



Pandemic and insurance purchase: How do people respond to unprecedented risk and uncertainty?

Shuo Chen^{a,*}, Zhuoer Lin^{b,1}, Xuanyi Wang^{c,1}, Xian Xu^{a,1}

^a School of Economics, Fudan University, 600 Guoquan Road, Shanghai 200433, China

^b Department of Health Policy and Management, Yale University School of Public Health, 60 College Street, New Haven, CT 06510, USA

^c European Bank for Reconstruction and Development (EBRD), 5 Bank Street, E14 4BG, London, UK

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ABSTRACT

We investigate how people insure themselves against an upsurge of risk and uncertainty during a pandemic. Using high-frequency, city-level insurance purchases data from the largest online insurance platform in China, we employ difference-in-differences strategies to quantify changes in insurance purchases before and after the COVID-19 outbreak relative to a corresponding period in 2019. We show that the pandemic induces a substantial increase in daily number of insurance purchase, with evident impact on both health and life insurance. We demonstrate that the increase mainly originates from an expanded number of consumers; and is not driven by compositional shifts. Particularly, we show that the observed increase is better explained by pandemic risk exposure than other mechanisms such as negative emotions and insurance awareness. Nevertheless, there is a notable discrepancy between changes in insurance purchases and COVID-19 risk exposure, which is driven by individuals' lack of information on pandemic. We find that the more direct and high-quality information people have, the more likely their decisions are to accord with the objective risk exposure. These findings reveal the key driving forces of the risk management responses under an unprecedented pandemic, and point to the importance and necessity of public information disclosure.

1. Introduction

In December 2019, a novel coronavirus disease (COVID-19) was reported in the city of Wuhan of Hubei province in China (Munster, Koopmans, van Doremalen, van Riel, & de Wit, 2020). With massive human mobility and person-to-person transmission, the virus spread rapidly throughout the world and quickly evolved into a global pandemic (World Health Organization, 2020). By the end of 2021, totals of 282 million cases and 5.4 million deaths have been confirmed globally, covering 226 countries, areas, or territories (World Health Organization, 2022).

The pandemic has triggered unprecedented spikes in risks and uncertainty, bringing great challenges to the society (Baker, Bloom, Davis, & Terry, 2020). A growing number of studies is being conducted to understand the impact of the pandemic on global economy (Atkeson, 2020; Baker, Bloom, et al., 2020; Guerrieri, Lorenzoni, Straub, & Werning, 2020), social well-being (Adams & Walls, 2020; Pfefferbaum & North, 2020; Shachat, Walker, & Wei, 2021), and policy interventions (Fang, Wang, & Yang, 2020; Qiu, Chen, & Shi,

* Corresponding author.

E-mail addresses: cs@fudan.edu.cn (S. Chen), zhuoer.lin@yale.edu (Z. Lin), xuanyi.wang@ebrd.com (X. Wang), xianxu@fudan.edu.cn (X. Xu).

¹ Co-first authors. The authors contributed equally to this work and were ordered alphabetically.

2020). Among them, one emerging strand of literature specifically focuses on economic behaviors under the pandemic, such as household spending (Baker, Farrokhnia, Meyer, Pagel, & Yannelis, 2020), consumption (Chen, Qian, & Wen, 2021), and labor market performance (Coibion, Gorodnichenko, & Weber, 2020; Kahn, Lange, & Wiczer, 2020). However, facing the massive risks and uncertainty, no study to date has examined how individuals insure themselves against the soaring risks and the extent to which their insurance decisions are rational. To fill the gap, this study explores the extent to which people employ insurance as a coping strategy for pandemic risk control. In particular, we attempt to answer two research questions: (a) Under the massive economic shock and the pandemic, can people actively respond to the soaring risks through the purchases of insurance? (b) If so, what are the driving forces of the insurance take-up decisions? Are the decisions rational in such unparalleled situation? Answers to these questions may have valuable implications for policies and practices.

Using pandemic and insurance purchases data in China, this study provides novel evidence on the impact of COVID-19 pandemic on insurance purchases, revealing key determinants of risk management behaviors during a pandemic. As the first country to experience the pandemic and face the massive spikes in risks and uncertainty, China is a valuable setting to understand changes in economic behaviors in such situation. In particular, the emergence of COVID-19 is an especially strong and unpredictable shock for the people back then as they are the very first to face this unknown and deadly virus with almost no effective treatment. This provides an exogenous, natural experiment to quantify the relative changes of insurance purchases before and after the COVID-19 pandemic. Moreover, the rich temporal and geographic variations in the COVID-19 risk exposure allow us to further investigate the underlying driving forces of the responses, and examine whether the major changes in insurance purchases are mainly explained by the dynamic changes in the COVID-19 risk exposure or other mechanisms.

In this study, insurance data are obtained from the largest private online insurance platform in China, which had in total insured >100 million people by the end of 2019. The great accessibility and responsiveness of the online platform makes it an excellent source of data to investigate insurance purchases behaviors. We use every two-day insurance purchases data from Dec 01, 2019 to Mar 16, 2020 (2019–2020) and the corresponding period in 2018–2019 for 294 prefecture-level cities; and a difference-in-differences (DID) approach is employed to identify the impact of COVID-19 pandemic on insurance purchases. Following prior literature (Brodeur, Clark, Fleche, & Powdhavee, 2021; Chen et al., 2021; Fang et al., 2020; He, Pan, & Tanaka, 2020), we consider 2019–2020 observations as a treatment group and 2018–2019 observations as a counterfactual control group.² Using the emergence of first COVID-19 cases in each prefecture city as a proximate start date for the COVID-19 outbreak, we estimate the changes in insurance purchases before and after the outbreak in the treatment period relative to the control.³ Our results indicate that the COVID-19 pandemic induces a substantial increase in the daily number of insurance purchases, with an average daily increase of 135% per city. The number of insurance purchases grows increasingly and dramatically in the initial few weeks, followed by a large but slightly shrinking percentage increase.⁴ Nonetheless, the increases in insurance purchases are not universal across insurance types. We show that the pandemic primarily increases the purchases of health insurance and life insurance; while for fields of insurance that had low risks during the pandemic (e.g., travel insurance), the purchases decrease.⁵

To further understand the market changes, we examine whether the increase in insurance purchases mainly reflects the changes at the extensive margin or the intensive margin. We show that the increases in insurance purchases is predominantly attributed to the sharp rise (169%) in the number of consumers (i.e., extensive margin) rather than insurance purchases per consumer (i.e., intensive margin), which implies an expanded number of people start to take up insurance during the pandemic. Moreover, we indicate that the increases are evident across a variety of consumer groups, though the magnitudes differ to some degrees. Females respond in a larger magnitude than males; and younger-aged and older-aged consumers reveal less of increases than do middle-aged consumers.

As for the underlying mechanisms, we first show that the pandemic effect is not driven by the compositional shifts from offline to online purchases related to lockdown and policy restrictions, and the effect is fairly large and evident even after accounting for such changes. Then, we test three important mechanisms suggested by prior literature that may potentially link the pandemic and insurance take-up decisions: *objective risks*, *negative emotions*, and *insurance awareness*. First, as insurance decisions largely depend on individuals' risk perceptions (Johnson, Hershey, Meszaros, & Kunreuther, 1993; Kunreuther & Pauly, 2006), the massive spike in risks and uncertainty induced by the pandemic (Baker, Bloom, et al., 2020) may drive up individuals' perceptions of risks and consequently affect their insurance take-up decisions. Second, during the pandemic an increased level of negative emotions such as fear, anxiety, and depression, may also affect individuals' insurance purchases by distorting their risk perceptions and decision-making (Bavel et al., 2020; Berezin, 2010; Harlé, Allen, & Sanfey, 2010; Hartley & Phelps, 2012; Simon, 1987). Finally, insurance purchases may change as

² This DID specification has the advantages of a clearer definition of comparison groups and an increased comparability between treatments and controls, compared to geographic DID that make comparison between cities with and without (severe) COVID-19 exposure. Importantly, it avoids the possible spillover and interference between treatments and controls that tend to be salient in geographic DID, thus is much less likely to suffer from attenuation bias. In fact, the spillover and interference problem could be large in geographic DID: even for cities with low COVID-19 cases, the emerging cases in neighbor cities and the soaring risks of the pandemic in the nation, might still to some extent affect their level of risk perceptions and insurance purchases. Nevertheless, in Appendix Table A2, we show the estimates of geographic DID and the results are robust to the specification.

³ An underlying assumption of this strategy is that the insurance purchases need to follow a common trend in 2019–2020 and 2018–2019 periods in the absence of COVID-19. Our data in Figs. 1 and 2 indicate that this is not likely to be a big concern. In particular, 2019–2020 and 2018–2019 have similar pre-treatment trends.

⁴ The findings are robust when accounting for different trends in treatments and controls, or controlling for supply-side changes, suggesting an active response to the pandemic.

⁵ The analysis has controlled for the supply-side liability changes for different types of insurance.

more people realize the important role of insurance and recognize it as a coping strategy under the pandemic (Wang et al., 2012). Focusing on the three suggested mechanisms, we show that the dynamic changes in objective risks of COVID-19 explain the largest portion of the baseline effect. Exposure to higher risks (i.e., more COVID-19 confirmed cases) lead to greater increases in the insurance purchases at the daily-city level. By contrast, people with higher levels of negative emotions are less likely to consider insurance as a coping strategy; and we find no evidence showing the impact of insurance awareness on insurance take-up decisions.⁶

Nevertheless, the three suggested mechanisms only account for some proportion of variations in insurance purchase decisions. In particular, the changes in insurance take-up cannot be largely explained by the geographic and temporal changes or differences in objective COVID-19 risk exposure, which may suggest potential biases in risk perceptions and economic decisions. Given the essential role of information in individuals' risk assessment and decision-making (Johnson et al., 1993; Spence & Zeckhauser, 1978), we hypothesize that the insurance decision making is bounded by the amount of information or knowledge people have about the pandemic (Gigerenzer & Selten, 2002).⁷ In other words, information and experience may influence or moderate the relationship between objective risk exposure and insurance purchases. To assess the role of information, we stratify our sample by the magnitude and the quality of information people are exposed to at the time of the COVID-19 outbreak, and calculate the relative proportion of pandemic effects that is explained by objective pandemic risks. We show that the insurance purchases or take-up decisions are far more likely to be explained by the objective risks among cities with more direct experience of the pandemic (i.e., cities in Hubei province) than others. Besides, we demonstrate that the quality of information is also important for the take-up decisions. People who are exposed to more direct and high-quality information of pandemic (i.e., COVID-19 statistics updates) tend to make the decisions more consistently with the risk exposure. Lastly, we test the influence of past pandemic experience and knowledge (e.g., 2003 SARS or 2009 H1N1 pandemic) on take-up decisions, where we find the exposure to the most recent pandemic of H1N1 can also lead to more rational decision-making during the current pandemic. These findings, overall, point to the importance of direct and high-quality information for insurance take-up decisions at the time of a pandemic.

