FinTech Risk-Sharing as Innovative Health Insurance?

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Abstract

Securing broader healthcare coverage at lower costs remains a pressing challenge worldwide. In response, FinTech has enabled the emergence of a novel sharing economy model known as online mutual aid (OMA). This model offers large-scale, quasi-health insurance coverage for critical illnesses in China, attracting over 100 million users at an annual cost of less than $20 per person. We investigate the economics of OMA using all claim cases (totaling 203,244) and approximately 200,000 members randomly drawn from a representative OMA platform. Despite concerns regarding OMA's financial sustainability due to its ex-post cost-sharing structure, there is compelling evidence of progressive cross-subsidies and advantageous selection. We also find that the inclusive but relaxed enrollment standards of OMA and the resulting adverse selection are counterbalanced by internal measures including varying indemnities to different age cohorts and rigorous claims investigations. Notably, during the COVID-19 pandemic, OMA claim processing time increased by only 4.25%, whereas traditional insurance companies nearly stopped processing altogether, highlighting the resilience and efficacy of the technology. We estimate that OMA has the potential to save up to $306.87 billion annually, extending $53.75 trillion worth of healthcare benefits to the entire population under age 70 in China. OMA, therefore, has the potential to significantly enhance the accessibility and affordability of healthcare, particularly during public health crises.

Keywords: FinTech, Health Economics, Insurance, Progressive Cross-Subsidies

JEL Classification: G22, I13, O30

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1. Introduction

Countries worldwide have allocated substantial resources to reform healthcare systems and improve the accessibility and affordability of health insurance, particularly for low-income individuals (Tebaldi, 2017; Finkelstein, Hendren, and Shepard, 2019; Lagomarsino et al., 2019; Banerjee et al., 2021). Yet, developed countries are still grappling with unaffordable and ever-rising healthcare spending, not to mention that achieving universal health insurance in developing countries is still challenging due to weak administrative capacity of the government and the erosion of tax base given a sizable informal sector (Banerjee et al., 2021).[2] A risk-sharing model that effectively addresses health risks and high healthcare expenditures, providing comprehensive coverage, particularly for low-income individuals, while maintaining lower enrollment costs in comparison to existing health insurance schemes is the holy grail.

With the development of FinTech, a new model in health care, online mutual aid (OMA), has quickly emerged in China. The OMA business is dubbed in the media as "one for all, all for one," in which online members can receive coverage for critical illness, as long as they agree ex ante to chip in for other participants' medical expenses.[3] With no premiums charged, members bear the risks and costs as a group on a decentralized online platform—the larger the pool, the lower the costs per capita. As of 2019, OMA had 150 million members, which

[2] The health care spending in the US grew 4.1 percent to reach $4.5 trillion in 2022, which accounts for 17.3 percent of the Gross Domestic Product (GDP) and ranks the highest among OECD countries. See, e.g., National Health Expenditures 2022 Highlights. https://www.cms.gov/files/document/highlights.pdf. Accessed on January 1, 2024. Another 14 high-income countries, such as Germany, France, Canada, and Japan, all allocated more than 10% of their GDP towards healthcare expenditures in 2022. See, e.g., Health expenditure and financing (oecd.org). https://stats.oecd.org/Index.aspx?DataSetCode=SHA. Accessed on January 1, 2024.

[3] For example, see the article *Can China's 'one for all, all for one' approach to health insurance work in SEA* from TechinAsia. Accessed from https://www.techinasia.com/chinas-approach-health-insurance-work-sea.

exceeded the number of individuals who purchased critical illness insurance and accounted for about 10.7% of the total population in China (Research Institute of Ant Group, 2020; Fang et al., 2021). The annual participation costs of a typical OMA platform are about 100 RMB (equivalent to US$ 15.8), which is much lower than the premiums of a comparable critical illness insurance product (Fang et al., 2021). OMA appears to provide a potential innovative market-based solution for enhancing the accessibility and affordability of healthcare coverage with low costs in this digital era.

Utilizing all claim cases and a random sample of approximately 200,000 members from a representative OMA platform, which has more than 100 million member and is the largest one in China, we conduct the first comprehensive empirical analysis of OMA and its cost-saving effects in comparison to a commercial health insurance scheme with similar coverage. Specifically, we delve into the three unique features of OMA that distinctly set it apart from traditional insurance and raise significant concerns.

First, unlike traditional insurers, OMA members share medical costs ex post as they arise, without any initiation fee or pre-funded insurance pool. This gives rise to critical concerns about its ability to provide coverage for members who suffer from critical illnesses and the overall financial sustainability of the system. To study these concerns, we start by analyzing the cross-sectional dimension to assess the overall balance of revenues and expenditures within the OMA program, as well as the occurrence of spontaneous cross-subsidization among members. Second, we address the inter-temporal dynamics by examining patterns of member exits, as a significant decline in OMA participation could trigger a ‘vicious cycle’ of rising

costs and further attrition among remaining members. Our findings suggest that members with better financial conditions are more likely to join OMA and participate in disproportionately more cost sharing over the long haul. This indicates the presence of progressive cross-subsidies and advantageous selection (Fang, Keane, and Silverman, 2008). Those remaining in the OMA pool are at lower financial risk in OMA's ex-post cost-sharing scheme.

The second feature we scrutinize is the OMA platform's lax enrollment criteria, which consequently gives rise to the issue of adverse selection. Joining OMA is a straightforward process: applicants complete an online form, self-report their health status without verification, and gain approval upon identity confirmation and denial of pre-existing conditions. This contrasts sharply with traditional insurance, which mandates medical examinations and verified health reports. While this streamlined process has significantly expanded OMA's membership, it raises concerns about the potential for attracting a disproportionately high-risk population, thereby exacerbating adverse selection. We indeed find evidence of adverse selection and further examine OMA's mechanisms to help mitigate this issue. Specifically, our results show that high-risk members are more likely to join OMA and file claims early; however, the OMA platform utilizes internal measures to alleviate adverse selection, including varied indemnities and rigorous claim investigations, i.e. OMA offers lower amounts of lump-sum benefits to claimants aging above 40 and is more likely to deny claim requests from high-risk members.

The third feature we investigate is the use of innovative technologies such as blockchain, artificial intelligence, and smart contracts on OMA platforms. These technologies streamline

the automation of user participation, cost-sharing, and claim investigations, distinguishing OMA from traditional insurance models. In considering the implications of these technologies, we question what benefits they bring to OMA platforms, particularly in terms of efficiency and resilience against unexpected disruptions.

We then leverage the outbreak of the COVID-19 pandemic as an exogenous shock to assess its impact on the claim processing capabilities of the OMA platform. Our results reveal that during the pandemic, the claim processing time by the platform increased by only 2.3 days, a mere 4.25% increase from the original processing time. In contrast, the claim preparation time for OMA members diagnosed with critical illnesses increased by 16.5 days, representing a 26.39% rise. Given that traditional insurers significantly delayed claim processing due to overwhelmed telephone lines and challenges in conducting in-person visits, the modest 2.3-day increase in OMA's processing time is particularly noteworthy. Furthermore, we delve into the cost-saving effects of OMA in comparison to a commercial health insurance scheme offering similar coverage. We posit that OMA could save approximately $306.87 billion annually, thereby extending healthcare benefits worth $53.75 trillion to 1.29 billion individuals. This finding highlights not only the potential for cost savings but also the enhanced global accessibility to healthcare in times of upheaval.

Without identifying any causal links, our goal is to offer a first economic analysis of a new risk sharing model empowered by FinTech. Our findings have great policy implications for the development of the sharing economy and the adoption of FinTech in health care. First, OMA has successfully maintained hundreds of millions of members for years; this is puzzling. We

quantitatively analyze the potential concerns of ex-post cost sharing and lax enrollment criteria, and further investigate OMA's interior mechanisms to demonstrate why these concerns are not as troubling as they appear to be. Second, governments worldwide have been actively seeking strategies to improve the accessibility and affordability of health insurance. The OMA practice in China reveals that FinTech has the potential to substantially facilitate health risk sharing among individuals at a much lower cost than traditional healthcare programs.[4] Our paper indicates that the OMA innovation can be used to guide health insurance reforms in both developed and developing countries, where voluntary health risk sharing through digital platforms offers a viable option.

As the first empirical study based on proprietary OMA member-level data, our study contributes to several strands of literature. First, our findings add to the research on the sharing economy and FinTech. Prior studies focus on other sectors and their strengths over traditional business models, for instance, Uber in the transportation sector (e.g., Cramer and Krueger, 2016; Ge et al., 2020; Liu, Brynjolfsson, and Dowlatabadi, 2021), Airbnb in the hospitality sector (e.g., Zervas, Proserpio, and Byers, 2017; Cui, Li, and Zhang, 2020), and peer-to-peer lending in the financial sector (e.g., Freedman and Jin, 2017; Galema, 2020; Gao, Lin, and Sias, 2021). Like the business models in those sectors, OMA completely disrupts the traditional insurance sector. In addition, several papers investigate how new technologies have changed the general risk sharing arrangements and exacerbated wealth inequality (Jack et al., 2013; Riley, 2018).

[4] In March 2020, the Chinese government formally recognized OMA as a component of China's healthcare system, emphasizing its potential to enhance the affordability and accessibility of healthcare coverage. However, several major OMA platforms voluntarily ceased operations due to the lack of necessary financial licenses.

