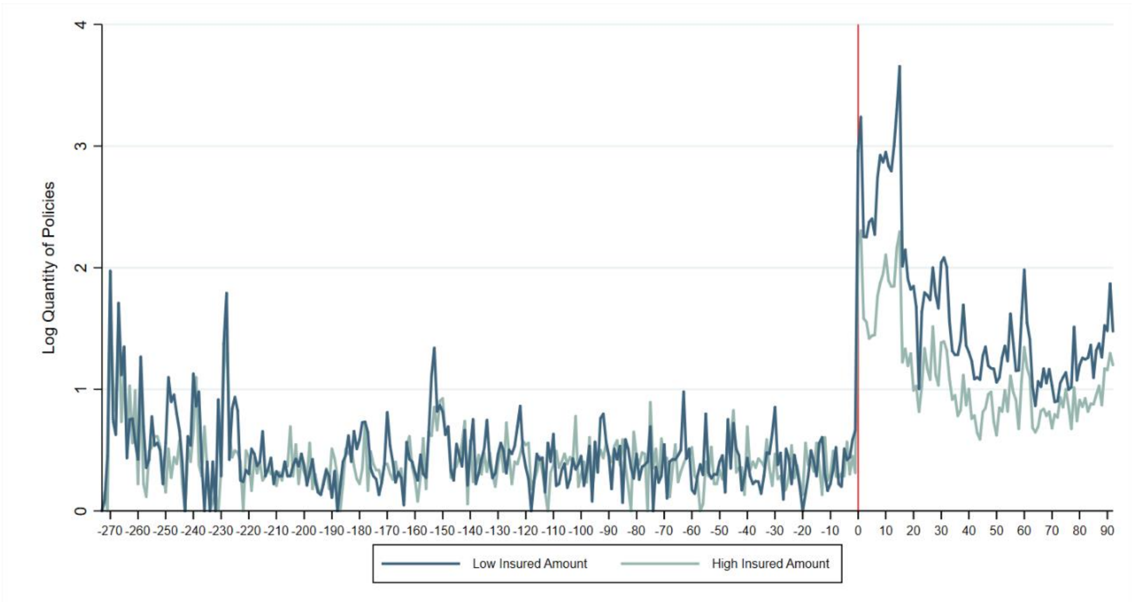

Figure 1. Trends of Log Daily Quantity for Low- and High-insured-amount Policies in

2016

Note: This figure plots the log daily sales quantity of low- and high-insured-amount policies for the days in 2016. Day 0 represents the introduction date of the mobile APP channel.