This paper contributes to existing insights in three major ways. First of all, our study joins a growing body of studies on the economic responses to the COVID-19 pandemic. Among them, the most relevant work is on household spending and consumption. For instance, Chen et al. (2021) find daily offline consumption in China fell by 32% during the pandemic and it responded negatively to the day-to-day reported changes in epidemic severity. Baker et al. (2020) find household spending in the United States increased sharply at the beginning of the pandemic but was followed by a sharp decline. However, to our best knowledge, no study to date investigates the insurance purchases behavior using high-frequency, city-level data, which could have quite different responses of changes to the pandemic compared to consumption in other categories. In particular, a nationwide upsurge in risks might drive people to increase their insurance purchases to avoid economic loss. Our results demonstrate that the pandemic co-occurs with a huge increase in insurance purchases with an expanded group of consumers, contrasting with the decreases observed in offline consumption and household spending. It implies that people do recognize the role of insurance in risk management and are willing to respond actively to the risks through the purchases of insurances, even though their levels of wealth and consumption are negatively affected by the pandemic (Baker, Farrokhnia, et al., 2020; Chen et al., 2021). Our study thus provides initial evidence on the patterns of insurance purchases associated with the COVID-19 pandemic and suggests the risk management responses individuals may have during a pandemic.

Additionally, this paper adds to an emerging set of research that link insurance purchase behaviors with natural disasters.⁸ There is growing evidence that the experience of flood and earthquake may lead to an elevated level of insurance demands for flood insurance (Gallagher, 2014) or earthquake insurance (Lin, 2020). Besides, the exposure of environmental health risks, such as air pollution, may also affect the insurance take-up decisions for health insurance (Chang, Huang, & Wang, 2018). In this study, we explore the insurance purchase decisions under the COVID-19 pandemic, which is a setting that is fundamentally different from other natural disasters. Particularly, while most of the natural disasters are infrequent, stochastic events, their origins and impacts are well-understood and the likelihood of an event is even predictable based on historical records (Gallagher, 2014). People usually have common knowledge on a certain natural disaster and can access detailed information on it whenever they want (e.g., flood). In contrast, the COVID-19 pandemic is an event that encompasses unprecedented risks and uncertainty. The infectiousness, prevalence, lethality of virus was unknown to the general public, and the duration and size of the pandemic could be hardly predictable when the pandemic first occurred (Baker, Bloom, et al., 2020). The decisions made in such setting to a larger extent depend on real-time observation rather than prior belief. This study thus provides first evidence on how people respond to an unparalleled disaster. In particular, we indicate that, under such uncertainty, people's decisions are hardly consistent with the objective risks they are exposed to; and the quality and amount of information people have for the emerging risks may have big impact on the rationality of insurance purchase decisions, which speaks to

⁶ We perform the standard three-step mediation type of analyses, where we assess (1) the effect of pandemic on mediators; (2) the effect of pandemic on insurance purchases; and (3) the effect of pandemic and mediators on insurance purchases. The results indicate that only objective risk exposure and negative emotions satisfy the three conditions of mediation effect and should be considered as valid mediators that explain the effect of pandemic on insurance purchases. By contrast, insurance awareness has no significant mediating effect.

⁷ In fact, people generally had limited information of COVID-19 during the initial stage of the pandemic.

⁸ Epidemic is a major type of natural disaster according to the classification of the International Disaster Database EM-DAT (<https://www.emdat.be/classification>).

the importance of information disclosure in a pandemic. In addition, this paper differs from previous studies in that it examines all types of insurance rather than a single type of disaster insurance (e.g., earthquake or flood insurance). We find that the COVID-19 pandemic can have positive effects on the demand of health and life insurances, advancing our knowledge on the impact of natural disaster on general insurance purchases.

Finally, this paper contributes to studies on the relationship between emotion and decision-making. Existing literature demonstrates that emotions often distort risk perceptions (Loewenstein, Weber, Hsee, & Welch, 2001; Slovic, Finucane, Peters, & MacGregor, 2004) and induce irrational economic decisions (Gao & Schmidt, 2005; Simon, 1987). Specifically, decision-making is often disturbed by fear (Witte & Allen, 2000), anxiety (Hartley & Phelps, 2012), depression (Harlé et al., 2010), and other emotions (Grable & Roszkowski, 2008; Nobrega, Hedayatmofidi, & Lobo, 2016). In this study, we find that negative emotions can negatively affect the insurance take-up decisions during the pandemic. Although we are not able to draw conclusion on its welfare implications, the finding does suggest the real-world impact of negative emotions on risk perceptions and financial decisions. Hence, future studies may use the pandemic as a test base to explore the relationship between emotions and other types of economic decisions.

The remainder of this paper is organized as follows. Section 2 describes data and variables. Section 3 introduces identifying strategy and econometric models. Section 4 presents baseline results and discusses heterogeneity. Section 5 examines pathways and mechanisms. Section 6 concludes.

2. Data and variables

2.1. Insurance data

Insurance data are obtained from the largest online insurance platform in China. Three features tend to make our data unique and valuable. First, the insurance platform covers a wide range of population and insurance services. By the end of 2019, it had insured >100 million users in total, and approximately one in every 15 persons in China had ever purchased insurance from it. The products the platform offers also contain all the typical types of insurance prevalent in China, guaranteeing the coverage of our insurance data. Second, the insurance platform closely connects with the two dominant social medium, instant messenger, and payment platforms in China, which have >1 billion monthly active users. The extensive coverage of the social medium thus ensures the accessibility of the insurance platform. Third, insurance purchases from the online platform are fairly easy and convenient. Consumers can browse insurance products and complete purchases solely relying on the social medium platforms and embedded payment tool, which is exceptionally important under a large-scale shutdown. The insurance platform, thus, may reflect and capture changes in insurance purchases instantly, especially during the pandemic.

In our study, aggregate insurance purchases data for 294 prefecture-level cities are collected every two days by the insurance platform, from Dec 01, 2019 to Mar 16, 2020 (2019–2020), and from a corresponding period in 2018–2019, which offers 27,342 observations.⁹ In particular, data on the total number of consumers are available for different ages, genders, and insurance beneficiaries, which enables us to explore the heterogeneity of the pandemic effects. The platform also provides purchases data for each type of insurance, including health insurance, life insurance, and other types of insurance (e.g., accident insurance and travel insurance).

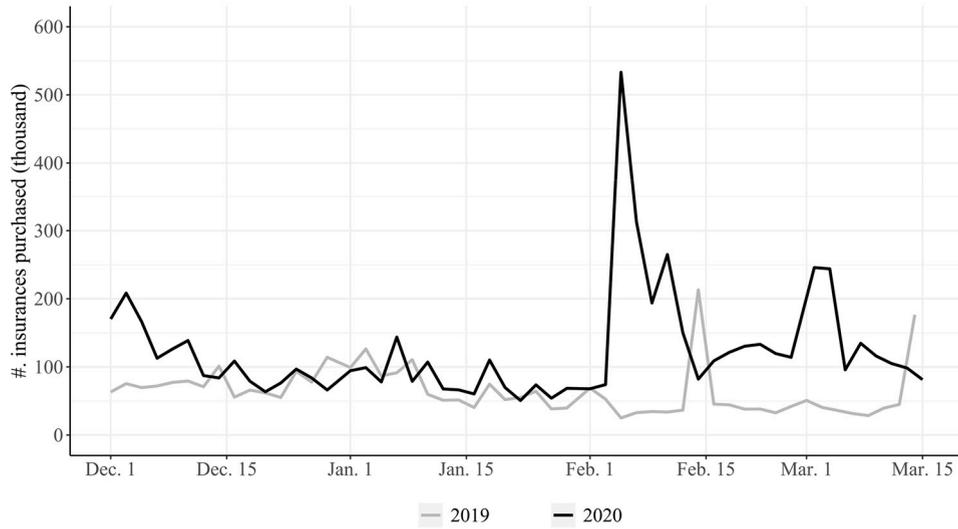
In Fig. 1 panel A, we present the dynamic time trends of national, daily insurance purchases for both treatment group (2019–2020 period; black line) and control group (2018–2019 period; grey line). As illustrated in the figure, in late January and early February of 2020, shortly after the COVID-19 outbreak, the number of insurance purchases grows increasingly and dramatically, while such is not the case for the corresponding period in 2019, which provides preliminary evidence on the pandemic's effects on insurance purchases. In addition, we find that insurance purchases in 2019 and 2020 follow similar trends before the COVID-19 outbreak in each city (i.e., "pre-treatment period"), suggesting the parallel trend assumption between treatments and controls are empirically plausible.¹⁰ On the other hand, in Fig. 1 panel B, we illustrate the geographic variations of insurance purchases over time. Panel B indicates that, compared to the 2018–2019 period (i.e., the top two maps),¹¹ insurance purchases increase much more substantially during the 2019–2020 period (i.e., the bottom two maps). Besides, we observe large geographic disparities in the figure, both in benchmark levels and in changes over time, which deserves further investigation.

⁹ We do apply for the data with longer sample periods as well as the data at daily-city level, but we are not allowed to extract this information due to confidentiality concerns.

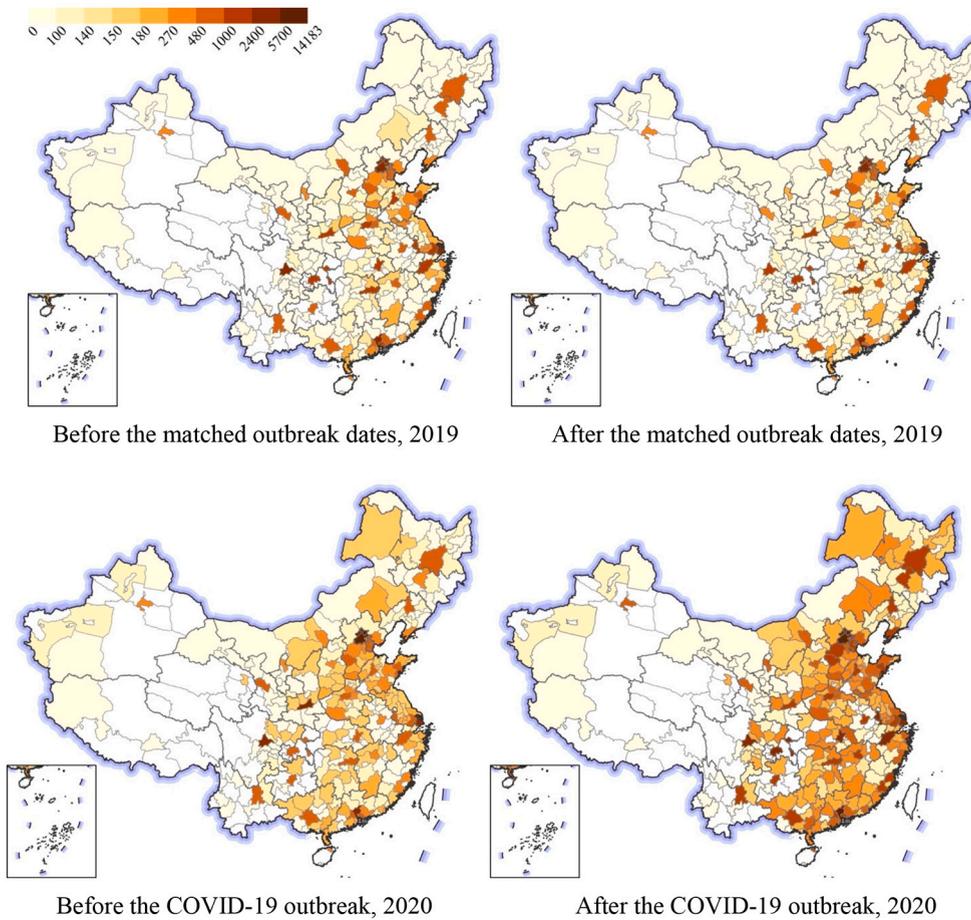
¹⁰ In the Model section (i.e., Section 3), we discuss the comparability and the validity of treatment and control groups in details.