Specifically, existing literature on household finance predominately documents a reverse Robin Hood effect or regressive cross-subsidies from low-income, less sophisticated consumers to high-income, more sophisticated consumers in various markets (Campbell, Ramadorai, and Ranish, 2019; Fisher et al., 2023; Agarwal et al., 2022; Bartlett et al.,2022; Fuster et al., 2022, Zhang, 2022). Our study reveals a striking finding that OMA achieves progressive cross-subsidies from high-income members to low-income members through market forces alone and offers a potential solution to alleviate inequity in household financial markets.

More specifically for OMA, our study provides the first detailed empirical analysis of the business model based on proprietary member-level data from a representative OMA platform. Although the rapid development of OMA in China has attracted the attention of both policy makers and scholars, there is little academic research on it due to data limitations. Three recent studies have attempted to approach the business model of OMA theoretically. Abdikerimova and Feng (2022) and Chen et al. (2023) examine the actuarial fairness of OMA following insurance-related theories and argue that the coarse design of OMA could cause adverse selection. On the contrary, Fang et al. (2021) point out that potential adverse selection may not be a big concern as there exists a Rothschild and Stiglitz (1976) separating equilibrium that finds low-risk individuals participating in OMA and high-risk individuals purchasing traditional insurance. Another issue raised in Fang et al. (2021) and Chen et al. (2023) is how to understand the low-cost advantage of OMA over traditional health insurance. Our findings align with certain predictions of theoretical models while also revealing several noteworthy

discrepancies.[5]

Because OMA represents a novel form of risk sharing for critical illness, our work also relates to the broader literature on health insurance and informal risk sharing. In the formal health insurance sector, although many countries have launched a series of reforms to enhance the insurance coverage, the poor's high price sensitivity and the weak administrative capacity are the main obstacles to achieve universal insurance coverage (Gruber, 2003; Dickstein et al., 2015; Finkelstein, Hendren, and Shepard, 2019; Banerjee et al., 2021). Even in the United States, universal insurance coverage has not been achieved, resulting in numerous preventable deaths and unnecessary costs, particularly during the COVID-19 pandemic (Galvani et al., 2022). Beyond formal health insurance, numerous studies have shown that informal risk sharing against health shocks is prevalent in developing regions, yet it is far from a complete healthcare solution for underserved populations, such as the poor (e.g., De Weerdt and Dercon, 2006; Bramoullé and Kranton, 2007; Mobarak and Rosenzweig, 2013). Moreover, recent studies have revealed a lack of resilience in existing healthcare systems during the COVID-19 pandemic, marked by significant disruptions in non-COVID healthcare provision and increased delays in patient care due to public health measures and infection-related concerns (Bhatt et al., 2020; Birkmeyer et al., 2020; De Filippo et al., 2020; Ziedan, Wing, and Simon, 2020; Cantor et al., 2022). Our research addresses this gap by showing how FinTech and the OMA model

[5] In Section 5, Fang et al. (2021) utilize data from XiangHuBao to demonstrate that the incidence rate of covered illnesses among its members is lower than that of comparable critical illness insurance. Similarly, in Section 5, Chen et al. (2023) employ proprietary data from a leading OMA platform between January 2018 and December 2018 to validate their theoretical model's prediction that adverse selection exists in the OMA model due to the lack of actuarial fairness. The empirical analyses in both studies are complementary, primarily serving to support their respective theoretical frameworks.

can expedite claim processing, thus enhancing the resilience of healthcare services and mitigating the impact of delays during public health crises.

The remainder of the paper is organized as follows. Section 2 introduces the OMA industry and describes the data. Section 3 discusses financial sustainability of the ex-post cost sharing scheme. Section 4 presents evidence of adverse selection in OMA and explores mechanisms to mitigate it. Section 5 examines the resilience of OMA during the COVID-19 pandemic and estimates the magnitude of cost-saving. Section 6 concludes.

2. Institutional Background and Data

In this section, we first provide an overview of the development of OMA in China. Next, we describe the data and variables used in this study. Additionally, in the Appendix, we compare the OMA business model with other risk-sharing models, including traditional insurance, peer-to-peer insurance (primarily emerging in Europe and the United States), and the health care sharing ministry model in the United States.

2.1 Evolution of Online Mutual Aid

Online mutual aid emerged in 2011 and experienced exponential growth between 2011 and 2016. Kangai Community, launched in May 2011, was the first OMA platform in China.[6] Individuals enrolled in Kangai without an initiation fee and committed to sharing the medical costs of other members diagnosed with cancer. This innovative business model garnered significant attention from venture capital, resulting in the establishment of over 120 online mutual aid platforms by the end of 2016.

[6] 'Kangai' is a Chinese word that translates to 'fighting cancer' in English.

Initially, some OMA platforms blurred the boundary between OMA and insurance. Notably, the OMA platforms were operated by tech firms without financial license to design or sell insurance products. Even without sufficient capital, some platforms made promises to guarantee every member's claims. In 2016, the China Insurance Regulatory Commission mandated that all OMAs cease false advertising, prominently display the statement 'online mutual aid is not insurance' on their websites, and refrain from establishing funding pools. The number of platforms fell to 50 in 2017 (Chen et al., 2023).

Beginning in 2018, several tech giants, including Ant Group, Tencent, and Meituan, entered the industry, revitalizing the OMA market. OMA programs became integrated into super-apps such as Alipay, WeChat, and Meituan Waimai. The membership application became streamlined: customers could complete the registration by a few clicks within the app. The applicants should promise that they have no pre-existing conditions and agree to share medical costs when other members are diagnosed with critical illnesses. The vast customer bases of super-apps enabled these tech giants to attract millions of individuals to their OMA platforms in a remarkably short time. As of 2019, there were 150 million OMA members, which accounted for 10.7% of China's total population.[7] Approximately 40,000 members had received payments totaling over 5 billion RMB (equivalent to approximately US$694 million) from OMA platforms (Research Institute of Ant Group, 2020).

A typical OMA program offers members a basic health plan that covers approximately 100 critical illnesses, including cancer, severe brain injuries, acute myocardial infarction (heart

[7] Individuals participating in multiple online mutual aid platforms are counted only once.

attack), and others. A member who is diagnosed with a covered critical illness can receive a lump-sum benefits of up to 300,000 RMB. The cost of the indemnity is evenly shared by all the other members within that specific OMA group.

The OMA model addresses a critical gap in China's healthcare system. While public health insurance covers 95% of the population, the scope of services and benefit levels vary significantly across programs, regions, and disease types.[8] China's healthcare system is designed to meet residents' basic medical needs, covering approximately half of total healthcare expenditures. However, out-of-pocket costs are substantially higher for critical and chronic illnesses. A 2015 survey by Ernst & Young found that only 14% of respondents had sufficient savings to cover unexpected medical expenses. Despite the broad coverage of public health insurance, benefit levels remain low, particularly for low-income individuals (Liu, Liu, and Huang, 2016; Chang, Huang, and Wang, 2018). Furthermore, most individuals cannot afford private commercial insurance to bridge coverage gaps. Premiums for critical illness insurance policies range from 3,000 to 5,000 RMB per year, exceeding half of the annual income of low-income individuals in China. In contrast, OMA is significantly more affordable and offers more accessible online enrollment. In 2019 and 2020, each member on the OMA platform we study contributed 29 RMB and 91 RMB respectively, which amounts to less than 5 percent of premiums for a standard critical illness insurance product in China.

Despite the widespread popularity of OMA, no financial licenses are available for OMA

[8] The public health insurance in China is composed of three programs: the Urban Employee Basic Medical Insurance for urban employees, the Urban Resident Basic Medical Insurance for non-employed urban residents, and the New Rural Cooperative Medical Scheme for rural residents.

platforms under the current regulatory framework. This gap underscores the need for specific regulatory guidance, calling for both rigorous investigations into this novel business model and innovations in regulatory technology.

2.2 The OMA platform

To conduct a comprehensive analysis of the OMA model, we obtained proprietary member-level data from the most dominant and representative OMA platform in China (referred to as "the OMA platform"). In 2018, a leading TechFin company introduced the OMA program, an embedded application within its e-wallet super-app, offering coverage for approximately 100 critical illnesses plus malignant tumors. The program is accessible to individuals aged between 30 days and 59 years who meet basic health and risk eligibility requirements, with no upfront initiation fee. Within just one year of its launch, the OMA program had attracted nearly 100 million participants.

We obtained a random sample of 202,173 members from the OMA platform's population and tracked their behaviors, including enrollment, cost-sharing activities, claims, and exits, over the period from January 1, 2019, to April 30, 2020. We excluded members who enrolled in the OMA program but exited on the same day, as these individuals did not engage in any cost-sharing activities and were likely motivated solely by curiosity. Our final sample consists of 194,697 members.

On the 7th and 21st of each month, the OMA platform publishes newly reviewed and verified claims, as determined by its investigation team over the preceding two weeks, on its public announcement bulletin. Seven days after the release, all platform members share the

claimants' indemnities equally, along with a management fee. Notably, OMA's management fee is set at only 8% of total indemnities, significantly lower than the administrative expenses of traditional insurance companies, which typically exceed 20%. The OMA platform leverages blockchain technology and smart contracts to automate the deduction of sharing costs directly from members' bank accounts, which are linked to their e-wallets. We also manually collected *all* claim cases from the OMA platform, totaling 203,244 cases, from its inception through April 28, 2022. Utilizing this comprehensive claim data, we analyze the strengths of the innovative risk-sharing technologies employed by the OMA platform. Specifically, we focus on how the platform's claim processing was influenced by the external shock of the COVID-19 pandemic.