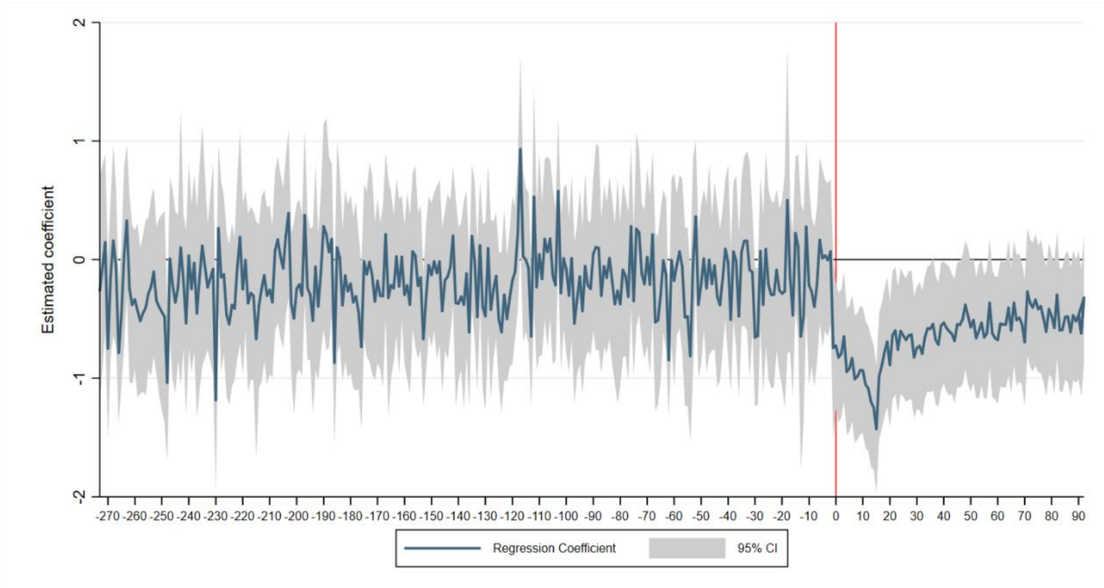

Figure 2. The Daily Dynamic Effects of the Mobile APP Channel Introduction

Note: This figure plots the estimated coefficients of the event study along with their 95% confidence intervals. Each coefficient represents the daily growth difference between low- and high-insured-amount policies. Day 0 represents the introduction date of the mobile APP channel.

4.2 Baseline Results

The result of the baseline DD estimator specified in Equation (6) is reported in Column (1) of Table 3, without controls of policyholder and policy characteristics. The significant and negative coefficient demonstrates that low-insured-amount policies exhibit higher growth when the Mobile APP channel was introduced. Specifically, as Column (1) indicated, the growth of high-insured-amount policies is 41% ($e^{(-0.523)-1}$) lower than the growth of low-insured-amount policies. Column (2) redo the analysis by further adding the aggregated controls of policyholder and policy characteristics[6]. The result is qualitatively consistent with Column (1) with a slightly smaller magnitude of growth difference ($e^{(-0.504)-1}$=40%). Column (3) reports the result of the individual policy level estimate, presenting a significantly negative relationship between the mobile APP channel choice and insured amount. On average, the policies purchased via the mobile APP channel have 7% ($e^{(-0.070)-1)}$ lower insured amount than those purchased on the non-APP channel. Therefore, all of the baseline results show that mobile insurance provides stronger incentives to low-insured-amount policies and thus is more inclusive than traditional non-APP channels.

Table 3. Results of Baseline Regressions

Variables	(1) $logY$	(2) $logY$	(3) $logI$	(4) $logY$	(5) $logY$
$Post_t \times LC_r$	-0.523***	-0.504***		0.024	0.002
	(0.030)	(0.034)		(0.033)	(0.009)
APP			-0.070***		
			(0.012)		
Adjusted R-squared	0.550	0.582	0.058	0.159	0.618
Observations	28,124	28,124	131,511	4,295	32,269
Controls	N	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y	Y

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Robustness Checks: A concern over our DD identification is the inherent growth difference between low- and high-insured-amount policies after the introduction of the

[6] We average the same controls as the individual policy level estimates by the insured amount level, prefecture and date. Taking *Gender* for example, for the low-insured-amount policies of each prefecture on each date, dummies of the female policyholder gender are averaged across the policies purchased in that prefecture and date, generating the percentage of females at a prefecture aggregate level control.

mobile APP channel due to some unobservable factor. We suggest two potential sources. First, the estimated growth difference could exist every year. Second, there could be some unobserved event around September 30th2016 that may also lead to the estimated growth difference.

To address this concern, we provide two placebo tests. The first test replaces the regression sample with policies sold in 2015. Specifically, we assume a virtual introduction date "September 30th, 2015", and repeat the same analysis of the DD estimate specification. A similar result should be expected if there was indeed a natural growth difference between low- and high-insured-amount policies. However, the result shown in Column (4) of Table 3 is insignificant and thus eliminates this concern. Our second placebo test is to use another cancer insurance product sold purely through the non-APP channel in 2016. If there was some concurrent unobserved event on the introduction date that leads to the estimated growth difference, we may find a similar result for this purely offline cancer insurance product. To test this, with a similar DD specification but changing the definition of LC_r into whether the insured amount is above 20 thousand yuan[7], we regress on the sample of the policies of the purely offline cancer insurance product. However, the result shown in Column (5) of Table 3 is also insignificant. Overall, our placebo tests minimize the concern of the inherent growth

[7] This is because this offline cancer insurance product is a relatively advanced product offering two options of insured amount: 20 and 30 thousand Yuan. Thus, we define LC_r, the dummy of a high-insured-amount policy when the insured amount is above 20 thousand yuan.

difference.