¹¹ In fact, the insurance purchases even slightly decrease during the 2018–2019 control periods.

Panel A: The time trends of insurance purchases for 2018-2019 and 2019-2020 periods



Panel B: The geographic variations of insurance purchases for 2018-2019 and 2019-2020 periods



(caption on next page)

Fig. 1. The temporal and geographic variations of insurance purchases.

Panel A: The time trends of insurance purchases for 2018–2019 and 2019–2020 periods.

Panel B: The geographic variations of insurance purchases for 2018–2019 and 2019–2020 periods.

Notes: Panel A shows the time trends for the daily number of insurance purchases (in 1000 s) in China respectively for 2019 (grey line) and 2020 (black line). Panel B illustrates the average number of insurance purchases per day for each prefecture-level city (294 cities in total) in China. The two maps at the bottom respectively present the distributions before the COVID-19 outbreak and after the outbreak for 2020, while the top two maps present the corresponding distributions for 2019. The outbreak dates for 2019 are matched using lunar calendar. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Mechanism variables

The pandemic may induce changes in purchase of insurance potentially through three major pathways, including *objective pandemic risks*, *negative emotions*, and *insurance awareness*.¹² To disentangle the pandemic effects attributable to the three pathways, we perform classical mediation type of analyses and introduce three sets of time-varying mechanism variables into the right-hand side of our DID model to illuminate the underlying mechanisms.¹³

2.2.1. The measurement of objective pandemic risks

Following prior literature (Chen et al., 2021; Fang et al., 2020; Qiu et al., 2020), pandemic risks are measured by the number of COVID-19 confirmed cases in daily-city level, which captures the objective risk of exposure within each city. Specifically, our data are acquired from the Chinese Center for Disease Control and Prevention (China CDC). We collect daily cumulative numbers of COVID-19 confirmed cases for each prefecture-level city from the first day that COVID-19 cases were reported, to the last day of our study periods. In total, the data cover 77,715 of COVID-19 confirmed cases in 294 prefecture-level cities in China. This time-varying variable thus encompasses both temporal and geographic variations as illustrated in Appendix Fig. A1. Panel A shows that the number of confirmed cases increases exponentially right after the emergence of COVID-19 in each city, indicating the rapid transmission of the virus and its great temporal variations; on the other hand, Panel B shows that there are also large geographic variations in pandemic risks. The “risk” variable thus can capture the dynamic variations at both the daily and city level; and by including this variable into the model, we are able to decompose the average treatment effect captured in the main DID estimate.

2.2.2. The measurement of negative emotions

Anxiety, fear, depression and other negative emotions may also distort risk perceptions and induce changes in insurance purchases. In this study, we use the searching frequency of mental health counseling as a measure of negative emotions based on Baidu Index. As the leading search engine in China, Baidu provides internet search services for the majority of Chinese users (over 80%) and collects timely search history data. Similar to Google Trends, it calculates and publishes an index called Baidu Index to report the weighted sum of the search volume for every particular keywords at the city-day level.¹⁴ It is increasingly recognized as a valuable source of data to monitor the temporal and geographical variation of searching frequencies (Brodeur et al., 2021; Carneiro & Mylonakis, 2009; Preis, Moat, & Stanley, 2013). The use of Baidu Index to measure health and well-being (e.g., negative emotion) is also very common and widely accepted in social science and public health literature, especially those related to COVID-19 (Chen et al., 2020; Fang et al., 2021; Wang, Xiao, Lin, Tang, & Unger, 2022). In specific, we use “mental health/psychological” + “counseling/services/hotlines” as our keywords to extract the Baidu Index at the city-day level and match it with our insurance data. We use this variable because during the pandemic, many people in China experience anxiety and mental health problems; and as a coping strategy, people seek for mental health services or psychological hotlines (Liu et al., 2020). The searching history of mental health counseling, thus, can be an objective measure of negative emotions.

2.2.3. The measurement of insurance awareness

Another potential pathway of the pandemic effect is insurance awareness. In this study, insurance awareness is similarly measured based on the Baidu Index, an open-access database of online searching frequency. We use “bao xian” (i.e., translated to “insurance” in English) as our keyword to extract the Baidu Index at the city-day level, and consider “insurance” searching frequency as an objective measure for insurance awareness. Such type of indexes have been increasingly used in economic research to monitor the temporal and geographical variations in the market changes (Brodeur et al., 2021; Preis et al., 2013; Wen, Xu, Ouyang, & Kou, 2019; Zhang & Wang, 2015). Particularly, the Index has been recognized as a rich measure to reflect consumers/investors’ interests and focuses (Preis et al., 2013; Wen et al., 2019; Zhang & Wang, 2015); and has been validated in Chinese studies to understand market attention (Wen et al., 2019; Zhang & Wang, 2015). Existing studies therefore provide grounded supports for the representativeness, effectiveness and validity of using Baidu Index to monitor the daily-city-level change in insurance awareness. While this may not fully account for

¹² There are certainly other factors, such as risk attitude and risk beliefs. But these factors are difficult to be directly tested without panel survey data.

¹³ As we highlight in Section 3 and 6, this type of analyses may not be causal, some biases may exist; nevertheless, it provides valuable and suggestive evidence that can help us understand the possible mechanisms, which may inspire future research to further explore these pathways with other data and variables.

¹⁴ Baidu index is essentially a Chinese version of Google Trends.

insurance awareness, it may serve as a proxy measure to capture the variations and changes in public consciousness, awareness, and attentiveness to the topic.

2.3. Variables of information and experience

To examine the impact of information and experience on the rational insurance purchase behaviors, we construct several variables to respectively measure the *magnitude* and the *quality* of information disclosure, as well as the experience of past pandemic/epidemic.

Information disclosure is mainly assessed by the information that is publicly disclosed by the local governments in social media. In specific, we web scrap all the tweets published by official accounts in Sina Weibo (the largest microblog platform) during our study periods.¹⁵ Similar to Twitter, Weibo is the largest microblogging platform and one of the most influential social media in China. It has about 500 million active users and is the one of the most prominent ways for the public communications. In our study, we use tweets data to measure the amount of information disclosure. The approach have been widely adopted in economic and political science research to understand policy/political related issues (Anderson, Buntaine, Liu, & Zhang, 2019; Barberá et al., 2019; Gorodnichenko, Pham, & Talavera, 2021; Hobbs & Lajevardi, 2019; Indaco, 2020; Munger, Bonneau, Nagler, & Tucker, 2019). Studies in China further testify the use of Weibo to understand the public information disclosure and communication (Anderson et al., 2019; Rauchfleisch & Schäfer, 2015; Wang, 2013). In our study, we count the total number of words in every tweets that contain keywords related to “COVID-19”, “coronavirus” and “pandemic” as a measure for the *magnitude* of information disclosure. On the other hand, we evaluate the quality of information by the number of high-quality tweets posted by local governments that are tagged as popular science, as well as by the number of government updates on COVID-19 statistics (e.g., suspect cases, confirmed cases, deaths); cities are then stratified based on their relative level of information quality.

As for the past pandemic/epidemic experience, there are two major epidemics that have left deep impressions on Chinese population in the past decades: one is 2003 SARS, which is similar to COVID-19 but not that severe (Pang et al., 2003); and the other is 2009 H1N1, which is the most recent large-scale epidemic in China other than COVID-19 (Fang et al., 2012). The strength of the pandemic experience is respectively evaluated by the corresponding number of total confirmed cases at each province.

The descriptive statistics of variables and measures used in our study are presented in Table 1 and Appendix Table A1.

3. Identification strategy and empirical models

To estimate the effects of the COVID-19 pandemic on insurance purchases, we employ a difference-in-differences (DID) strategy that has been increasingly used in recent studies on COVID-19 (Brodeur et al., 2021; Chen et al., 2021; Fang et al., 2020; He et al., 2020).¹⁶ The regression equation can be specified as follows,

$$Y_{it} = \alpha + \beta_1 Treat \times Post_{it} + Treat + Post_{it} + \lambda_i + \omega_t + \varepsilon_{it} \quad (1)$$

where Y_{it} represents the outcomes of insurance purchases measured in prefecture-level city i , at time t , such as the log number of insurance purchases and the log number of consumers. The dummy variable $Treat$ is defined as 1 for 2019–2020 observations and 0 for 2018–2019 observations. For 2019–2020 observations, $Post_{it}$ is defined as 1 after the emergence of first COVID-19 cases in city i , and 0 otherwise¹⁷; for 2018–2019 observations, $Post_{it}$ is defined as 1 after the corresponding dates matched using the lunar calendar for 2018–2019 observations, and 0 otherwise. λ_i are city-fixed effects that control for the time-invariant unobservables across cities, such as GDP per capita and population size. ω_t are date-fixed effects that account for the time-related differences.¹⁸ β_1 accordingly, estimates the differences of changes between treatment periods and parallel control periods, before and after the COVID-19 outbreak (Brodeur et al., 2021; Chen et al., 2021; Fang et al., 2020; He et al., 2020), thus capturing the average treatment effect of the COVID-19 pandemic on insurance purchases. We also use Eq. (1) to examine and compare the responses of insurance purchases across ages, genders, and insurance beneficiaries, to examine the effect heterogeneity.

We adopt this DID strategy for two major reasons. On the one hand, the use of 2019–2020 as treatments and 2018–2019 as controls can address the potential interference and spillover between treatments and controls that may be salient in the classical geographic DID specification (which makes comparisons between cities with more versus less COVID-19 exposure). As almost all cities in China experienced COVID-19 epidemic and the pandemic were deadly and unprecedented for people back then, exposure to COVID-19 (even less severe) would be a big shock to them and thereby affected the insurance purchases for all cities. Besides, even for cities with low COVID-19 exposure, the emerging pandemic in the province and the nation might still affect the local level of risk perceptions and

¹⁵ Weibo is a major source of information Chinese people obtain information from. Among the 294 prefecture-level cities, 268 had official Weibo accounts and 266 ever posted tweets in the sample period. In particular, 243 cities, on average, posted at least one tweet each day.