The OMA platform provides varying lump-sum benefits to claimants based on their age and the severity of the illness. For severe critical illnesses, such as paralysis, the benefits are set at 300,000 RMB for members under the age of 40 and 100,000 RMB for those aged 40 and above. For mild critical illnesses, such as early-stage prostate cancer, the benefits are 100,000 RMB for members under the age of 40 and 50,000 RMB for those aged 40 and above. Additionally, there is a 90-day waiting period from the date of enrollment until the effective start date of coverage for OMA members.

2.3 Variables of Interest

For the random sample, our dataset includes comprehensive information on members' basic demographics, such as age and gender, as well as their enrollment date in the OMA platform. Additionally, we capture detailed participation records, including the number of times each

member engaged in cost-sharing, their accumulated sharing costs, and their exit date from the platform. The dataset also encompasses members' claim history, including whether a claim was filed, the timing of the claim, the type of critical illness involved, the OMA platform's decision on each claim (approval or rejection), the reason for rejection (if applicable), and the indemnity amount received by each claimant.

A distinctive feature of this OMA platform, consistent with most leading platforms of its kind, is its seamless integration with an e-wallet super-app ecosystem. This integration provides members with the convenience of digital payments and access to a broad array of financial products. The digital ecosystem facilitated by the super-app allows us to observe variables that serve as measures of members' income and financial conditions. These variables include wealth (measured by the cash flow into a member's e-wallet over the preceding year), consumption levels (derived from spending habits within the e-wallet), the number of bank cards linked to a member's e-wallet, and an indicator of whether a member has linked a credit card to their e-wallet.

Table 1 presents the descriptive statistics of the key variables in the random sample used in our analysis. On average, a member participates in cost-sharing 15.74 times, contributing a cumulative total of 32.41 RMB. During the sample period, approximately 4.72% of members file claims, with 0.66% submitting a claim within 150 days of enrollment. Among members who file claims, 52.19% are rejected by the platform. Approximately 32.17% of members exit the platform during the sample period, either voluntarily or involuntarily (due to cost-sharing deduction failures or after receiving indemnities for severe illnesses). On the OMA platform,

39.11% of OMA members are female, and the average member age is 34. In terms of financial behavior, the average OMA member has a wealth level of 2.58 and a consumption level of 2.82, placing them in the upper-middle distribution of all e-wallet users. Additionally, the average member has 1.76 bank cards linked to their e-wallet, and 32.99% of members have a credit card linked to their e-wallet.

Table 1 Summary Statistics of Variables in the Random Sample

This table reports the descriptive statistics of the main variables in the random sample. The sample consists of 194,697 members from January 1, 2019, to April 30, 2020. *Indemnity_m* denotes the amounts of indemnities for approved claims; *D_claim* is a dummy variable that equals one if a member files a claim on the OMA platform; *Cost_share_m* denotes the accumulated amounts of cost sharing for each member on the OMA platform; *Cost_share_n* denotes the number of times each member participated in cost sharing on the OMA platform; *Female* is a dummy variable that equals one for female members, and zero for male members; *Age* denotes members' age; *L_consumption* is a categorical variable that ranges from 1 to 3, with a higher value indicating a higher consumption level within the e-wallet; *N_bankcard* denotes the number of bank cards linked to the e-wallet; *D_creditcard* is a dummy variable that equals one if a member has a credit card linked to the e-wallet; *L_wealth* is a categorical variable that captures the member's cash flows on the e-wallet over the prior year, which ranges from 1 to 3 with a higher value indicating a higher level of wealth; *Joinday* is calculated as the difference between the enrollment day of each member and the inception day of the platform; *D_early_claim* is a dummy variable that equals one if a member files a claim within 150 days after enrolling in the OMA platform; *D_40+* is a dummy variable that equals one if a member's age is above 40; *D30-40* is a dummy variable that equals one if a member's age ranges between 30 and 40; *D40-50* is a dummy variable that equals one if a member's age ranges between 40 and 50; *D50+* is a dummy variable that equals one if a member's age is above 50; *D_exit* is a dummy variable that equals one if a member exits the OMA platform; *D_exit_fp* is a dummy variable that equals one if a member exits the OMA platform due to deduction failure of cost sharing; *D_exit_vlt* is a dummy variable that equals one if a member voluntarily exits the OMA platform; *D_exit_clm* is a dummy variable that equals one if a member exits the OMA platform after receiving lump-sum benefits from the OMA platform; *D_reject1* is a dummy variable that equals one if the platform rejects the claim filed by a member, and equals zero if the platform approves a member's claim; and *D_reject2* is a dummy variable that equals one if the platform rejects a member's claim, and equals zero if a member does not file a claim.

Variables	N	Mean	Std. Dev.	Min	Max
OMA-related variables:					
Cost_share_n	194,697	15.7437	9.4690	0	31
Cost_share_m (unit:RMB)	194,697	32.4117	18.2843	0	50.5900
D_claim	194,697	0.0472	0.2120	0	1
Indemnity_m (unit: 10,000 RMB)	194,697	0.3437	2.7717	0	35
Joinday	194,697	229.0502	128.8708	35	519

D_early_claim	163,323	0.0066	0.0812	0	1
D_exit	194,697	0.3217	0.4671	0	1
D_exit_fp	151,411	0.1278	0.3339	0	1
D_exit_vlt	172,237	0.2332	0.4229	0	1
D_exit_clm	135,175	0.0230	0.1500	0	1
D_reject1	9,188	0.5219	0.4995	0	1
D_reject2	190,304	0.0252	0.1567	0	1
Demographic variables:					
Female	194,697	0.3911	0.4880	0	1
Age	194,697	34.1493	9.5534	18	61
D_40+	194,697	0.3179	0.4656	0	1
D30-40	194,697	0.3231	0.4677	0	1
D40-50	194,697	0.2418	0.4282	0	1
D50+	194,697	0.0766	0.2659	0	1
Financial variables:					
L_consumption	194,697	2.8196	1.0078	1	5
N_bankcard	194,697	1.7631	1.0203	0	3
D_creditcard	194,697	0.3299	0.4702	0	1
L_wealth	194,697	2.5760	0.6651	1	3

For the claim data manually collected from the public announcement bulletin on the OMA platform (see Figure 1 for an example of a claim case published on the bulletin), we obtained detailed information, including the release date, the type of OMA program, the claimant's name, gender, age, the location (province) of the hospital where the diagnosis was made, the number of days the claimant participated in the OMA platform, the total number of members assisted by the claimant, the cumulative costs shared by the claimant, the type of critical illness, the benefit amounts received from the OMA platform, and a detailed case description. From the case description, we extracted the diagnosis date and the hospital where the diagnosis occurred. We identify the hospital grade and the city where the hospital is located through the medical institutions search website organized by the National Health Commission of the People's

Republic of China.[9] In addition, we have access to the date when the claimant applied for a claim, the claimant's national identity number, the city of residence, whether the claimant participates in the OMA platform in person or by proxy, and the date when the claimant participated in the OMA platform from the business information system of this e-wallet super-app.[10] We identify the province where a claimant was born through the first two digits of the claimant's national identity number. Our claim data include a total of 203,244 claim cases from January 2019 to April 2022.

[9] http://zgcx.nhc.gov.cn:9090/unit.

[10] The national identity number in China contains 18 digits. We have access to the first two digits and the 9-14th digits.



Figure 1. An example of a claim case released on the public announcement bulletin

For each claim case, we calculate claim processing time as the number of days between the application date for the claim and the release date of the claim on the platform's bulletin board. For comparison, we also calculate claim preparation time as the number of days between the date when the claimant was diagnosed with a critical illness and the application date for the

claim. To examine the impact of the COVID-19 shock on claim processing and claim preparation, we identify the city where the claimant was diagnosed, and construct an indicator variable that equals one if new confirmed COVID-19 cases were reported in the city during a specified time interval.

3. Financial Sustainability of OMA: Cross-Subsidies and Exit Patterns

There are three unique features that make OMA strikingly different from traditional insurance: ex post cost sharing, lax enrollment criteria, and the extensive use of digital technologies. In Sections 3 to 5, we investigate the potential questions raised by each of these three features.

The first distinctive feature of OMA is the absence of ex-ante premiums and the implementation of cost sharing ex post. This characteristic sets OMA apart from traditional insurance and has a significant impact on the financial sustainability of the program. We examine this feature and evaluate its impact on OMA's financial sustainability from two distinct perspectives. The first analysis focuses on the cross-sectional dimension by providing a holistic glance on the overall revenues and expenses of the OMA program. In particular, we investigate whether there is spontaneous cross-subsidization among members, even though the benefits to claimants are evenly shared by each member. The second analysis focuses on the intertemporal dynamics and addresses the concern regarding the "ex-post" pattern of cost sharing. A critical factor for the success of the ex-post cost sharing scheme is to maintain a stable membership base. A substantial decline in membership could trigger a sharp rise in costs for remaining participants, potentially initiating a vicious cycle of escalating costs and further exits. To comprehend these dynamics thoroughly, we investigate the exit patterns of its

members.