4.3 Unequal Inclusion of Mobile Insurance

In this subsection, we analyze the heterogeneity in the inclusion of mobile insurance by comparing the inclusive impacts of the Mobile APP channel introduction between high- and low-income prefectures. In operation, we divide prefectures by GDP per capita into trisections: high-GDP, medium-GDP and low-GDP groups, forming three corresponding dummies $HGDP$, $MGDP$ and $LGDP$. By interacting these dummies with the double difference term in Equation (6), we isolate the inclusive impact of the Mobile APP channel for each trisection through the below specification.

$$logY_{i,t,r} = \alpha + \beta_1 HGDP \times LC_r + \beta_2 HGDP \times LC_r + \beta_3 HGDP \times LC_r + RISK + \mu_i + \upsilon_t + \varepsilon_{i,t,r}$$

The results are reported in Columns (1) and (2) of Table 4, keeping the same set of controls and fixed effects as in Columns (1) and (2) of Table 3. Both columns clearly show that the higher GDP per capita, the larger the growth difference between low- and high-insured-amount policies. That is, the extent to which low-insured-amount policies have higher growth than high-insured-amount policies is greater for prefectures with higher GDP per capita. This implies that the inclusion of mobile insurance is unequal – it is more pronounced in richer regions. The regional inequality of mobile insurance inclusion is considerable, as the magnitude of the estimated growth difference between low- and high-insured-amount policies is approximately 1.3 (= $\frac{e^{(-0.617)}-1}{e^{(-0.446)}-1}$) to 1.4 (= $\frac{e^{(-0.722)}-1}{e^{(-0.476)}-1}$) times greater in high-GDP prefectures than in low-GDP prefectures.

Table 4. Heterogeneous Mobile Insurance Inclusion by Different Prefecture Income

Variables	(1) $logY$	(2) $logY$
$Interaction\ with\ HGDP$	-0.722***	-0.617***
	(0.059)	(0.043)
$Interaction\ with\ MGDP$	-0.578***	-0.551***
	(0.069)	(0.050)
$Interaction\ with\ LGDP$	-0.476***	-0.446***
	(0.089)	(0.041)
Adjusted R-squared	0.597	0.619
Observations	28,124	28,124
Controls	N	Y
Fixed Effects	Y	Y

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

For robustness, apart from GDP per capita, we also use another three indicators related to macroeconomic performance to measure the prefecture income, including log fiscal revenue, log average salary of employees and urbanization rate sourced from the 2016 China City Statistical Yearbook. After repeating a similar procedure of dividing prefectures by these indicators into low-income and high-income areas as well as using the same regression specifications of interactions, we present the results in Table A2. They are all significantly negative and thus corroborates the evidence that richer areas have greater inclusion of mobile insurance than poorer areas.

5 Mechanisms

5.1 Why is Mobile Insurance More Inclusive?

5.1.1 Transaction Cost of Insurance

As elaborated by the framework in subsection 2.2.2, the reduced transaction cost of mobile insurance incentivizes low-income people to diversify risk. This leads a higher growth of low-insured-amount policies than high-insured-amount policies. To examine this mechanism, we measure the offline insurance transaction costs by employing two datasets. The first dataset is the longitude and latitude of the addresses of all insurance company branches throughout China in 2016, provided by BAIDU Map[8], one of the largest private digital map providers in China. The second dataset is the grid-cell data of population density at the accuracy level of one square kilometer throughout China in 2016, which is publicly available on the website of WorldPop[9]. Each insurer branch and population grid-cell are matched to the corresponding prefecture according to their coordinates.