¹⁶ This strategy has been increasingly used in COVID-19 research because it can address the potential interference and spillover between treatments and controls in the geographic DID (which makes comparisons between high-risk cities and low-risk cities over a same observation period).

¹⁷ The emergence of first COVID-19 cases can be defined as early as Jan 20, 2020, when the Chinese government first officially announce the existence and control of the COVID-19. Although the initial cases occurred in Wuhan were later confirmed as COVID-19, they were not officially recognized as a public health issue until Jan 20, 2020. We adopt this as our main specification to ensure the best accuracy of the timing, and our results are fairly robust to the alternative definitions.

¹⁸ We also follow the methods used in Besley and Burgess (2004) to account for the potential differences in time trend, and allow cities to have different time trends in 2018–2019 and 2019–2020; the results are also similar to the estimates in the baseline.

Table 1
Descriptive statistics.

Variable	Source	N	Mean	S.D.
Key Dependent Variables				
#. insurance purchases	The insurance platform	27,342	321.487	986.771
#. platform visits	The insurance platform	27,342	1915.21	4575.56
#. insurance purchase per visit	The insurance platform	27,342	0.168	0.124
#. consumers	The insurance platform	27,342	196.355	730.485
#. insurance purchases per consumer	The insurance platform	27,276	1.925	0.599
Key Independent Variables				
Treat	Authors' definition	27,342	0.495	0.500
Post	Authors' definition	27,342	0.405	0.491
Treat × Post	Authors' definition	27,342	0.197	0.398
Other Variables				
Baidu index of insurance	Baidu Index	26,877	71.430	65.422
Baidu index of mental health counseling	Baidu Index	26,877	0.969	7.993
#. of confirmed cases	China CDC	27,342	34.658	919.893
#. of SARS cases in 2003	MOH, China	27,342	160.459	414.454
#. of H1N1 cases in 2009	MOH, China	27,342	2400.40	2336.91
#. words in COVID-19 tweets from gov.	Weibo	27,342	776.824	3021.70
#. of tweets tagged as popular science	Weibo	27,342	0.425	1.802
#. of tweets disclosing COVID statistics	Weibo	27,342	0.589	2.116

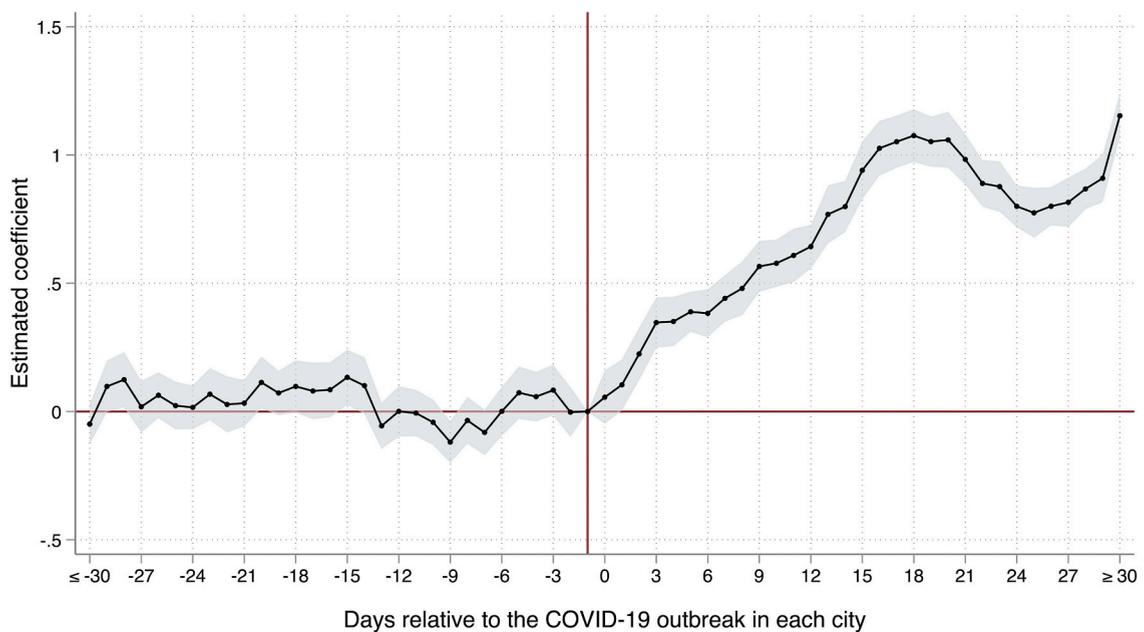


Fig. 2. The dynamic effects of the COVID-19 pandemic on the number of insurance purchases.
Notes: The dynamic effects are estimated using a DID regression by interacting pretreatment dummies (before the COVID outbreak in each city) and posttreatment dummies (after the outbreak) with the treatment dummy. Each black point denotes the estimated coefficient of the interaction term, which represents the estimated change of average daily insurance purchases between the periods (of X axis) in 2020 and the corresponding periods in 2019 matched using the lunar calendar date. The shaded area indicates the 95% confidence intervals of the estimated effects. The vertical line denotes the date of COVID-19 outbreak (the emergence of first COVID-19 cases) in each city. Standard errors are clustered at prefecture-city level.

insurance purchases. The spillover and interference therefore would lead to substantial attenuation biases and great underestimation. This issue is much less salient in our setting because the observations in 2018–2019 (i.e., control group) are almost surely unaffected by the COVID-19 pandemic and the related changes in 2020, which eliminates the possibility of interference and spillover and ensure the clean comparisons between treatment and control.¹⁹ On the other hand, the use of first case at the city-level as the start of outbreak explicitly accounts for the geographic and temporal variation in outbreak timing and help us better differentiate between the pandemic effect and the effect driven by other policy changes (e.g., lockdown). As shown in Fig. A1, the number of COVID-19 cases increase exponentially right after the first date in each city, indicating a rapid and sudden disease outbreak. The emergence of first COVID cases at the local city level thus signals the rapid transition from non-COVID to COVID-19 pandemic for the local residents; and the use of different timing for each city can effectively capture such changes and transitions. Additionally, the use of first emergence of COVID cases at the city level as the start time can greatly reduce the overlap between the time of pandemic and other policy changes (e.g., lockdown), allowing us to further decompose the various sources of changes.

Moreover, to characterize the dynamic evolution of the pandemic effects, we introduce the following model,

$$Y_{it} = \alpha + \sum_{j=-m}^m \beta_j \text{Treat} \times \text{Post}_{itj} + \text{Treat} + \text{Post}_{it} + \lambda_i + \omega_t + \varepsilon_{it} \quad (2)$$

where Post_{itj} represents a set of dummy variables that are defined as 1 for j days relative to the COVID-19 outbreak in each prefecture city. In specific, we include 30 dummies before the outbreak to denote pretreatment periods, and 30 dummies after the outbreak to denote as posttreatment periods. β_j then estimate the changes in insurance purchases at each time period relative to the outbreak.

Lastly, to understand the mechanisms through which the pandemic may affect insurance purchases, we introduce three sets of time-varying variables into the baseline DID model (i.e., Eq. (1)) to parse out the differential effects of *objective pandemic risks*, *negative emotions*, and *insurance awareness*. The regression model is specified below:

$$Y_{it} = \alpha + \beta_1 \text{Treat} \times \text{Post}_{it} + \beta_2 \text{Risk}_{it} + \beta_3 \text{Emotion}_{it} + \beta_4 \text{Awareness}_{it} + \text{Treat} + \text{Post}_{it} + \lambda_i + \omega_t + \varepsilon_{it} \quad (3)$$

where Risk_{it} denotes the risk measure, i.e., the number of COVID-19 confirmed cases, in city i , time t . Emotion_{it} denotes the level of negative emotions, and Awareness_{it} denotes the level of insurance awareness in city i , time t . By adding these time-varying measures into the model, we are able to understand: 1) the dynamic relationship between the mechanism variables and the insurance purchases; 2) how much of the (average) changes in insurance purchases before and after the outbreak (i.e., main DID estimate) can be explained by the dynamic changes in these mechanism variables.²⁰ β_2 thus accordingly captures the changes in insurance purchases attributable to pandemic risks; and β_3 captures the changes attributable to negative emotions, and β_4 captures the changes attributable to insurance awareness. These variables are added cumulatively into the model to disentangle their independent effects on insurance purchases. While this mechanism analysis is not causal and can only provide some suggestive evidence, it may have important implications for related policy and practice.

4. The impacts of COVID-19 pandemic on insurance purchase

4.1. Impacts of the pandemic at an aggregate level

We estimate the average treatment effects of the COVID-19 pandemic on insurance purchases using a DID model (Eq. (1)), which quantifies the relative changes in insurance purchases before and after the COVID-19 outbreak for each city in the treatment group (2019–2020 observations) relative to the control group (2018–2019 observations). In Table 2, we present the estimated effects for different outcomes, where column 1 shows the estimates using the log number of insurance purchases as our main outcome; and columns 2 and 3 present the estimates using the log number of platform visits and the log number of insurance purchases per visit as our additional outcomes. We find that the quantities of insurance purchases and platform visits increase dramatically after the pandemic. Specifically, the coefficient of the interaction term $2020 \times \text{Post}$ (in column 1) indicates that, the COVID-19 pandemic in 2020 increases the number of insurance purchases by 135% (i.e., $\exp(0.855) - 1$) relative to the counterfactual periods without the COVID-19 pandemic, which is a huge pandemic effect. Although the pandemic also increases the number of platform visits as shown in column 2, the effect (70%) is smaller than that for the quantity of insurance purchases. Thus, in column 3, we observe an increased number of insurance purchases per platform visit (2.17%), suggesting a slightly accelerated decision-making manner of purchases

¹⁹ Although this strategy is grounded on the assumption that the treatment period should follow a common time trend as control period in the absence of COVID-19, our raw data in Fig. 1 and the dynamic estimates in Fig. 2 shows that this is not likely to be a big concern.

²⁰ This is essentially a mediation type of analyses that parse out the effect by including potential mediators. This is not causal. As we will present in Section 5.2, we follow the standard Baron and Kenny three-steps approach to first 1) test whether the mechanism variable changes before and after the COVID outbreak; and then 2) test whether the insurance purchases change before and after the COVID outbreak; and finally, 3) test whether the dynamic changes in mechanism variable are significantly associated with the dynamic changes in insurance purchases.

Table 2
The effects of the COVID-19 pandemic on insurance purchases.