3.1 Revenues, Expenses, and Cross-Subsidies

We start our analyses by examining the factors that influence the "revenues" and "expenses" of OMA. For an OMA platform, "revenues" are aggregate cost-sharing contributions from members, while "expenses" are payouts made to members who file claims after being diagnosed with a critical illness. To operationalize these concepts at the individual level, we construct two measures of revenue contribution: (1) the frequency of a member's participation in cost-sharing activities (*Cost_share_n*) and (2) the cumulative monetary contributions made by the member toward cost sharing (*Cost_share_m*). Similarly, we measure OMA's expenses using two variables: (1) a binary indicator for whether a member files a claim (*D_claim*) and (2) the total amount of benefits received by a claimant (*Indemnity_m*).

Building on the theory of traditional insurance, coupled with OMA's unique features, we consider two factors that may affect the cost sharing and claim filing of OMA members. First, age and gender are commonly used by insurance companies to determine the premiums ("revenues") of health insurance products, as they are good predictors of disease risks.[11] For an OMA platform, it is essential that members' disease risks remain within a moderate range to prevent sudden spikes in cost-sharing obligations. This balance is critical to maintaining the financial stability and sustainability of the platform. Second, given OMA's ex-post cost sharing scheme, it is critical to account for members' financial risks. Unlike traditional insurers, which

[11] In China, traditional insurers determine premiums for critical illness insurance using the **Standard Critical Illness Incidence Rate Table (SCIIR Table)**, which is published by regulatory authorities. This table provides the incidence rates of critical illnesses stratified by age and gender, serving as a foundational tool for pricing insurance products.

are insulated from such risks due to their ex-ante premium collection, OMA platforms rely on the ability to collect cost-sharing contributions smoothly, which is directly influenced by members' financial stability. In this study, we measure financial risks using four variables: (1) wealth level, (2) consumption level, (3) the number of bank cards linked to the e-wallet, and (4) an indicator for whether a credit card is linked to the e-wallet. We posit that financial risks are lower for members with higher wealth, greater consumption, more linked bank cards, and ownership of a credit card.

We perform the corresponding regression model specified as follows:

$$y = \beta_0 + \beta_1 Female + \beta_2 Age + \beta_3 L_{consumption} + \beta_4 N_{bankcard} + \beta_5 D_creditcard + \beta_6 L_wealth + \lambda_{ct} + \varepsilon, \quad (1)$$

where the dependent variables are four measures that proxy for OMA's revenues and expenses. We focus on six factors that may affect the cost sharing and claim filing of OMA members: two factors that capture disease risks (*Female* and *Age*) and four factors that capture financial risks (*L_consumption*, *N_bankcard*, *D_creditcard*, and *L_wealth*). To control for time-varying local factors, we include members' city of residence by the period of members' enrollment fixed effects (λ_{ct}). Since the OMA platform releases claims filings and deducts sharing costs every two weeks, there are two periods in each month. In this model specification, we are comparing the behavior of members who reside in the same city and enroll in the OMA during the same period. Standard errors are corrected for clustering at the city level.

Here we focus on the following questions. Do members with higher disease risks, who are more likely to file claims, also contribute more to OMA's revenues? Do members in a better

financial position contribute more or less to OMA's revenues? Are they more or less likely to file claims? Addressing these questions allows us to make a preliminary assessment of the sustainability of the OMA model.

Table 2 presents the regression results. Regarding proxies for disease risks, we find that older members contribute more to OMA's revenues evidenced by a higher frequency of cost sharing and more cumulative monetary contributions, they are also more likely to file a claim and receive more indemnities from the OMA platform. In addition, female members contribute less to OMA's revenues, but they are more likely to file a claim and receive more indemnities. These findings suggest that older members and female members exhibit higher disease risks compared to younger members and male members in our sample. The result on females is consistent with the Standard Critical Illness Incidence Rate Table (SCIIR Table) released by China's regulatory authorities to guide the pricing of critical illness insurance for traditional insurance companies. Notably, the average age in our random sample is 34, and the SCIIR Table indicates that females have a higher incidence rate of critical illnesses than males before the age of 55.

Regarding the three financial variables (*L_consumption*, *N_bankcard*, and *D_creditcard*), members with lower financial risks (proxied by higher consumption levels, a greater number of linked bank cards, and ownership of a credit card) contribute more revenues to the OMA platform while their likelihood of filing a claim and the amounts of indemnities received are similar to or even less than those of members with higher financial risks. These findings suggest that members with less financial risks are subsidizing those with more financial risks, since the

former's contributions to the platform do not match the benefits they receive from the platform.

For the financial risk variable *L_wealth*, we find that members' wealth levels are positively associated with both cost-sharing contributions and claim filings. The contributions of wealthier members match the benefits they receive from the OMA platform. As a financial risk measure, *L_wealth* also exhibits predictive power for disease risks, as indicated by the positive and statistically significant coefficients in columns (3) and (4). One plausible explanation is that *L_wealth* not only proxies for members' wealth levels but may also capture other factors, such as their level of engagement or activeness in using the e-wallet.

Table 2 Revenues and Expenses of OMA

This table reports the factors that influence the revenues and expenses of OMA. The sample consists of 194,697 OMA members from January 1, 2019, to April 30, 2020. The dependent variables are the number of times a member participates in cost sharing (*Cost_share_n*) in column (1), the accumulated amounts of sharing costs (*Cost_share_m*) in column (2), a dummy variable indicating whether a member files a claim (*D_claim*) in column (3), and the amounts of received indemnities (*Indemnity_m*) in column (4). The independent variables include members' gender (*Female*) and age (*Age*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), as well as a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, city-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Cost_share_n	*Cost_share_m*	*D_claim*	*Indemnity_m*
	(1)	(2)	(3)	(4)
Female	-0.2148***	-0.3987***	0.0163***	0.0913***
	(0.0308)	(0.0805)	(0.0012)	(0.0135)
Age	0.0700***	0.1865***	0.0033***	0.0098***
	(0.0021)	(0.0058)	(0.0001)	(0.0005)
L_consumption	0.6451***	1.7907***	0.0003	0.0018
	(0.0134)	(0.0357)	(0.0005)	(0.0063)
N_bankcard	0.2071***	0.5770***	0.0005	0.0042
	(0.0132)	(0.0335)	(0.0006)	(0.0075)
D_creditcard	0.5267***	1.4063***	-0.0027**	0.0099
	(0.0322)	(0.0816)	(0.0012)	(0.0147)
L_wealth	1.2289***	3.5479***	0.0230***	0.1975***
	(0.029)	(0.0791)	(0.0009)	(0.0091)

Constant	7.9136***	10.5302***	-0.1306***	-0.5515***
	(0.1258)	(0.3504)	(0.0043)	(0.0326)
*City*period FE*	YES	YES	YES	YES
Observations	194,697	194,697	194,697	194,697
R^2	0.0532	0.0631	0.0250	0.0032

In the above regression, with the inclusion of city-period fixed effects, we document the presence of progressive cross-subsidies from members with less financial risks to those with more financial risks within a city. Next, we examine whether cross-subsidy exists across cities. While China has experienced remarkable economic growth over the last 30 years, there are huge disparities in economic development across regions (Fleisher, Li, and Zhao, 2010; Lessmann, 2013). Following China's city tier classification system, we categorize cities in our sample into distinct tiers. First-tier cities are defined as major metropolises with significant economic influence, including Beijing, Shanghai, Guangzhou, and Shenzhen. Second-tier cities consist of provincial capitals or regional economic centers, such as Chengdu, Chongqing, Dalian, Hangzhou, Nanjing, Qingdao, and Tianjin. All remaining cities are classified as third-tier cities or below. We construct a dummy variable, *T3_city*, which takes the value of one for members residing in third-tier cities or below, and include it as an additional control variable in our analysis. Furthermore, to accommodate the inclusion of *T3_city*, we replace city-period fixed effects with province-period fixed effects. Table 3 presents the regression results. It is evident that members in three-tier cities or below contribute less revenues to the OMA platform while they receive higher amounts of indemnities from the platform. Progressive cross-subsidies exist across cities from members in first- or second-tier cities to those in third-tier cities or below.