Following Roca and Puga's (2017) method, we construct a measure of offline insurance transaction costs with the correlation between the insurer branch distribution and population distribution. This measure exploits the covariance of population and

[8] Seen on https://lbsyun.baidu.com/

[9] Available on https://www.worldpop.org/

distance to the insurer branch across the grid cells inside a prefecture, as shown in Equation (9).

$$\boldsymbol{TC}_i = \frac{Covariance(\boldsymbol{dist}_{i,k}, \boldsymbol{pop}_{i,k})}{\boldsymbol{AD}_i \times \boldsymbol{AP}_i} \tag{9}$$

Where for prefecture i and grid cell $k \in i$, $\boldsymbol{TC}$ denotes the offline insurance transaction cost, $\boldsymbol{dist}_{i,k}$ denotes the distance from the grid cell center to the nearest branch of the investigated insurer and $\boldsymbol{pop}_{i,k}$, the grid cell population. The numerator is a covariance, $\boldsymbol{AD}_i$ the average of $\boldsymbol{dist}_{i,k}$ and $\boldsymbol{AP}_i$ denotes the average of $\boldsymbol{pop}_{i,k}$ across grid-cells of the prefecture. This measure, essentially, illustrates how the distance to the insurer branch changes with the population density across grid-cells inside a prefecture and captures the degree to which the insurer branches are located in more populated areas. Specifically, with higher population and more insurer branches, then the distance to the insurer branch should strongly negatively correlate with the population density in that prefecture. Conversely, the less negative correlation, the greater bias between the population and insurer branch distributions, and the higher offline insurance transaction costs. Therefore, the smaller $\boldsymbol{TC}$ in Equation (9), the lower offline transaction cost. Of note is that this measure standardizes $\boldsymbol{dist}_{i,k}$ and $\boldsymbol{pop}_{i,k}$ by dividing their averages, excluding the influence of endogenous factors associated with distance[10].

[10] Directly using distance to measure offline transaction cost could incur endogeneity with the insurer's preference on branch locations. For instance, a rational insurer is probably more inclined to set up more branches in higher-income residential districts.

Considering that there may be branches of other life insurers in the vicinity, and that consumers tend to search for multiple insurers' products and shop around before making the final purchase decision, for robustness, we also replace $\boldsymbol{dist_{i,k}}$ with the distance to the nearest branch of local life insurers (not only including the branches of the investigated insurer) and then recalculate $\boldsymbol{TC}$. We report the estimates with $\boldsymbol{TC}$ calculated by both distances.

We confirm the transaction cost mechanism by interacting the double difference term with $\boldsymbol{TC}$ in Equation (6)[11] and interacting APP with $\boldsymbol{TC}$ in Equation (8), keeping the same set of controls and fixed effects as in Table 3. The results are presented in Columns (1) to (4) of Table 5. They show that the estimates with $\boldsymbol{TC}$ calculated by different distances consistently yield significant and negative coefficients, indicating that the higher offline transaction cost, the larger difference in average insured amount between the APP and non-APP channels. In this way we show that, on average, the insured amount of the mobile APP channel is lower than the offline channel and this insured amount difference increases with offline transaction cost.

Table 5. Examining the Transaction Costs Mechanism of Mobile Insurance Inclusion

	Distance to insurer branch	Distance to life insurance industry branch

[11] The full empirical specification can be written as: $logY_{i,t,r} = \alpha + \beta Post_t \times LC_r \times TC_i + \beta_1 Post_t \times LC_r + \beta_2 Post_t \times TC_i + \beta_3 LC_r \times TC_i + LC_r + RISK + \mu_i + \upsilon_t + \varepsilon_{i,t,r}$, where TC_i denotes one of the digital infrastructure indicators.