	(1)	(2)	(3)
	Log number of insurance purchases	Log number of platform visits	Log number of insurance purchases per visit
2020 × Post	0.855*** (0.018) [135.10%]	0.532*** (0.017) [70.32%]	0.021*** (0.002) [2.17%]
Constant	4.464*** (0.004)	6.486*** (0.003)	0.146*** (0.000)
Observations	27,342	27,342	27,342
R-squared	0.908	0.954	0.547
Prefecture FE	YES	YES	YES
Date FE	YES	YES	YES
Treat and Post FE	YES	YES	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. The percentage changes shown in square brackets are calculated using the corresponding coefficient estimates (i.e., $\exp(\beta) - 1$). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

during the pandemic.²¹

The results are fairly robust to the alternative specifications as shown in Table A2. First, we show that the effects on insurance purchases are similar when we define the time of the outbreak at broader levels, such as at the provincial level or national level, which might be earlier than the city level dates defined in our main specification. Specifically, in column 2, we define the start of the COVID-19 outbreak as the emergence of first COVID-19 cases at the provincial level (i.e., provincial shock); and in column 3, we use the Wuhan lockdown as the start of the COVID-19 outbreak (i.e., national shock). The results are almost the same. Second, we show that our finding is robust even if we use classical geographic DID that only uses data in 2019–2020 periods and compares cities with more versus less severe COVID-19 total exposure. In column 4, we compare cities with more COVID-19 total cases (treatments) and less total cases (controls) measured at the end of the study periods; and in column 5, we compare Wuhan and similar early-lockdown cities (H. Fang et al., 2020). We find that, despite the potentially large attenuation bias and underestimation,²² the effect is still large and significant in both cases. These results thus overall consolidate our findings.

To explore the dynamic evolution of the responses of purchases, we plot the coefficient estimates of Eq. (2) in Fig. 2, showing the estimated dynamic effects of the COVID-19 pandemic on the number of insurance purchases. Our results indicate that insurance purchases increase substantially right after the COVID-19 outbreak in each city, and the effects are large for weeks following. Specifically, as shown in Fig. 2, there is a sharp spike in insurance purchases around the second and the third weeks after the COVID-19 outbreak in each city, and it remains substantially high even at the end of the first month. On the other hand, there is no significant changes in insurance purchases before the outbreak. During pretreatment periods, the effect coefficients all center around zero, which support the parallel assumption of our DID design. We also explicitly test the time trend during the pretreatment periods, and the effect size of pre-trend is very small and insignificant as shown in Table A3, providing additional support to our revised study design.

While we observe a large increase in the total number of insurance purchases, the insurance demands may change differently across insurance types. As the pandemic directly increases the risks relevant to the health, the need for health and life insurance is expected to increase given their coverage and compensation for health loss²³ and the magnitude is likely to be large; while for other aspects, the predicted impact of COVID-19 is ambiguous. It is possible that the increased purchases of health insurance have a positive spillover, or crowd out insurance that covers minor or reduced risks during the pandemic (e.g., travel insurance). Therefore, to understand how people change their insurance purchase strategies during the pandemic, we estimate the effects of COVID-19 for different types of

²¹ In addition to regular insurance products, the platform also tentatively provides an insurance policy covering severe disability and mortality with limited to no premium. As the policy formally requires consumers to make a contract with the insurance companies and cover health loss, we still consider it as an insurance take-up decision and include it in our analysis. Nevertheless, as a sensitivity check, we try a couple of ways to control for this supply-side changes (e.g., using restricted sample without such policy), and our findings are fairly robust to these specifications.

²² In fact, even for cities with relatively less severe COVID pandemic, we still observe considerable increases (over 100%) in insurance purchases after the COVID outbreak in local cities. If we use these “less severe” cities as controls, these increases will (by design) be “subtracted” from the main DID estimate, thereby leading to great underestimation.

²³ During the pandemic, the insurance beneficiary of health insurance would be 1) compensated at a daily basis if they were admitted to a hospital due to COVID-19; 2) compensated in a lump sum amount if they were critically ill because of COVID-19; 3) compensated in a lump sum amount if they died because of COVID-19 (though in a relatively lower amount compared to life insurance). The insurance beneficiary of life insurance would be compensated in a lump sum amount if they became disabled or died due to COVID-19. Hence, even though the COVID treatment is covered by the government, the commercial health insurance can provide direct compensation for COVID-related illness. These compensations are not related to the COVID-related medical expenses but related to the clinical diagnosis, classification, and outcomes of COVID conditions. Besides, COVID-19 may also lead to severe long-term complications and sequela (i.e., Long COVID or Post-COVID Conditions) and may exacerbate other diseases or illnesses. Most of these Post-COVID conditions and related illnesses are not (fully) covered by the social health insurance or public finance, which can be further covered by commercial health insurance. Therefore, the insurance beneficiary can directly benefit from the commercial health insurance during COVID pandemic, and these additional benefits have almost no overlap with the coverage of COVID treatment provided by the Chinese government. We thank the referee for pointing this out and encouraging us to analyze it more conceptually.

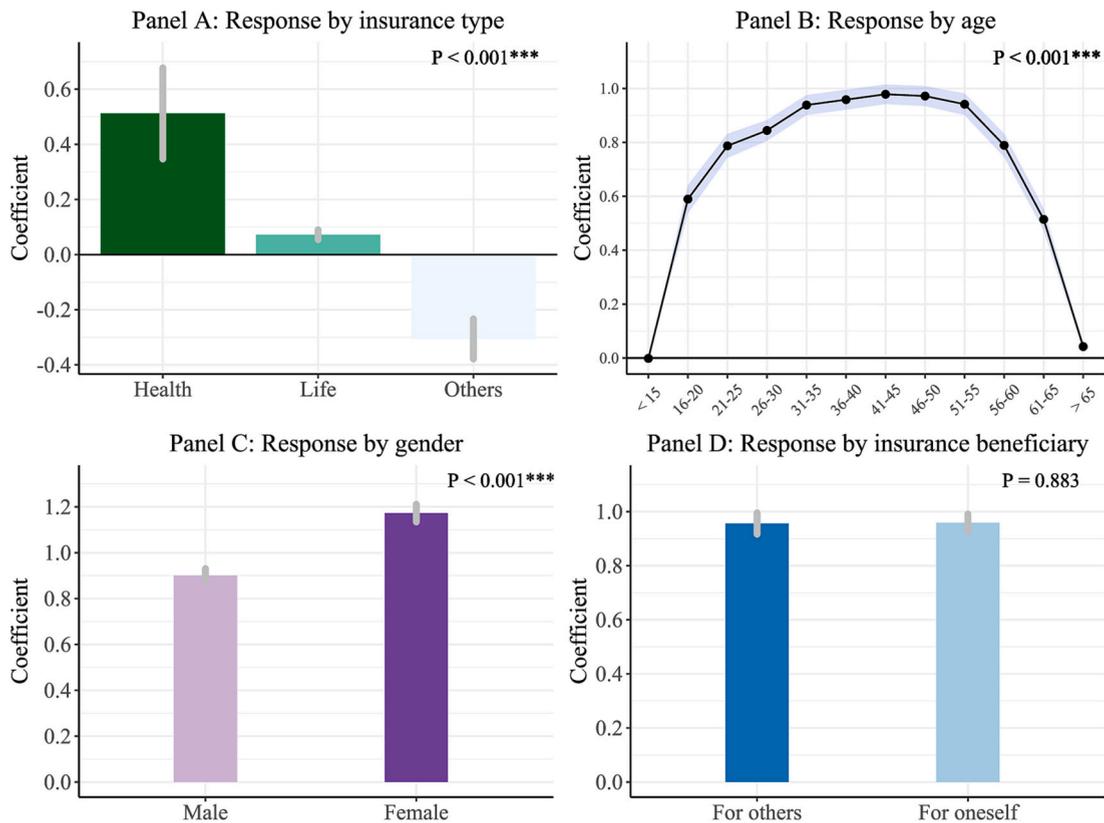


Fig. 3. Effects of the COVID-19 pandemic on insurance purchases by insurance types and consumer groups.

Notes: The bars in panel A denote the estimated effects of the COVID-19 pandemic on insurance purchases for different types of insurance. The bars in panel C and D illustrate the estimated effects of the pandemic on number of consumers, stratified by gender and insurance beneficiaries. 95% confidence intervals of the effects are shown in the grey error bars. The black dots in Panel B denote the estimated effects stratified by different age groups, where the shaded area indicates the 95% confidence interval of the estimated effects. Standard errors are clustered at the prefecture-city level. In each panel, the p -value is presented at the right-top of the panel to denote the statistical significance of the difference in coefficients between/across subgroups estimated using bootstrap approach. The supporting regression results of these graphs are presented in Appendix Tables A6–A8. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

insurance (using Eq. (1)),²⁴ including (a) health insurance, which covers health and disease risks including COVID-19; (b) life insurance, which covers disability and mortality risks; and (c) other types of insurance (e.g., accident and travel insurance). Indeed, Fig. 3 Panel A demonstrates that, the pandemic leads to significant increases in the purchases of health and life insurance and the increase in health insurance is the biggest among all, which is consistent with our prediction. By contrast, the effect on other types of insurance is negative, which reconciles with the low level of risks related to these insurance (e.g., car accidents). Overall, we find significant differences in pandemic effects across insurance types ($P < 0.001$).

4.2. Impacts of the pandemic at the extensive and intensive margin

While the COVID-19 pandemic overall contributes to a large general increase in the total number of insurance purchases, it is important to know how much of the increase is due to changes at the extensive or the intensive margin. The movements at these two margins may have different implications: an expanded group of consumers (i.e., extensive margin) may suggest that the pandemic induce more people to start taking up insurance; whereas an extended insurance demand per consumer (i.e., intensive margin) may suggest that the pandemic encourages each consumer to on average purchase more insurance. Hence, to provide a clear picture of these changes, we split the overall level of insurance purchases into the number of consumers who purchased insurance (i.e., extensive margin) and the average number of insurance purchases per consumer (i.e., intensive margin); and then, we estimate the effects of the pandemic at each margin respectively (using Eq. (1)). The results are shown in Table 3, where column 1 provides the estimates at the extensive margin and column 2 presents the ones at the intensive margin.

We find that the number of consumers increase tremendously during the pandemic. The pandemic significantly increases the

²⁴ Fixed effects are also included to account for the potential changes in insurance.

Table 3
The pandemic effects at the extensive and intensive margin.