Table 3 China's city tier system and cross-subsidies

This table reports whether the cross-subsidies exist across cities in our sample. The sample consists of 194,697 OMA members from January 1, 2019, to April 30, 2020. The dependent variables are the number of times a member participates in cost sharing (*Cost_share_n*) in column (1), the accumulated amounts of sharing costs (*Cost_share_m*) in column (2), a dummy variable indicating whether a member files a claim (*D_claim*) in column (3), and the amounts of received indemnities (*Indemnity_m*) in column (4). The independent variables include a dummy variable that equals one for members residing in the third-tier cities or below (*T3_city*), members' gender (*Female*) and age (*Age*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), as well as a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, province-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

	Cost_share_n	*Cost_share_m*	*D_claim*	*Indemnity_m*
	(1)	(2)	(3)	(4)
T3_city	-0.0976**	-0.2923***	0.0012	0.0625***
	(0.0395)	(0.1092)	(0.0017)	(0.0159)
Male	-0.2057***	-0.3740***	0.0166***	0.0938***
	(0.049)	(0.1333)	(0.0017)	(0.0183)
Age	0.0695***	0.1857***	0.0032***	0.0096***
	(0.0021)	(0.0058)	(0.0001)	(0.0007)
L_consumption	0.6401***	1.7795***	0.0004	0.0028
	(0.0119)	(0.0364)	(0.0006)	(0.0071)
N_bankcard	0.2023***	0.5677***	0.0005	0.0036
	(0.0138)	(0.0345)	(0.0005)	(0.0076)
D_creditcard	0.5197***	1.3921***	-0.0030**	0.0097
	(0.0448)	(0.1211)	(0.0014)	(0.0150)
L_wealth	1.2180***	3.5225***	0.0229***	0.1960***
	(0.0406)	(0.1137)	(0.0015)	(0.0104)
Constant	8.0428***	10.8500***	-0.1306***	-0.5802***
	(0.1441)	(0.4057)	(0.0073)	(0.0439)
*Province*period FE*	YES	YES	YES	YES
Observations	193631	193631	193631	193631
R^2	0.0533	0.0635	0.0253	0.0033

The presence of progressive cross-subsidies within OMA is noteworthy. Prior studies on household finance usually document regressive cross-subsidies from low-income, less sophisticated individuals to high-income, more sophisticated individuals, which lead to greater wealth inequality in the market (e.g., Campbell, Ramadorai, and Ranish, 2019; Agarwal et al.,

2022; Fisher et al., 2023). Public insurance systems can achieve progressive cross-subsidies, empowered by government mandates and progressive tax regimes. For instance, the U.S. government provides substantial subsidies to low-income populations through programs such as the Medicaid program. However, many countries face challenges in realizing these objectives within their public insurance frameworks, often due to suboptimal design and a misalignment between risk profiles and the level of protection offered (Liu, Liu, and Huang, 2016). Our study reveals a striking finding that OMA achieves progressive cross-subsidies from high-income members to low-income members through market forces alone and offers a potential pathway to mitigate wealth inequity in household financial markets.

3.2 Exit Patterns and Advantageous Selection

With the presence of progressive cross-subsidies in the cross-sectional dimension, the OMA model has the potential to maintain financial sustainability through equitable ex-post cost sharing among all members. However, a critical question remains: Are members with lower disease risks more likely to exit the platform over time? Such behavior could lead to increased cost-sharing burdens due to the higher disease risks of the remaining self-selected members. Additionally, it is essential to examine whether members in stronger financial positions—such as wealthier individuals—are more likely to exit, as this could further exacerbate challenges in collecting cost-sharing contributions and threaten the platform's financial stability.

In practice, a member may exit the OMA platform for three primary reasons: (1) the diagnosis of a critical illness, which results in benefit receipt and subsequent removal from the

program; (2) the inability to fulfill cost-sharing obligations due to unsuccessful payment deductions; or (3) voluntary withdrawal. To capture these exit behaviors, we construct four dummy variables: 1) *D_exit* is equal to one if a member quits from the platform, and zero if a member does not exit; 2) *D_exit_fp* is equal to one if a member exits due to failure to meet cost-sharing obligations, and zero if a member does not exit; 3) *D_exit_vlt* is equal to one if a member voluntarily exits, and zero if a member does not exit; and 4) *D_exit_clm* is equal to one if a member exits after receiving indemnities from the platform, and zero if a member does not exit. Then we regress these four dummy variables on member characteristics separately in Table 4.

In Column (1), we examine the relationship between member characteristics and the overall exit. We find no significant difference in exit patterns between male and female members. However, younger members exhibit a significantly higher likelihood of exiting the platform. As a result, the OMA's projected sharing costs may increase due to higher disease risks from older members who remain on the platform.

When comparing the results for different exit types in Columns (2), (3), and (4), we find that male members are more likely to exit due to payment deduction failures, whereas female members are more likely to exit voluntarily or due to critical illnesses. Given that female members have a higher likelihood to file claims (see Table 2), their voluntary exits reduce the disease risks among the remaining members on the platform. Additionally, while older members are more likely to exit due to critical illnesses, they are less likely to exit voluntarily or because of payment deduction failures.

Regarding factors that reflect financial risks, the coefficients on four variables are all negative and statistically significant at the 1% level in Columns (1)–(3), suggesting that members in stronger financial positions are more likely to retain their membership on the OMA platform, indicating advantageous selection in OMA financing. In line with De Meza and Webb (2001), Fang, Keane, and Silverman (2008), and Ail, Mihm, Siga, and Tergiman (2021), advantageous selection occurs when individuals who purchase more insurance are of lower risk. As a result, the average financial capacity of the remaining members improves, as those with higher financial risks exit the OMA pool. As shown in Column (4), wealthier members are more likely to exit due to critical illnesses, which is also consistent with the finding in Table 2 that they are more likely to file a claim.

Table 4 Member characteristics and exit behavior

This table reports the relation between member characteristics and exit behavior. We create four dummy variables as dependent variables in the regression: *D_exit* is equal to one if a member quits from the platform, and zero if a member does not exit; *D_exit_fp* is equal to one if a member exits due to failure to meet cost-sharing obligations, and zero if a member does not exit; *D_exit_vlt* is equal to one if a member voluntarily exits, and zero if a member does not exit; *D_exit_clm* is equal to one if a member exits after receiving indemnities from the platform, and zero if a member does not exit. The independent variables include members' gender (*Female*) and age (*Age*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), as well as a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, city-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	D_exit	*D_exit_fp*	*D_exit_vlt*	*D_exit_clm*
Female	0.0015	-0.0422***	0.0283***	0.0053***
	(0.0028)	(0.0023)	(0.0024)	(0.0009)
Age	-0.0056***	-0.0048***	-0.0047***	0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)
L_consumption	-0.0569***	-0.0548***	-0.0299***	-0.0013***
	(0.0013)	(0.0014)	(0.0012)	(0.0005)

N_bankcard	-0.0195***	-0.0236***	-0.0071***	0.0002
	(0.0011)	(0.0010)	(0.0011)	(0.0005)
D_creditcard	-0.0521***	-0.0277***	-0.0387***	-0.0046***
	(0.0026)	(0.0016)	(0.0025)	(0.0010)
L_wealth	-0.1026***	-0.1565***	-0.0225***	0.0152***
	(0.0023)	(0.0028)	(0.0019)	(0.0008)
Constant	0.9886***	0.9162***	0.5562***	-0.0752***
	(0.0120)	(0.0124)	(0.0103)	(0.0038)
*City*period FE*	YES	YES	YES	YES
Observations	194,697	151,411	172,237	135,175
R^2	0.0610	0.1857	0.0190	0.0130

In summary, we identify heterogeneous exit patterns among OMA members across disease risk and financial risk dimensions. In the disease risk dimension, older members are more likely to remain in the OMA group, whereas younger members exhibit a higher propensity to exit. This dynamic may increase the average disease risk of the remaining members, thereby driving up cost-sharing obligations. In this sense, the concerns about the OMA's financial sustainability are reasonable. However, in the financial risk dimension, members with weaker financial positions are more likely to exit, which raises the average financial capacity of the remaining OMA members in cost-sharing arrangements.

The presence of advantageous selection in the dimension of members' financial risks has significantly alleviated concerns regarding the ex-post cost-sharing scheme. This advantageous selection may be unique to OMAs embedded in super-apps, where members are incentivized to fulfill their financial obligations to the OMA platform to enhance their credit scores within the e-wallet ecosystem and gain access to additional e-wallet services. As summarized by the results in Tables 2 to 4, members with stronger financial conditions are more likely to participate in cost-sharing arrangements and less likely to exit the OMA platform. This

demonstrates advantageous selection in the funding dimension, consistent with findings on traditional insurance by De Meza and Webb (2001) and Fang, Keane, and Silverman (2008).

4. Lax Enrollment and Adverse Selection

We now turn to the second unique feature of OMA: the lax enrollment criteria. Individuals can join OMA with just a few clicks on their mobile phones, without the need to submit verified health reports. However, this ease of enrollment raises a potential concern: high-risk individuals may join the platform more actively, leading to adverse selection. In this section, we examine whether adverse selection exists and, if so, whether the OMA platform has implemented internal measures to mitigate it.

4.1 Adverse Selection in the Dimension of Disease Risk

Based on the results in Table 2, high-risk members in our sample are older members and females, who, on average, exhibit a higher likelihood of experiencing critical illnesses. We first investigate whether these high-risk members are more likely to join the OMA platform early and file claims shortly after enrollment.

We measure the timing of a member's enrollment in the OMA platform by calculating the number of days between the member's enrollment date and the inception date of the OMA platform (*Joinday*). A member is classified as an early claimant (*D_early_claim* = 1) if they file a claim within 150 days of enrolling in the OMA platform. We then regress these two outcome variables on member characteristics. When the outcome variable is *D_early_claim*, we exclude members who joined the OMA platform within 150 days of the sample period's end date (April 30, 2020) and who retained their membership without filing a claim by that

date.

Table 5 presents the regression results, which indicate that older members and female members are more likely to join the OMA platform early and file a claim shortly after enrollment. The lax enrollment criteria of the OMA platform do indeed cause adverse selection. Individuals with higher disease risks appear to enroll in the OMA platform more actively and files claims soon after joining. For the financial risk variable *L_wealth*, we find that members' wealth levels are positively associated with both early enrollment and early claim filings. For the other three financial factors (*L_consumption, N_bankcard, and D_credit*), the results show that members with better financial conditions are more active in OMA enrolment but do not file a claim shortly after enrollment.