Variables	(1) $logY$	(2) $logY$	(3) $logY$	(4) $logY$
$Post_t \times LC_r \times TC$	-0.123***	-0.110***	-0.098***	-0.090***
	(0.041)	(0.034)	(0.030)	(0.027)
Adjusted R-squared	0.571	0.596	0.551	0.562
Observations	28,124	28,124	28,124	28,124
Controls	N	Y	N	Y
Fixed Effects	Y	Y	Y	Y

Note: Columns (1) and (2) use the transaction costs calculated by the nearest distance to branches of the investigated insurer. Columns (3) and (4) use the transaction costs calculated by the nearest distance to branches of the local life insurance industry. Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2 Why is Mobile Insurance Inclusion Unequal?

An intuitive reason for the observed regional inequality of the inclusion of mobile insurance is the digital divide (Vasile et al., 2021; Odei et al., 2022). A reasonable conjecture is that, if people are less able to use digital devices such as mobile internet, they will be less likely to be affected by the Mobile APP channel introduction. To examine this conjecture, we study how the estimated effects change with different levels of digital infrastructure and then test for the relationship between digital infrastructure and economic development.

In operation, we use three indicators to measure digital infrastructure: internet ownership per 100 households, mobile phone ownership per capita and the proportion of IT employees among the urban working population. These indicators source from the 2016 China Urban Statistical Yearbook[12]. We investigate by interacting the double difference term with these digital infrastructure indicators (denoted as $Tech$) in the DD

[12] In this yearbook, there are a few cities lacking the data of these three indicators on digital infrastructure. Thus, the policies from these cities are dropped in the regressions of Table 6.

estimator[13], with the same sets of controls and fixed effects as in Column (2) of Table 3. The results, presented in Columns (1) to (3) of Table 6, are all significant and negative, showing that with a higher level of digital infrastructure, we see a stronger effect of mobile insurance inclusion.

Figures A1 (a), (b) and (c) in the Appendix plot how digital infrastructure changes with economic development. We note that each of the three indicators of digital infrastructure presents an apparent positive correlation with GDP per capita. This is consistent with some prior studies pointing out economic imbalance as the primary cause of a digital divide (Mutula, 2008; Billon et al., 2020). Up to this point, we demonstrate that digital infrastructure mediates the relationship between economic development and mobile insurance inclusion.

Table 6. The Impacts of Digital Divide on Mobile Insurance Inclusion

	IT Industry	Internet Band	Mobile Phone
	(1)	(2)	(3)
Variables	$logY$	$logY$	$logY$
$Post_t \times LC_r \times Tech$	-0.404*	-0.118**	-0.222**
	(0.219)	(0.047)	(0.025)
Adjusted R-squared	0.604	0.608	0.601
Observations	27,829	27,921	27,921
Controls	Y	Y	Y
Fixed Effects	Y	Y	Y

Note: Columns (1), (2) and (3) respectively use the Internet band ownership per 100 households, the mobile phone ownership per capita and the proportion of IT employees among the urban working population to measure the prefecture digital infrastructure level. Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[13] The full empirical specification can be written as: $logY_{i,t,r} = \alpha + \beta Post_t \times LC_r \times Tech_i + \beta_1 Post_t \times LC_r + \beta_2 Post_t \times Tech_i + \beta_3 LC_r \times Tech_i + LC_r + RISK + Controls + \mu_i + \upsilon_t + \varepsilon_{i,t,r}$, where $Tech_i$ denotes one of the digital infrastructure indicators; $Controls$ is a vector of policyholder and policy characteristics averaged by the insured amount level, date and prefecture, as specified in Footnote 6.

6 Additional Results on Inclusive Impacts of Mobile Insurance

To this point, our analyses on mobile insurance inclusion focuses on insurance purchases. In this section, we additionally analyze whether mobile insurance also generates inclusive impacts on after-purchase activities such as the claims and indemnity.