	(1)	(2)
	Log number of consumers (Extensive margin)	Log number of insurance purchases per consumer (Intensive margin)
2020 × Post	0.990*** (0.016) [169.10%]	−0.095*** (0.004) [−9.11%]
Constant	3.849*** (0.003)	1.073*** (0.001)
Observations	27,342	27,276
R-squared	0.919	0.523
Prefecture FE	YES	YES
Date FE	YES	YES
Treat and Post FE	YES	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. The percentage changes shown in square brackets are calculated using the corresponding coefficient estimates (i.e., $\exp(\beta) - 1$). The number of insurance purchases per consumer is calculated as the ratio of the number of insurance purchases and the number of consumers. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

number of consumers by about 169% relative to the counterfactual periods without the COVID-19 pandemic, denoting great changes at the extensive margin. On the other hand, because the average number of insurance purchases per consumer (i.e., intensive margin) is calculated as the ratio of the total number of insurance purchases and the number of consumers (i.e., extensive margin), we would predict a negative change at the intensive margin given the relatively larger increase in the denominator (169% increase in the number of consumers) than the numerator (135% increase in the total number of insurance purchases). Indeed, the average number of insurance purchases per consumer mildly decrease by 9.1% during the pandemic, possibly due to the influx of new consumers.²⁵ This is not that surprising as the influx of “new” consumers who purchases insurance solely due to COVID-19 tend to have lower insurance demands compared to “existing consumers” who would have purchased insurance even without COVID-19. Their influx may consequently pull down the average level of insurance purchases per consumer (i.e., intensive margin). Besides, during the pandemic, people primarily focus on health and life insurance and the demands for other insurance may decrease (as shown in Fig. 3), which may also lead to a small decline at the intensive margin. These findings overall suggest that the general increase in the number of insurance purchases is predominantly attributed to an expanded size of consumer group. In other words, it reflects an increasing number of people starting to recognize the important role of insurance and taking-up insurance as a risk management strategy during a pandemic.²⁶

To examine the heterogeneity of the pandemic effects, we further dissect the consumers by ages, genders, and insurance beneficiaries, and estimate the effects of the COVID-19 pandemic for each subgroups²⁷ (Fig. 3). As shown in Panel B, there is an evident heterogeneity across age groups. The effects of the pandemic on the number of consumers show an inverted U shape with respect to ages: middle-aged consumers respond more strongly to the pandemic than younger and older adults.²⁸ The differences across ages are significant at 1% level ($P < 0.001$). Besides, Panel C indicates that the responses of insurance purchases to the pandemic are larger among females than males ($P < 0.001$). This finding accords with the experimental evidence that females are more risk averse than males (Charness & Gneezy, 2012). In Panel D, we demonstrate that the pandemic not only leads to an increase in the number of consumers who purchased insurance for themselves but also for others; and the effects are not significantly different between the two groups ($P = 0.883$). The evident increase in insurance purchases for others therefore may suggest a close family tie.

5. The mechanisms of the pandemic effect

Understanding the driving forces of the pandemic response is critical for policy and practices. In this section, we discuss the possible explanations of the pandemic effect and its mechanisms. In Section 5.1, we perform a series of analyses to explicitly disentangle the main pandemic effect and the lockdown effect, as lockdown and related policy restrictions may to some extent lead to compositional shifts from offline to online purchases. We show that the pandemic effect is not driven by the compositional shifts, and the effect is fairly large even after accounting for such changes. In Section 5.2, we further explore three key mechanisms suggested by existing literature and examine the extent to which these mechanisms may explain the pandemic effect, including *objective risks*, *negative emotions*, and *insurance awareness*. We show that the changes in insurance purchases may to a larger extent explained by the temporal and geographic variation in objective risk exposure than negative emotions and insurance awareness. Nevertheless, the dynamic changes in risk exposure can capture some of the changes in insurance purchases, with other effect remained unexplained. Therefore, in Section 5.3, we hypothesize that the information exposure and past pandemic experience may serve as an effect modifier (i.e.,

²⁵ These new consumers may have relatively lower insurance demands compared to those who are active prior to the pandemic.

²⁶ The results are also robust to the control of supply-side changes.

²⁷ Because of data availability, we are only able to obtain the estimates on the number of consumers (i.e., extensive margin) within each group, while cannot do the analysis for the number of insurance purchases per consumer (i.e., intensive margin).

²⁸ The smaller effect in older adults is possibly due to the fact that older adults may not be allowed to purchase some insurance plans due to age restrictions.

moderating factor) and influence the relationship between objective risk and insurance purchases. We show that for cities with more direct and high-quality information exposure and past pandemic experience, the objective risk does account for a larger proportion of the pandemic effect than other cities. It thus highlights the important roles information plays in moderating the relationship between risk and insurance purchase and inducing rational insurance take-up decisions.

5.1. Policy restrictions and compositional shifts

During the pandemic, some cities in China have experienced lockdown and related policy restrictions; the restrictions related to lockdown may to some extent drives people to shift their insurance purchases from offline to online (i.e., compositional shift). Therefore, in this section, we carefully differentiate between the pandemic periods (before lockdown) and the lockdown periods to disentangle the compositional shift from the main pandemic effect. Specifically, two types of analyses are performed to explicitly account for the compositional shifts driven by policy restrictions.

First, we exclude the periods after the lockdown (that is respectively defined for each city) and only use the periods before the lockdown to re-estimate the pandemic effect. Since the periods used in the analysis have not yet been affected by the lockdown, the estimated effect would be largely free from the compositional shifts driven by lockdown and related policy restrictions. As shown in the column 2 of Table 4, while the effect size slightly declines from 0.855 (i.e., 135%) to 0.757 (113%), the effect is still large and significant even after excluding the post-lockdown periods. This suggests that the majority of the pandemic effect is not driven by the lockdown and related policy restrictions.

Second, we explicitly disentangle the pandemic effect and the effect of compositional shifts driven by lockdown and related policy restrictions. Instead of excluding post-lockdown periods, we introduce the lockdown dummy into the model and interact it with the main DID estimates using our full data. As shown in the column 3 of Table 4, the main coefficient estimate of $2020 \times Post$ represents the pandemic effect that is free from the lockdown impact, and the coefficient estimate of $2020 \times Post \times After_{lock}$ represents the additional effect that is driven by lockdown, which encompasses the effects of composition shifts. We find that the pandemic introduces a 0.755 (112.8%) increase for periods without the impact of the lockdown related policy restrictions; and an additional 0.251 (28.6%) for periods after the lockdown. It thus implies that the majority of the pandemic effect is not driven by the compositional shifts, even though the lockdown and policy restrictions may lead to some increases in insurance purchases (possibly due to the compositional shifts).

Moreover, as the COVID-19 outbreaks mostly occur during the Spring Festival (i.e., Chinese national holidays) and the offline purchases have always been limited during the national holidays, we restrict our estimation to the periods of Spring Festival to further eliminate the concern of possible compositional shifts from offline to online. Specifically, as the offline business and purchases have always been very limited due to the temporary offline business closures during the holidays (i.e., holiday closure/shutdown), the possible compositional shifts from offline to online purchases induced by pandemic policy changes would be very minimal during this period. While such restriction to shorter periods might lead to great underestimation of pandemic effect (i.e., shorter-term effect), by excluding the periods after the Spring Festival, we could obtain a cleaner estimate with much less impact of compositional shifts. In Appendix Table A4, we show that the identified short-term pandemic effect is fairly large and significant even if we exclude the periods after Spring Festival. Although as expected the effect size is not as large as the main estimates since we restrict our sample to a very

Table 4

The pandemic effect and policy restrictions: disentangling the main pandemic effect and the compositional shifts driven by lockdown and related policy restrictions.

	(1)	(2)	(3)
	Baseline	Before Lockdown	Pandemic Effect vs. Lockdown Effect
$2020 \times Post$	0.855*** (0.018) [135.1%]	0.757*** (0.024) [113.1%]	0.755*** (0.023) [112.8%]
$2020 \times Post \times After_{lock}$			0.251*** (0.028) [28.6%]
Constant	4.464*** (0.004)	4.446*** (0.003)	4.478*** (0.005)
Observations	27,342	22,8491	27,342
R-squared	0.908	0.902	0.909
Prefecture FE	YES	YES	YES
Date FE	YES	YES	YES
Treat and Post FE	YES	YES	YES
Post Lockdown FE	NO	NO	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. The percentage changes shown in square brackets are calculated using the corresponding coefficient estimates (i.e., $exp(\beta) - 1$). In column 1, we rerun the baseline regression. In column 2, we exclude the periods after the lockdown to eliminate the lockdown effect. In column 3, instead of excluding post-lockdown periods, we explicitly disentangle the pandemic effect and the effect of compositional shifts (driven by lockdown and related policy restrictions) by introducing the lockdown dummy into the model, and interact it with the main DID estimate using full data. The lockdown dates are specifically defined for each city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

short period of time, the estimates demonstrate that the pandemic effect are fairly robust to the exclusion of compositional shifts. The effect also barely changes when we additionally account for the impact of lockdown and related policy restrictions (as shown in columns 2 and 3 of Table A4), which further alleviates the concerns.

Overall, the analyses above demonstrate that the main pandemic effect is not driven by the compositional shifts due to the lockdown or related policy restrictions. In next section, we explore three key mechanisms suggested by prior literature that may explain the changes in insurance purchases.

5.2. Objective risks, negative emotions, and insurance awareness

In our baseline analysis, the main DID estimate captures the average changes in insurance purchases before and after COVID-19 outbreak and suggests that the insurance purchases are on average higher during post-COVID periods than pre-COVID periods relative to the controls. However, it cannot tell us what factors that dynamically change over time can drive such change in insurance purchases before and after the outbreak. This motivates us to include a couple of “time-varying” mechanism variables (mediators) into the model to understand 1) the dynamic relationships between the mechanism variables and the insurance purchases; and 2) how much of the changes in insurance purchases before and after the outbreak can be explained by the dynamic changes in mechanism variables.

Existing research suggests that three potential pathways might link the pandemic with insurance purchase: *objective risks*, *negative emotions*, and *insurance awareness*. First, insurance purchases may be driven by an upsurge of risks stemming from the pandemic. Economic theory implies that insurance decisions largely depend on individuals’ perceptions of the risks that challenge them (Johnson et al., 1993; Kunreuther & Pauly, 2006). As the pandemic induces massive spikes in risks and uncertainty (Baker, Bloom, et al., 2020), it may consequently lead to higher risk perceptions, and thus to an increased level of insurance purchases. Second, insurance purchases may also be affected by the level of negative emotions among the public. Social and behavioral science research indicates that negative emotions, such as fear, anxiety, and depression, often impact individuals’ risk perceptions and decision-making (Berezin, 2010; Harlé et al., 2010; Hartley & Phelps, 2012; Simon, 1987). During the pandemic, people may have increased level of negative emotions (Bavel et al., 2020), which may distort their insurance purchases decisions. Finally, people may purchase insurance as they begin to realize the importance of insurance. Research indicates that people in China may not recognize the significant role of insurance in covering potential losses (Wang et al., 2012). The emergence of pandemic may to some extent stimulate the public awareness of risks and insurance and encourage people to consider insurance as a potential coping strategy. Given the evidence, the three factors are considered as the potential mechanism variables as they might a) greatly change over time before and after the COVID outbreak, and b) might directly lead to changes in insurance purchases.

To investigate the three pathways identified from the literature, we construct measures respectively for *objective risks* (i.e., number of COVID-19 confirmed cases), *negative emotions* (i.e., the level of negative emotion), and *insurance awareness* (i.e., the level of insurance awareness),²⁹ and follow the standard classical Baron and Kenny approach to perform the mediation type of analyses in three steps (Baron & Kenny, 1986). Specifically, we first 1) test whether the mechanism variables change before and after the COVID outbreak (i.e., effect of the pandemic on the mediators); and then 2) test whether the insurance purchases change before and after the COVID outbreak (i.e., effect of the pandemic on the insurance purchases); and lastly 3) test whether the dynamic changes in mechanism variable are significantly associated with the dynamic changes in insurance purchases (i.e., effect of the mechanism variables on insurance purchases). The potential pathway holds only if all of the three conditions are met.