Table 5 Early enrollment and early claim filings

This table reports the regression results on OMA members' early enrollment and early claim filings. The sample consists of 194,697 members from January 1, 2019, to April 30, 2020. The dependent variables are the number of days between the enrollment day of a member and the inception day of the OMA platform (*Joinday*) in column (1) and a dummy variable (*D_early_claim*) that equals one if a member files a claim within 150 days after enrolling in the platform. To mitigate selection bias, when the dependent variable is *D_early_claim*, we exclude members who joined the platform too late to have been observed for at least 150 days in our sample. Specifically, we remove those who enrolled in the OMA program within 150 days of the sample period's end date (April 30, 2020) and retained their membership without filing a claim by that date. The independent variables include members' gender (*Female*) and age (*Age*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), as well as a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). The city-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Joinday	*D_early_claim*
	(1)	(2)
Female	-5.4425***	0.0024***
	(0.5912)	(0.0004)
Age	-1.5146***	0.0005***
	(0.0308)	(0.0000)

L_consumption	-3.6450***	-0.0004**
	(0.2981)	(0.0002)
N_bankcard	-4.9159***	0.0004
	(0.3006)	(0.0002)
D_creditcard	-23.337***	0.0001
	(0.6560)	(0.0005)
L_wealth	-15.936***	0.0022***
	(0.4606)	(0.0003)
Constant	350.5957***	-0.0152***
	(1.8362)	(0.0016)
City FE	YES	NO
*City*period FE*	NO	YES
Observations	194,697	163,323
R^2	0.0332	0.0031

4.2 Internal Measures to Alleviate Adverse Section

In the financial risk dimension, we find progressive cross-subsidies and advantageous selection within the OMA platform, which is beneficial for OMA's financial sustainability. In the disease risk dimension, by contrast, we identify the presence of adverse selection within the OMA platform, which could increase cost-sharing obligations and threaten the platform's stability. Given this, an ensuing question is whether the OMA platform has internal mechanisms to alleviate adverse selection in the disease risk dimension. We explore two potential mechanisms: varying indemnities across different age cohorts and rigorous claims investigations.

(1) Varying indemnities to different age cohorts

In Table 5, we find that older members and female members are more likely to join the OMA platform early and file a claim shortly after enrollment. While the OMA programs do not differentiate indemnities by gender, they typically offer varying indemnities across different age cohorts. For members below 40 years of age, the OMA platform we study provides

indemnities of either 300,000 RMB or 100,000 RMB, depending on the severity of the critical illness. For members above 40 years of age, the indemnities are 100,000 RMB or 50,000 RMB, respectively. This design is commonly used by OMA platforms to mitigate the adverse selection of the elderly against the young. We evaluate whether this design is effective and whether the age cutoff of 40 is reasonable.

To check it, we replace the age variable in Eq. (1) with a dummy variable indicating whether a member is older than age 40 (*D_40+*). As can be seen in columns (3) and (4) of Table 6, while members above 40 years old are more likely to file claims than younger members, they receive lower indemnities for those claims. Overall, this design is effective, as the platform offsets the higher disease risks of older members by providing lower indemnities.

Table 6 The effectiveness of varying indemnities to different age cohorts I

This table evaluates the effectiveness of varying indemnities to different age cohorts. The sample consists of 194,697 members from January 1, 2019, to April 30, 2020. The dependent variables are the number of times a member participates in cost sharing (*Cost_share_n*) in column (1), the accumulated amounts of sharing costs (*Cost_share_m*) in column (2), a dummy variable indicating whether a member files a claim (*D_claim*) in column (3), and the amounts of received indemnities (*Indemnity_m*) in column (4). The independent variables include members' gender (*Female*), a dummy variable indicating whether a member is older than age 40 (*D_40+*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), and a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, city-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Cost_share_n	*Cost_share_m*	*D_claim*	*Indemnity_m*
	(1)	(2)	(3)	(4)
Female	-0.1815***	-0.3126***	0.0180***	0.1043***
	(0.0309)	(0.0809)	(0.0013)	(0.0135)
D_40+	1.0238***	2.7973***	0.0443***	-0.0747***
	(0.0429)	(0.1122)	(0.0013)	(0.0111)
L_consumption	0.6313***	1.7556***	-0.0004	-0.0054
	(0.0135)	(0.0361)	(0.0005)	(0.0063)
N_bankcard	0.1930***	0.5410***	-0.0003	-0.0027
	(0.0133)	(0.0336)	(0.0006)	(0.0075)

D_creditcard	0.6099***	1.6273***	0.0012	0.0231
	(0.0331)	(0.084)	(0.0012)	(0.0146)
L_wealth	1.1776***	3.4171***	0.0203***	0.1726***
	(0.0293)	(0.0800)	(0.0009)	(0.0088)
Constant	10.1343***	16.4016***	-0.0251***	-0.1054***
	(0.0844)	(0.2334)	(0.0025)	(0.0235)
*City*period FE*	YES	YES	YES	YES
Observations	194,697	194,697	194,697	194,697
R^2	0.0473	0.0571	0.0139	0.0023

However, is the age cutoff of 40 reasonable? Is a single cutoff sufficient to ensure fairness across different age cohorts? To address these questions, we further categorize OMA members in our sample into four age cohorts: <30, 30–40, 40–50, and >50, and create four dummy variables (*D<30*, *D30–40*, *D40–50*, and *D>50*). We add three dummy variables into the regression with members below age 30 as the benchmark group. The results in columns (3) and (4) of Table 7 show that members with age 30-40 appear to receive preferential treatments from the OMA platform: they receive significantly higher indemnities compared to the <30 and 40–50 cohorts, while their contributions are the second lowest (see column (2)). Additionally, members above age 50 receive the highest indemnities, yet their cost contributions are somewhat lower than those of the 40–50 cohort. These findings suggest that the current design is overly simplistic and insufficient to address the adverse selection problem. More nuanced designs are needed to accurately reflect the varying disease risks across different age cohorts.

Table 7 The effectiveness of varying indemnities to different age cohorts II

This table evaluates the effectiveness of varying indemnities to different age cohorts. The sample consists of 194,714 members from January 1, 2019, to April 30, 2020. The dependent variables are the number of times a member participates in cost sharing in column (1), the accumulated amounts of sharing costs in column (2), a dummy variable indicating whether a member files a claim in column (3), and the amounts of received indemnities in column (4). The independent variables include members' gender (*Female*), a dummy variable indicating whether a member's age is between 30 and 40 (*D30-40*), a dummy variable indicating whether a member's age is between 40 and 50 (*D40-50*), a dummy variable indicating whether a member's age is above

50 (*D50+*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), and a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, city-period fixed effects are included to capture the impact of time-variant local factors. Robust standard errors, clustered at the city level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Cost_share_n	*Cost_share_m*	*D_claim*	*Indemnity_m*
	(1)	(2)	(3)	(4)
Female	-0.2044***	-0.3715***	0.0171***	0.0947***
	(0.0309)	(0.0808)	(0.0013)	(0.0135)
D30-40	1.1791***	3.0771***	0.0251***	0.3018***
	(0.0431)	(0.1164)	(0.0011)	(0.0175)
D40-50	1.6013***	4.3332***	0.0430***	0.0920***
	(0.0616)	(0.1629)	(0.0014)	(0.0129)
D50+	1.6141***	4.2314***	0.1119***	0.3141***
	(0.0635)	(0.1701)	(0.0029)	(0.0218)
L_consumption	0.6356***	1.7651***	0.0005	-0.0002
	(0.0134)	(0.0359)	(0.0005)	(0.0063)
N_bankcard	0.2061***	0.5747***	0.0003	0.0030
	(0.0132)	(0.0334)	(0.0006)	(0.0075)
D_creditcard	0.4827***	1.2925***	-0.0001	-0.0052
	(0.0319)	(0.0806)	(0.0012)	(0.0148)
L_wealth	1.2180***	3.5208***	0.0221***	0.1909***
	(0.0286)	(0.0782)	(0.0009)	(0.0090)
Constant	9.4798***	14.7051***	-0.0454***	-0.3318***
	(0.0893)	(0.2507)	(0.0028)	(0.0269)
*City*period FE*	YES	YES	YES	YES
Observations	194,697	194,697	194,697	194,697
R^2	0.0541	0.0641	0.0234	0.0044

(2) Stringent investigations into claim filings

In addition to providing varying indemnities for different age cohorts, the OMA platform implements stringent investigations into claim filings. When a member is diagnosed with a critical illness, they complete an electronic form, upload photographs of all relevant medical records, and submit these documents to the platform online. The platform employs an artificial intelligence-driven image recognition system to extract and analyze unstructured information. Subsequently, it randomly assigns an investigator to conduct an interview with the member.