Indemnity

Does digital distribution also bring inclusive impacts on indemnity? To test this, we replace the outcome variable in Equation (6) with the logarithm of indemnity aggregated by insured amount level, date and prefecture[14]. This captures the difference in the impact of the mobile APP channel on indemnity between low- and high-insured-amount policies. The result of the DD estimator (Column (1) of Table 7) shows that the indemnity of low-insured-amount policies has a 51% ($e^{(-0.720)}$-1) lower growth than that of high-insured-amount policies due to the introduction of the mobile APP channel. We can conclude that a similar inclusive impact of the mobile APP channel is observed for indemnity.

By comparing the estimated coefficients in Column (1) of Table 7 and Column (1) of

[14] For unclaimed policies or rejected claims, the indemnity is zero. For the insured amount level r, prefecture i and date t, we sum the indemnity of all the purchased policies.

Table 3, we note that the Mobile APP channel introduction elicits a larger growth difference between low- and high-insured-amount policies for indemnity than for policy quantity, showing a more substantial inclusive impact on indemnity than on policy quantity. This contrast suggests that relative to high-insured-amount policies, the compensation rate of low-insured-amount policies increases after introducing the Mobile APP channel. We provide the evidence of this suggestion using the following individual policy level specification.

$$Comps_{i,j,t,r} = \alpha + \sigma APP_{i,j,t} \times LC_r + \beta APP_{i,j,t} + LC_r + risk + Controls + \mu_i + v_t + \varepsilon_{i,j,t,r} \tag{10}$$

Where $Comps_{i,j,t}$ is a dummy of whether there is an insurance compensation under the policy and indemnity triggered. The result in Column (2) shows that for low-insured-amount policies, the compensation probability of the Mobile APP channel is higher than the non-APP channels by 0.011 percent points, while for high-insured-amount policies, the difference in compensation probability between APP and non-APP channels is close to zero (=0.011-0.012). This suggests more relaxed risk control of low-insured-amount policies purchased through the APP channel than non-APP channels.

Claim Rejection

A major source of insurance disputes between insurers and policyholders is claim rejection. To test whether the mobile APP channel has an inclusive impact on claim rejection, we use a specification similar to Equation (8) but replace the outcome variable with $Rej_{i,j,t}$, a dummy of whether the claim was rejected, restricting the sample to only claimed policies. The result, reported in Column (3) of Table 7, is statistically insignificant, indicating no inclusive impact of the mobile APP channel on claim rejection.

Welfare of Insurance Consumers

The welfare of insurance consumers depends on the difference between paid premiums and expected indemnity. Therefore, the inclusive impact of mobile insurance on indemnity should also incur welfare difference between purchasers with low- and high-insured-amount policies. To test this, we calculate policyholders' welfare on a daily and prefecture basis by the following equation:

$$Benefit_{i,t,r} = \ln\left(\frac{\sum_{j\in(i,t,r)} Indemnity_j}{\sum_{j\in(i,t,r)} Premiums_j}\right) \tag{11}$$

where j denotes an individual policy of insured-amount-level r purchased on date t and prefecture r. This equation essentially measures the average received indemnity per paid premium for the policies of each insured-amount-level per day and per prefecture. Relacing the outcome variable in Equation (8) with $Benefit_{i,t,r}$, we can identify the difference in the impacts of the mobile APP channel introduction on insurance purchasers' welfare. As expected, the result presented in Column (4) of Table 7 is significantly negative and thus confirms an inclusive impact of mobile insurance on the welfare of insurance purchasers.