We show that the onset of the pandemic can significantly increase the level of objective risk, negative emotions and insurance awareness (Appendix Table A5), which support the validity of the first condition (i.e., step 1). Besides, in Table 5 column 1, we present the baseline estimates and show that the insurance purchases significantly increase after the outbreak, which satisfies the second criteria (i.e., step 2). This estimate is considered as our benchmark estimate without any controlled mechanism variables. Lastly, we subsequently introduce the time-varying mechanism variables (i.e., mediators) into the right-hand side of the DID model to parse out the independent effect of the three suggested pathways (i.e., step 3). In Table 5 column 2, we first introduce the measure of risk exposure into the model; and then in column 3, we control the negative emotions; and lastly in column 4, we add the measure of insurance awareness (Eq. (3)).

As shown in Table 5 column 2, we find a strong positive effect of the COVID-19 cases (i.e., objective risk), indicating that insurance purchases significantly increase as the number of COVID-19 cases grows. This effect of objective risk remains largely unchanged as we further control negative emotions and insurance awareness in columns 3 and 4. We show that negative emotions have a negative effect on insurance purchases, suggesting that people with higher level of negative emotions are less likely to take-up insurance than others. Nevertheless, insurance awareness has no independent and significant effect on insurance purchases. These results indicate that only risk and negative emotions satisfy the three conditions and should be considered as valid mediators that explain the effect of pandemic

²⁹ Another way to assess insurance awareness is to look at the patterns of insurance purchases in a longer term. If the insurance purchases remain to be high for a long period of time, it might suggest that the effect is associated with an increased level of insurance awareness; while if the insurance purchases decline to a similar level as pre-pandemic period, it might suggest that the effect is probably not due to the change in insurance awareness. Unfortunately, we don’t have enough data to test this hypothesis, which deserves more investigation in future studies.

Table 5

The mechanisms of the pandemic effect: objective risks, negative emotions, and insurance awareness.

	Baseline	Risk	Risk + Emotion	Risk + Emotion + Awareness
Dep. var.: Log (#. insurance)	(1)	(2)	(3)	(4)
2020 × Post	0.855*** (0.018) [135.1%]	0.657*** (0.036) [92.97%]	0.651*** (0.037) [91.78%]	0.650*** (0.037) [91.49%]
Log (#. confirmed cases)		0.067*** (0.010)	0.070*** (0.010)	0.070*** (0.010)
Negative Emotions			−0.013* (0.007)	−0.012* (0.007)
Insurance Awareness				0.003 (0.002)
Constant	4.464*** (0.004)	4.464*** (0.004)	4.457*** (0.004)	4.448*** (0.007)
Observations	27,342	27,342	26,877	26,877
R-squared	0.908	0.909	0.909	0.909
Prefecture FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Treat and Post FE	YES	YES	YES	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. The percentage changes shown in square brackets are calculated using the corresponding coefficient estimates (i.e., $\exp(\beta) - 1$). Column 1 represents the second step of the mechanism/mediation analysis (i.e., the effect of pandemic outbreak on the insurance purchases); and columns 2–4 represent the third step of the mediation analysis (i.e., the effect of the mechanism variables/mediators on the insurance purchases). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

on insurance purchases. Overall, controlling for pandemic risks, the coefficient of 2020 × Post drops from 0.855 to 0.657. Dynamic variation in objective risk exposure thus accordingly attenuates and explains 23.2% of the increase in insurance purchases observed in the baseline analysis.³⁰ Further, by adding negative emotions and insurance awareness, we additionally explain 1.1% of the increase, which is much weaker than that for objective risk exposure.³¹

All in all, our results indicate that objective risk exposure account for the most considerable portion of the pandemic effect; and it has significant and positive relationship with insurance purchases. On the other hand, controlling for pandemic risks, the impacts of negative emotions and insurance awareness on insurance purchases are weak and less important compared to objective risk exposure.

5.3. Information exposure and past pandemic experience

The three suggested mechanisms only account for a small proportion (24.3%) of the baseline effects. In particular, there is a large discrepancy between the changes in insurance take-up decisions and dynamic variation in the objective risk exposure. It may point to the potential bias in people's risk perception and assessment relative to the risks that objectively challenge them. As information is fundamental for rational economic decisions (Johnson et al., 1993; Spence & Zeckhauser, 1978), and experience and knowledge can influence over the perception of risks and the insurance take-up decisions in experimental settings (Cai & Song, 2017), we hypothesize that the discrepancy of insurance decisions may result from individuals' lack of information and experience on the COVID-19 pandemic. Specifically, information and experience may serve as an effect modifier (moderating factor) and affect how people assess or perceive the objective risk they are exposed to, changing the relationship between objective risk exposure and the insurance purchases. That is to say, the extent to which objective risk affect insurance purchases may depend on the information and experience individuals have. With limited or even distorted information, people may suffer from considerable biases in their probability assessment and risk perceptions, which to a large extent bound the rationality of their decision-making.

Therefore, we perform stratified analyses to test the hypothesis of effect modification³² and assess whether the proportion of pandemic-induced insurance purchases explained by objective risk (i.e., risk effect) would be different between subsamples with more versus less information exposure and experience. Specifically, we test whether people with greater magnitude and quality of pandemic information exposure, or with stronger past pandemic experience, are more likely to have insurance purchase decisions in accord with their objective risk exposure.

In particular, the magnitude of information exposure is examined in two dimensions. First, since the pandemic originates from the city of Wuhan in Hubei province, we examine whether people in Hubei province, who have more direct experience and knowledge of the pandemic, reacts more consistently to the objective risks they are exposed to relative to people in other provinces. Using similar strategy in the mechanism analysis, we respectively estimate the proportion of the insurance increase attributable to the objective pandemic risks, for Hubei and for other provinces. Second, we classify cities into two groups based on the amount of information

³⁰ The proportion is obtained from calculating the relative changes in coefficient estimate of the pandemic effect (i.e., 2020 × Lock) before and after controlling objective risks. It can be denoted as $(\beta_1 - \beta_1')/\beta_1 \times 100\%$, where β_1 is the coefficient estimate of pandemic effects (Equation 1) without any mechanisms control (i.e., 0.855), while β_1' is the coefficient estimate of pandemic effects controlling for risks (i.e., 0.657).

³¹ In fact, the findings are very similar when we further control for the lockdown effect as in Section 5.1.

³² Stratified analysis is often recommended due to its high flexibility and less assumptions compared to others.

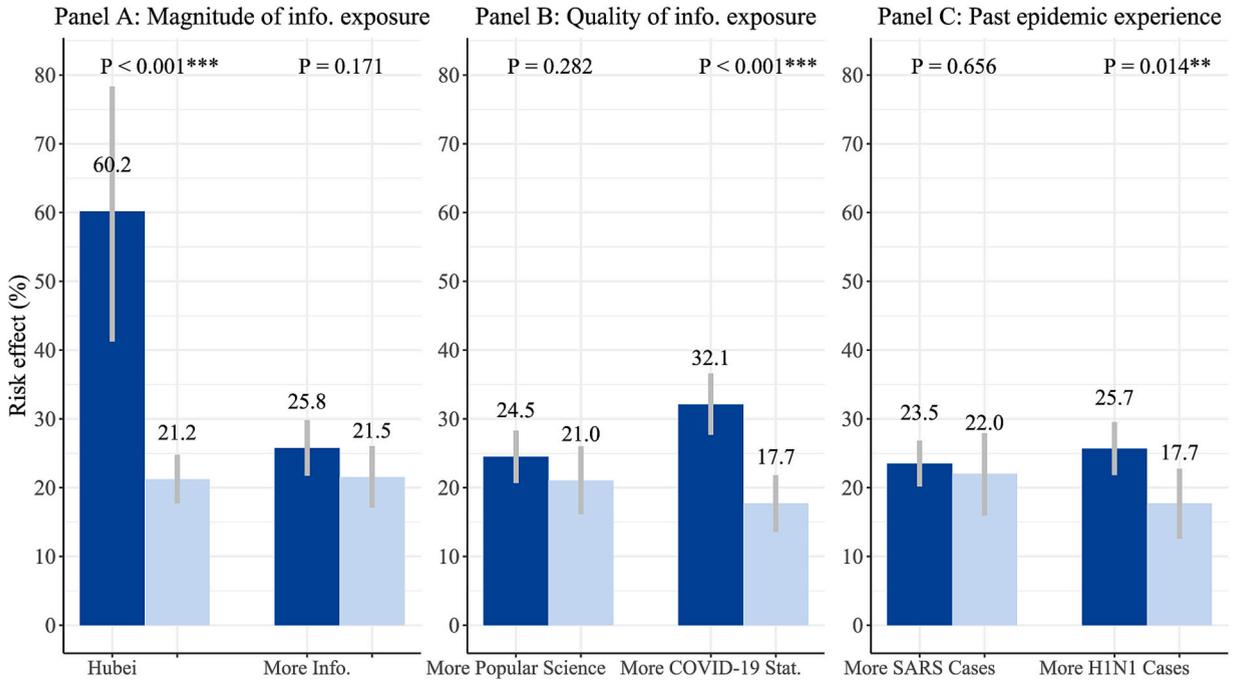


Fig. 4. Impact of information exposure on the relative proportion of pandemic effect attributable to objective risks.
Notes: The bars illustrate the estimated proportion of pandemic effect that is explained by objective risks (i.e., risk effects) for each subsample. The proportion is obtained by calculating the relative changes in coefficient estimate of the pandemic effect (i.e., $2020 \times Post$) before and after controlling objective risks. It can be denoted as $(\beta_1 - \beta_1')/\beta_1 \times 100\%$, where β_1 is the coefficient estimate of pandemic effects (Eq. (1)) without any mechanisms being controlled, while β_1' is the coefficient estimate of pandemic effects controlling for risks. Panel A shows the estimated proportion for cities with (Hubei provinces) and without (other provinces) the most direct experience of the pandemic (where Hubei is the epicenter of the pandemic); and for cities with more versus less information disclosure (stratified by median). These two stratification are based on the magnitude of information exposure. Panel B shows the estimates for cities with better versus worse quality of COVID-19 information exposure (stratified by median). The quality of information is respectively measured by the number of tweets tagged as popular science and the number of disclosed COVID-19 statistics. Panel C shows the estimates for cities with high versus low SARS or H1N1 cases (stratified by median). Bootstrapped 95% confidence intervals are presented in grey bars, the p-values are presented at the top of the panels to denote the statistical significance of the difference in coefficients between each pairs of subgroups. The supporting regression results of this figure is in Appendix Table A9. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

disclosed by local governments. We calculate the proportion of baseline effects explained by the risks for cities with more versus less information disclosure (stratified by median). As shown in Fig. 4, Panel A, direct pandemic exposure has large impact on insurance take-up decisions. Among cities with the most direct experience of the COVID-19 pandemic (i.e., those in Hubei province), about 60.2% of the baseline effect is explained by their variation in objective risks, which is significantly much larger than the proportion (21.2%) among other cities ($P < 0.001$). However, the impact of public information disclosure seems to be small, with minor difference between cities with different amount of information disclosure ($P = 0.171$). Indeed, the official information disclosed by government in China might be partial and limited during the initial stage of the pandemic, which is not as useful for risk assessment as direct experience and exposure.