The interview process is recorded, and the video is uploaded to a blockchain-based mini-program for transparency and verification. If necessary, the investigator may visit the hospital to validate the member's medical records. Additionally, the OMA platform uses its online system to verify whether the member has medical records at other hospitals in recent years. Members' digital footprints within the e-wallet ecosystem further assist the platform in assessing the validity of critical illness claims. Through these rigorous investigations, the OMA platform identifies problematic claims and ineligible members. Problematic claims typically involve claimants who either falsify an illness or report a critical illness not covered by the OMA program. Ineligible members, on the other hand, often have pre-existing conditions that disqualify them from enrolling in the OMA platform at the outset. To maintain cost-sharing obligations within a reasonable range, the OMA platform rejects both problematic claims and unqualified members. In our sample, the platform rejected 52.19% of claim requests (see Table 1). Here we examine whether the platform rejects claim requests in an appropriate and effective manner.

To this end, we first construct two dummy variables with distinct reference groups. *D_reject1* equals one if a member's claim is rejected by the platform and zero if the claim is approved. *D_reject2* equals one if a member's claim is rejected by the platform and zero if the member does not file a claim. We then regress these two dummy variables on member characteristics. Based on the results in column (1) of Table 8, the platform rejects a higher proportion of claims from older members compared to the reference group of members whose claims are approved. Similarly, the results in column (2) of Table 8 indicate that the platform

rejects more claims from female and older members relative to the reference group of members who do not file any claims.

While the OMA platform's stringent investigations effectively identify high-risk members, the high rejection rate (52.19%) raises potential concerns. Although this high rate may partially reflect the efficacy of new technologies in detecting problematic claims and ineligible claimants, it could undermine members' trust in the OMA platform and harm its reputation. Among the rejected claims in our sample with clear reasons for rejection, approximately 76.11% are due to pre-existing conditions, with females and older members facing a higher likelihood of rejection. The platform's lenient enrollment criteria rely, to some extent, on applicants' careful review of the OMA's terms and conditions and their understanding of risk-sharing principles. However, in developing countries with underdeveloped insurance markets, such as China, it is common for customers to lack basic insurance knowledge. As a result, some ineligible members may not have been aware of their disqualification due to pre-existing conditions when they initially enrolled.

Table 8 Member characteristics and rejection of claim requests

This table evaluates the effectiveness of stringent investigations into claim requests. We create two dummy variables as dependent variables in the regression: *D_reject1* is equal to one if a member's claim is rejected by the platform and zero if a member's claim is approved; *D_reject2* is equal to one if a member's claim is rejected by the platform and zero if a member does not file a claim. The independent variables include members' gender (*Female*) and age (*Age*), members' wealth level (*L_wealth*), consumption level (*L_consumption*), the number of bank cards linked to the e-wallet (*N_bankcard*), as well as a dummy variable indicating whether a member has a credit card linked to the e-wallet (*D_creditcard*). In addition, city-period fixed effects are included to capture the impact of time-variant local factors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	D_reject1	*D_reject2*
Female	-0.0092	0.0078***

	(0.0122)	(0.0010)
Age	0.0059***	0.0021***
	(0.0007)	(0.0001)
L_consumption	0.0011	0.0000
	(0.0064)	(0.0004)
N_bankcard	-0.0074	0.0004
	(0.0068)	(0.0004)
D_creditcard	0.0277**	-0.0015*
	(0.0131)	(0.0009)
L_wealth	-0.1311***	0.0092***
	(0.0126)	(0.0006)
Constant	0.6471***	-0.0728***
	(0.0498)	(0.0030)
*City*period FE*	YES	YES
Observations	9,188	190,304
R^2	0.0351	0.0163

5. Technology-Enabled Resilience and Cost-Saving During the Pandemic

The third distinguishing feature of the OMA platform is its extensive use of state-of-the-art technologies to minimize human involvement and reduce operational costs. This is evident in three key aspects. First, the platform achieves full automation of user participation. Embedded within an e-wallet super-app, individuals can join the OMA platform with just a few clicks on their mobile devices. Second, leveraging artificial intelligence (AI), the platform partially automates the claims investigation process, significantly reducing the need for human intervention. When a member diagnosed with a critical illness submits a claim online, the platform may assign an investigator registered on its blockchain-based claims management mini-program to verify the claim's validity, depending on its complexity. If the hospital collaborates with the OMA platform on medical data sharing, the platform can directly retrieve claimants' medical records online, eliminating the need for onsite visits by investigators. Third,

through the application of blockchain technology and smart contracts, the platform automates the collection of cost-sharing contributions. On the 14th and 28th of each month, each member's cost-sharing amount is automatically deducted from their bank account linked to the e-wallet.

The aforementioned technologies have the potential to enhance the resilience of the OMA platform during public health crises while simultaneously achieving higher healthcare insurance coverage. In this section, we first exploit the COVID-19 pandemic as an external shock and examine how it affects claim processing of the OMA platform. After that, we conduct an estimation to show the cost-saving effect of OMA in achieving higher healthcare insurance coverage.

5.1 The Resilience of OMA During the COVID-19 Pandemic

It is widely acknowledged that the outbreak of COVID-19 has had a profound impact on the entire healthcare system. However, with the extensive use of cutting-edge technologies, we anticipate that the impact of the COVID-19 pandemic on OMA's claim processing can be mitigated or even minimized. Once claim materials are submitted online, the AI-based claim management system conducts a preliminary analysis without human intervention. We provide a detailed description of the platform's claim handling process in the Appendix. In a seminal study, Fuster et al. (2019) find that FinTech lenders in the U.S. mortgage market process and originate loans 20% faster than traditional lenders by automating the loan application process. This raises an intriguing question: To what extent has the COVID-19 pandemic affected the

claim processing time of the OMA platform?

To establish a benchmark for potential delays caused by the COVID-19 pandemic, we also examine the claim preparation time for OMA members before they submit claims online. This process, in contrast to the automated claim processing by the OMA platform, may be significantly affected by the pandemic. Each claimant is required to prepare a discharge summary to verify their hospital discharge. While the OMA platform automates the claim application, it cannot influence the hospitalization of members diagnosed with critical illnesses. The COVID-19 pandemic has had a substantially adverse impact on hospitals' ability to deliver healthcare for non-COVID diseases (Ziedan, Wing, and Simon, 2020). Additionally, patients may delay seeking healthcare due to shelter-in-place policies and fears of COVID-19 infection in hospitals (Cantor et al., 2022). Given these factors, we anticipate that the COVID-19 pandemic may prolong the time required for medical care, thereby increasing the claim preparation time for OMA claimants.

We define claim processing time as the number of days between the application date for the claim and the release date of the claim on the platform's bulletin board. For comparison, we define claim preparation time as the number of days between the date when the claimant was diagnosed with a critical illness and the application date for the claim. To examine how claim processing by the OMA platform and claim preparation by OMA members are affected by the COVID-19 pandemic, we manually collect the whole claim data (a total of 203,244 claim cases from January 2019 to April 2022) from the bulletin board of the OMA platform and identify the city where each claimant was diagnosed with a critical illness. We then

construct an indicator variable (*COVID_dc*) that equals one if new confirmed COVID-19 cases are reported in the city during a specific time interval.[12] We estimate the following regression model:

$$Claim_Process(Claim_Prepare) = \alpha + \beta COVID_{dc} + \gamma' Control + \delta_{program} + \phi_{illness} + \gamma_{city*year} + \varphi_{month} + \varepsilon, \quad (2)$$

where *Claim_Process* represents the claim processing time of each case and *Claim_Prepare* represents the claim preparation time of each case. The key independent variable of interest is *COVID_dc*.[13] The control variables include the gender (*Gender*=1 for male and 0 for female), claimant's age and its square (*Age* and *AgeSq*), the timing of a OMA member's enrollment defined as the number of days between the inception date of the OMA platform and the member's enrollment date (*Joindays*), the amounts of indemnities that the claimant received from the OMA platform (*Indemnity*), and an ordinal variable ranging from 0 to 9 that proxies for the grade of the hospital where the claimant was diagnosed (*G_hostpital*). To ensure a clean identification, we include a bunch of fixed effects, including program type fixed effects, critical illness type fixed effects, city-year fixed effects, as well as month fixed effects. In this model

[12] One challenge lies in defining the time interval, as the length of claim preparation time and claim processing time varies significantly across claimants. If the time interval is defined as the claim preparation time (or processing time) for each case, the indicator variable (*COVID_dc*) is more likely to equal one when the time interval is longer, creating a spurious positive correlation between the COVID-19 pandemic and claim preparation time (or processing time). To address this concern, we define the time interval as the smaller of the claim preparation time (or processing time) for each case and the sample median. For example, if Claimant A has a claim processing time of 35 days, which is below the sample median of 55 days, the time interval for Claimant A is 35 days. Conversely, if Claimant B has a claim processing time of 60 days, the time interval for Claimant B is 55 days, the sample median of claim processing time.

[13] We also conduct a robustness check by defining the incidence of COVID-19 based on the city of each claimant's residence, rather than the city where the claimant was diagnosed with a critical illness. To implement this, we construct a dummy variable, *COVID_dr*, which equals one if new confirmed COVID-19 cases are reported during a specified time interval in the claimant's city of residence. The main results remain consistent and unchanged.

specification, for claim cases with the same critical illness under the same OMA program, the estimated effects of the COVID-19 pandemic on claim processing time (or preparation time) are derived solely from temporal variation in new COVID-19 confirmed cases over the time interval within a year at the same city, excluding variation in new COVID-19 confirmed cases across cities in the same month.