Table 7. The Inclusive Impact of Digital Distribution on Indemnity

Variables	(1) $logIDM$	(2) $Comp$	(3) Rej	(4) $Benefit$
$Post_t \times LC_r$	-0.720***			-0.051***
	(0.088)			(0.012)
$APP \times LC_r$		-0.012**	0.029	
		(0.005)	(0.080)	
APP		0.011***	-0.105	
		(0.002)	(0.064)	
Adjusted R-squared	0.105	0.095	0.107	0.097
Observations	28,124	131,511	4,480	28,124
Controls	Y	Y	Y	Y
Fixed Effects	Y	Y	Y	Y

Note: Robust standard errors clustered at the prefecture level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

7 Conclusion

Using a unique dataset containing the policies of a best-selling mobile insurance product, this paper empirically investigates the relationship between mobile technology and insurance inclusion. We find that the introduction of the mobile APP channel produces a 40% higher growth of low-insured-amount policies than high-insured-amount policies. The insured amount per policy of the APP channel is on average 7% lower than that of the non-APP channels. They both demonstrate that mobile insurance provides higher incentives to low-insured-amount policies which are closely associated with low-income population. This indicates that mobile insurance is more inclusive than traditional insurance. Examining mechanisms, we theoretically show that low-income people are more sensitive to a reduction in transaction costs induced by mobile insurance leading to the observed inclusion-effect of mobile insurance. This mechanism is further empirically confirmed by using the correlation between the distributions of insurer branch and population density to measure offline insurance transaction costs.

However, the inclusion of mobile insurance is unequal between high- and low-income areas– the magnitude of the estimated growth difference between low- and high-insured-amount policies is 1.3 to 1.4 times greater in high-GDP prefectures than in low-GDP prefectures. We find that the digital divide across prefectures contributes to this inequality. This is because the digital divide positively correlates with both regional economic development and mobile insurance inclusion. This shows that the strengthening digital infrastructure in low-income areas will help improve mobile insurance inclusion in general.

In addition, we also provide empirical evidence on the inclusive impact of mobile insurance on after-purchase activities including claims and indemnity. The mobile APP channel shows an even stronger inclusive impact on indemnity than on policy quantity, suggesting more relaxed risk control measures on low-insured-amount policies compared to the non-APP channel. This also affects the welfare benefits of insurance consumers which depends on paid premiums and received indemnity. Consequently, we also find that the introduction of the mobile APP channel brings higher welfare improvements for the policyholders of low-insured-amount policies. However, we do not observe any inclusive impact of mobile insurance on claim rejection.

Overall, our analysis shows that the inclusion of mobile insurance is comprehensive - not only reflected in insurance demand, but also reflected in insurance compensation and consumer welfare. This paper complements much of the previous literature that uses mobile insurance directly as a measure of insurance inclusion. Finally, it should be noted that this paper is restricted by the data caveat. Whether the inclusion of mobile insurance also exists in other countries or other insurance types remains an open question for future research.

Appendix

Table A1. Value Ranges of Policyholder and Policy Characteristics of the Mobile APP and non-APP channels

	Mobile APP		Non mobile APP	
Variables	Min	Max	Min	Max
Insured amount	100000	200000	100000	200000
Age	21	73	21	68
Gender	0	1	0	1
Advanced education	0	1	0	1
Financial employee	0	1	0	1
Insurance period (in years)	10	35	10	35
Unit premium	0	0.078	0	0.095
Self-insured relation	0	1	0	1
Indemnity	0	200000	0	200000
Hesitation period (in days)	10	10	10	10
Waiting period (in days)	30	30	30	30
Premium term (in years)	10	10	10	10

Table A2. Heterogeneous Inclusion of Mobile Insurance by Different Prefecture Fiscal

Revenue, Average Salary and Urbanization

Variables	Fiscal Revenue (1) $logY$	Salary (2) $logY$	Urbanization (3) $logY$
$Post_t \times LC_r \times I_r$	-0.061***	-0.380***	-1.040*
	(0.019)	(0.103)	(0.616)
Adjusted R-squared	0.614	0.605	0.576
Observations	28,124	28,124	28,124
Controls	Y	Y	Y
Fixed Effects	Y	Y	Y

Note: Column (1), (2) and (3) uses prefecture fiscal revenue, average salary of urban employees and urbanization rate as the indicator to measure prefecture economic development, respectively. In each column, I_r is a dummy of whether the corresponding indicator is above the median level across all prefectures.

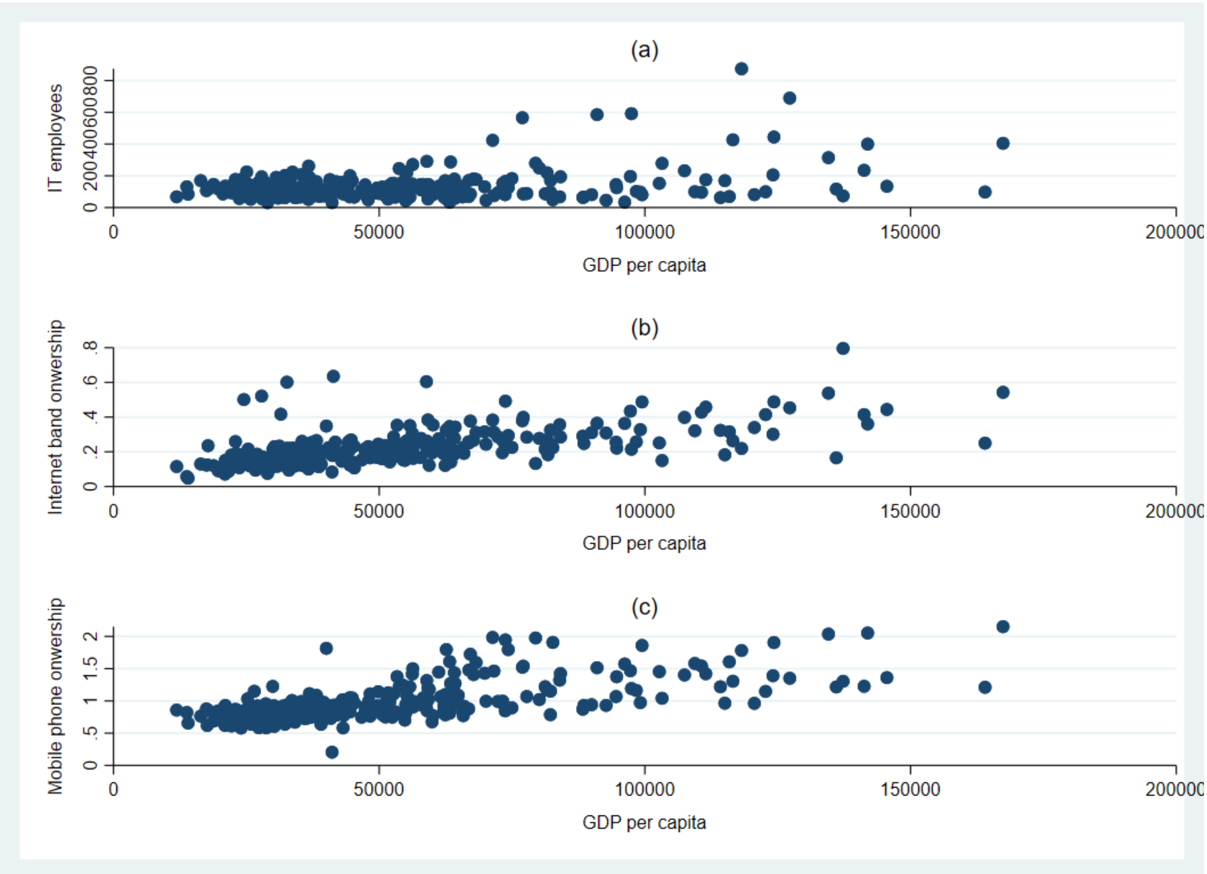

Figure A1. The Positive Correlation between Digital Infrastructure and GDP Per Cap-

ita

Note: The scatter graphs (a), (b) and (c) show how GDP per capita changes with the Internet band ownership per household, the mobile phone ownership per capita and the proportion of IT employees among the urban working population, respectively.

Abbreviations

APP: Application

Non-APP: Non-Application

DD: Difference-in-Difference

GDP: Gross Domestic Product

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