Table 9 presents the regression results examining the impact of the COVID-19 pandemic on claim processing time and claim preparation time. Notably, in our sample, approximately 84% of claimants chose to undergo checkups and receive medical treatment at local hospitals within their city of residence (referred to as "local claimants"), while the remaining 16% sought treatment at hospitals outside their city of residence (referred to as "external claimants"). We present the regression results for these two groups separately in Table 9. For local claimants, the claim preparation time increases by 16.5 days when new COVID-19 cases are confirmed in the city where the claimant was diagnosed, representing a 26.39% (44.53%) increase relative to the average (median) claim preparation time. In contrast, the claim processing time increases by only 2.3 days, corresponding to a 4.25% (4.20%) increase relative to the average (median) claim processing time. Similar conclusions are reached for external claimants. Relative to the profound impact of the COVID pandemic on claim preparation, its impact on claim processing is minimal.

Table 9 Claim preparation and processing time during the COVID-19 pandemic

This table reports the impact of the COVID-19 pandemic on claim processing time and claim preparation time. In columns (1) and (3), we present the results for local claimants, who chose to undergo checkups and receive medical treatment at local hospitals within their city of residence. In columns (2) and (4), we present the results for external claimants, who sought treatment at hospitals outside their city of residence. The dependent variable in column (1)

and (2) is *Claim_Prepare*, defined as the number of days between the date when the claimant was diagnosed with a critical illness and the application date for claim requests. The dependent variable in column (3) and (4) is *Claim_Process*, defined as the number of days between the application date for claim requests and the release date on the bulletin board of the OMA platform. The indicator variable *COVID_dc* indicates whether there are new confirmed COVID-19 cases in the city where the claimant was diagnosed over a time interval. The control variables include the gender (*Gender*=1 for male and 0 for female), claimant's age and its square (*Age* and *AgeSq*), the timing of enrollment defined as the number of days between the inception date of the OMA platform and the member's enrollment date (*Joindays*), the amounts of indemnities that the claimant received from the OMA platform (*Indemnity*), and an ordinal variable ranging from 0 to 9 that proxies for the grade of the hospital where the claimant was diagnosed (*G_hostpital*). We additionally control an array of fixed effects including the program type FEs, the critical illness type FEs, the city×year FEs, and the month FEs. The standard errors, clustered at the city×year level, are shown in parentheses. *, **, and *** represent the significance at the 10%, 5%, and 1% level, respectively.

	Claim preparation time		*Claim processing time*	
	Local	External	Local	External
	(1)	(2)	(3)	(4)
COVID_dc	16.475***	20.742***	2.310***	2.987***
	(1.213)	(2.422)	(0.606)	(0.937)
Gender	-1.551***	0.654	0.199**	0.201
	(0.493)	(1.110)	(0.092)	(0.234)
Age	-0.209*	0.427**	0.051**	0.118***
	(0.115)	(0.167)	(0.021)	(0.036)
AgeSq	0.005***	-0.002	0.000	-0.001
	(0.001)	(0.002)	(0.000)	(0.000)
Joindays	0.035***	0.034***	0.001***	0.000
	(0.003)	(0.005)	(0.000)	(0.000)
Indemnity	-0.725	-3.133	0.010***	0.010***
	(1.433)	(2.891)	(0.001)	(0.002)
G_hospital	-0.850***	-1.156*	0.004	0.087
	(0.192)	(0.600)	(0.034)	(0.110)
Program type FEs	YES	YES	YES	YES
Illness type FEs	YES	YES	YES	YES
City × Year FEs	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES
Constant	61.428***	48.823***	68.947***	68.325***
	(4.135)	(8.303)	(1.030)	(1.800)
Obs.	166,728	31,231	166,780	31,200

5.2 An Estimation on the Magnitude of Cost-Saving via OMA

Both developing and developed countries have spent an enormous amount of money and

launched a series of reforms to enhance the accessibility and affordability of health insurance, with a special focus on low-income individuals (Tebaldi, 2017; Finkelstein, Hendren, and Shepard, 2019; Lagomarsino et al., 2019; Banerjee et al., 2021). A prominent example is the United States, where the Affordable Care Act (ACA) was enacted in 2010 to expand insurance coverage. Despite this effort, during the post-ACA, pre-COVID period, 12.5% of individuals under 65 are uninsured at a point in time and 25% are uninsured at some point over a two-year span (Einav and Finkelstein, 2023). Under the U.S. health insurance scheme, federal government expenditures were about US$ 812 billion in 2014 and further rose to US$ 1.43 trillion in 2020.[14] The continuously rising healthcare costs discourage patients from seeking necessary medical services, even among those with health insurance coverage.[15]

The practice of OMA in China demonstrates that it is possible to address the healthcare needs of low-income individuals, enabling them to obtain coverage for critical illnesses through market forces. According to a 2020 survey conducted by the Research Institute of Ant Group, among 58,721 participants in OMA programs, 79.46% reported an annual income below 100,000 RMB (approximately US$13,889), and 68.40% had no private health insurance. China's innovations in the OMA sector offer a potential solution for other countries grappling with insufficient and high-cost health insurance systems.

In this section, we provide a back-of-the-envelope calculation to estimate the extent to which OMA reduces individuals' participation costs for sharing disease risks compared to

[14] Authors' calculations based on Hartman et al. (2022).

[15] According to the Health and Healthcare poll conducted by Gallup, 25% of Americans delayed treatment for a serious medical condition in 2019 due to high medical costs. The situation is more pronounced among low-income groups, with 36% of Americans from households earning less than USD $40,000 delaying treatment.

private health insurance. We calculate the average costs per member per year for both OMA and private insurance as follows:

(1) The average cost of OMA

We first calculate the average sharing costs of OMA members for each settlement period (the OMA platform has two settlement periods per month) by dividing the total sharing costs (the sum of benefits provided to claimants and management fees) by the number of OMA members participating in cost-sharing during that period. Next, we aggregate the average sharing costs across all periods from January 2019 to January 2022 and divide this total by the number of periods to obtain the period-level average sharing costs for OMA. The annual average sharing costs of OMA are then calculated by multiplying the period-level average by 24, representing the number of settlement periods in a year. Based on our calculations, this figure amounts to 91.42 RMB.

(2) The cost saving of OMA compared with private insurance

In comparison, the annual premiums for comparable private critical illness insurance with benefits of 300,000 RMB are between 1,800 RMB and 3,000 RMB.[16] The cost savings for each member would amount to at least 1,708.58 RMB, calculated as the difference between 1,800 RMB and 91.42 RMB.

According to the data from the Seventh National Population Census of China, as of November 2020, the population of China below the age of 70 was 1,293,149,004. If all the population below 70 participate in OMA rather than private critical illness insurance, the total

[16] https://asia.nikkei.com/Spotlight/Caixin/China-s-new-mutual-aid-platforms-fill-hole-in-health-care-coverage.

saving costs would amount to 2.21 trillion RMB (approximate US$306.87 billion) with the health care benefits of 387 trillion RMB=1.29 billion×300,000 RMB (approximate US$53.75 trillion).

6. Conclusion

We examine a novel health risk-sharing model in the FinTech era—online mutual aid. Using a random sample of proprietary member-level data and all claim data from a representative OMA platform in China, we provide a comprehensive analysis of its mechanisms and sustainability. Unlike traditional health insurance, OMA is characterized by three unique features: ex post cost sharing, lax enrollment criteria, and the extensive use of innovative digital technologies. We find that the ex-post cost sharing scheme achieves financial sustainability as evidenced in the progressive cross-subsidies in the cross-sectional dimension and advantageous selection in members' exit pattern in the dynamic dimension. We also find that the lax enrollment criteria cause adverse selection, but the OMA platform alleviates this problem by offering varying indemnities to different age cohorts and conducting stringent claims investigations. In addition, the use of cutting-edge technologies—such as blockchain, artificial intelligence, and smart contracts—enables the OMA platform to automate member participation, cost sharing, and claim processing. These technological advancements appear to have significantly enhanced the platform's resilience during the COVID-19 pandemic and substantially reduced operational costs.

Although several major OMA platforms voluntarily paused their businesses later due to lack of financial licenses, the documented OMA popularity indicates the urgent demand for

low-cost medical insurance services.[17] Our study provides not only policy recommendations for future OMA regulation but also an innovative approach to enhancing the accessibility and affordability of healthcare coverage at a low cost. We estimate that, compared to the average premiums charged by traditional insurers, OMA could save up to $306.87 billion annually, extending $53.75 trillion worth of healthcare benefits to the entire population under 70 in China. This demonstrates the potential of OMA to significantly improve the accessibility and affordability of healthcare globally, particularly during public health crises.

Notably, nearly all leading OMA platforms in China are embedded in super-apps launched by TechFin giants, enabling them to attract huge numbers of participants in a short time. By leveraging internet-based technologies, other countries can adopt the OMA model pioneered in China and extend this innovative risk-sharing approach to the general public. For instance, tech giants such as Meta and PayPal in the U.S. could launch their own OMA programs, utilizing their payment ecosystems to facilitate seamless ex-post cost sharing among members. Similarly, countries in South Asia have the potential to implement OMA programs, given the widespread adoption of super-apps like Grab and Gojek in the region.

[17] For a detailed discussion on the voluntary shutdown of several large OMA platforms and related regulatory considerations, please refer to the Appendix.

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