To understand whether high-quality information is beneficial for decision-making, we further classify the information disclosed by the local governments (Fig. 4, Panel B). Information is considered to be high quality if it promotes scientific knowledge on the COVID-19, or discloses exact statistics of the pandemic (e.g., cases, deaths); and we stratify cities into two groups by the number of tweets tagged as popular science, or by the number of COVID-19 statistics.³³ We find insurance purchases are much more likely to be accord with objective risk exposure among cities that promote more COVID-19 statistics ($P < 0.001$). Nevertheless, provision of scientific knowledge (i.e., popular science) only has limited influence over the objective risks and insurance purchases ($P = 0.282$). The findings thus suggest that both the quality and the types of information disclosed are important for insurance take-up decisions. As COVID-19 statistics provide more direct information on local risk exposure, it can help people make more informed decisions than other types of information.

Finally, as past pandemic experience may serve as a prior knowledge for the current pandemic, we examine whether past SARS-pandemic experience in 2003 or H1N1-pandemic experience in 2009 would lead to differential behaviors of insurance purchases in response to risks (Fig. 4, Panel C). For each past pandemic, we subdivide our national samples into two groups—provinces with more versus less case exposure stratified by median, and for each group, we estimate the proportion of baseline effects explained by the objective risks. Our results demonstrate that the objective risks can account for a significantly higher proportion of insurance purchases among cities with more severe H1N1 exposure than those with less exposure ($P < 0.001$). Nevertheless, the difference is not as large as current COVID-19 information exposure.

Overall, we find that the more direct and high-quality information people have about the pandemic risk, the more likely people are to make rational decisions. These findings emphasize the important role information play in decision-making, suggesting the necessity and importance of public information disclosure.

6. Discussion and conclusion

This study is one of the first to use high-frequency, city-level insurance data to examine risk management behaviors under an unprecedented pandemic. We document the overall pattern of the responses in insurance purchases, and illustrate how people insure themselves against an upsurge of risks during the COVID-19 pandemic. Deciphering the mechanisms of the pandemic effects, we demonstrate the relative importance of objective risks, negative emotions, and insurance awareness, and illuminate the essential role of information in decision-making.

Our findings have valuable implications for researchers and policymakers. First of all, we indicate that a pandemic induces a substantial increase in insurance demand. It implies that individuals can actively respond to soaring risks by taking up insurance, even though their wealth and consumption are negatively affected by the pandemic and economic downturn (Baker, Farrokhnia, et al., 2020; Chen et al., 2021). More importantly, we find that the increase in insurance purchases can be predominantly attributed to the changes at the extensive margin. In other words, the overall increase originates from a wide expansion of consumer group; and there is an increasing number of people realizing the important role of insurance and starting to take up insurance during the pandemic. A higher insurance take-up rate is meaningful both in the short-term and long-term. On the one hand, it increases social welfare in a short-term as more people are being insured and covered by insurance. On the other hand, it may potentially raise the public awareness of private insurance; and the newly acquired experience and knowledge may have a salient impact on individuals' attitudes toward insurance, encouraging more insurance take-up in a longer term (Cai & Song, 2017).

Second, we find that the pandemic greatly induces the demand for private health insurance (PHI), which may have profound impact on the development of private health insurance market. In China, PHI is increasingly recognized as an important supplementary insurance for catastrophic medical cost and health loss, and the government has promoted a growing set of incentives to increase the take-up of PHI (Jiang & Ni, 2020; Liu, Gao, & Rizzo, 2011). However, the take-up rate of PHI is still quite low (<4%) (C. Zhang, Lei, Strauss, & Zhao, 2017), which limit people's access to services that are not covered by the basic social health insurance. Therefore, the increases in insurance purchases during the pandemic are potentially beneficial for the expansion of PHI as well as the development of a "multi-level health insurance system" (Jiang & Ni, 2020).

Third, we find some suggestive evidence indicating the impact of negative emotions on insurance decisions, where a higher level of negative emotions is associated with a lower magnitude of insurance purchases. Although we are not able to infer its impact on social welfare, the finding suggests that the negative emotion (e.g., anxiety) may distort individuals' risk perceptions and insurance take-up decisions. Hence, targeted informational campaigns or psychological interventions can be provided to ensure a more rational manner of decision-making.

³³ Similar to the amount of information disclosure, the classification here is also based on median level.

Finally, we illuminate the critical role information may play in rational economic decision making, especially in a setting involving great uncertainty. While objective pandemic risk is the most important mechanism among the three examined pathways, we find that there is a large discrepancy between the insurance purchases and the objective risks exposure; and an important driving force of the discrepancy is the magnitude and the quality of information people have during the pandemic. We show that, without enough information on the pandemic, people's insurance purchase decisions are hardly consistent with the objective risks they are exposed to; and the more direct and exact information people have, the more likely they will be to make rational economic decisions. These findings jointly emphasize the significance of information provision and disclosure in a large-scale, unprecedented pandemic. With limited information, people who are distant from the epicenter may have big biases in their risk perceptions, or even make their assessments based on a particular piece of information, such as public health restrictions. Therefore, public information disclosure, would be a critical and valuable strategy to ensure the rationality of decision making. An improved knowledge of risks among the public, would effectively reduce the problem of bounded rationality (Gigerenzer & Selten, 2002) and lead to well-informed economic decisions. Countries and governments thus should introduce more public information programs to help people with their rational decision-making, especially during a pandemic.

Several limitations may warrant further investigation. First, our insurance purchases data is extracted at the prefecture-city level rather than at the individual level. While it is sufficient for our identification, we are not able to test the differential effects for individual-level characteristics, such as education, income, and risk preferences. Future studies hence need to collect micro-level data to investigate the heterogeneity across various groups, reveal their mechanisms, and offer additional policy implications. Second, although previous literature suggests that the decisions might be affected by insurance awareness, there is no evident effect revealed in this study, possibly due to our data and measures. In particular, the variable we use may not fully capture the actual awareness of insurance. Similar issues may also exist in some other measures constructed using social media and search trend data.³⁴ For example, the lack of effect of negative emotions could also be due to the limitation of the measure. Therefore, future research may need to link it with more accurate and representative data sources to better capture the variations. Finally, aside from the three underlying pathways examined in this study—objective risks, negative emotions, insurance awareness—the pandemic may affect insurance purchases through other channels, such as increased health literacy and health awareness, which requires individual-level data to explore the relationship. Besides, the mediation type of mechanism analyses conducted in this study is not causal. To this end, more investigation is needed to reveal a more complete picture of the mechanisms than is currently available.

Despite these limitations, this paper is one of the first to use large-scale, nationwide, and comprehensive data to explore changes in risk management behaviors under the unprecedented risks and uncertainty during a pandemic and to reveal the key driving forces of the responses. Our findings may provide valuable insights for other countries and regions that are facing ongoing pandemic risks and spur targeted policy interventions.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Data availability

The authors do not have permission to share data.

Acknowledgements

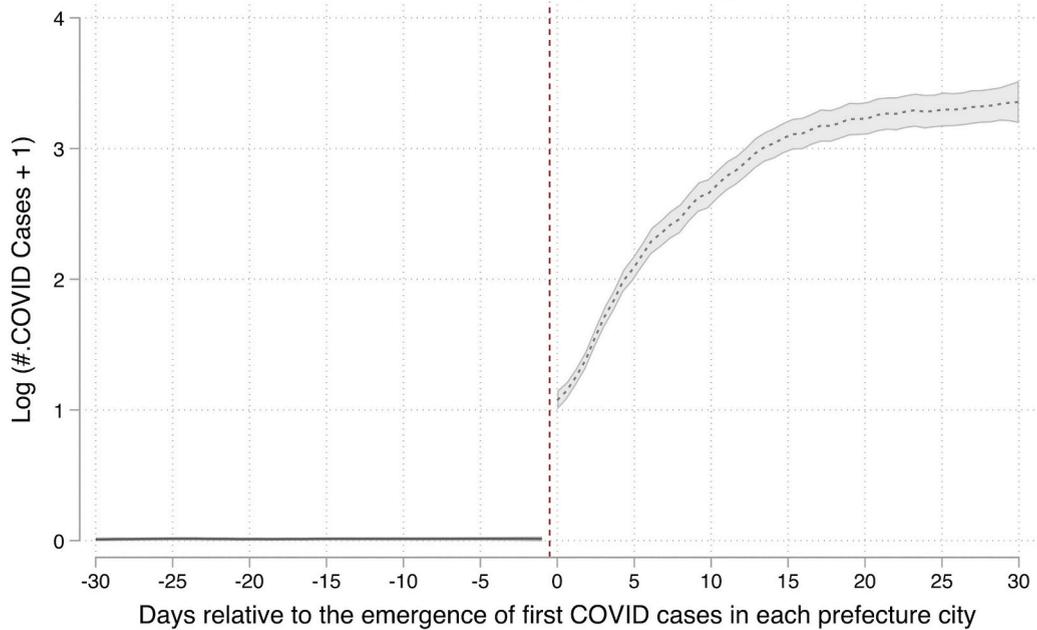
We thank the co-editor Dr. Jessica Leight and the three anonymous referees for valuable comments and guidance. The authors would like to acknowledge the funding support from the National Natural Science Foundation of China (71933002; 72121002; 71673050), the British Academy Newton Advanced Fellowship (NAFR2180130), Zhuoyue Talent Project, and Theoretical Economics Peak Program and Legendary Project on Humanities and Social Sciences (XM04221238) at Fudan University. The four authors have contributed equally to this work. The opinions expressed are the authors and not necessarily those of the affiliated institutions (e.g., EBRD). All remaining errors are our own.

Appendix A. Appendix

³⁴ Despite the potential limitations, these data and measures are especially suitable for our study for two reasons. First, our insurance data are collected at the daily-city level. The use of web-based data allows us to track daily changes in these measures for all our studied prefecture level city, and thereby facilitating the analysis of mechanisms. Other types of data, such as survey data, do not have comparable coverage and representativeness. Second, since the insurance data are obtained from an online insurance platform, the internet access would not be an issue for their consumers: most of them are active internet users despite the potential differences in consumer background. In this sense, the use of Baidu Index and Weibo data can effectively reflect the attention, attitudes, responses, and exposures for this population; and the potential concerns related to representativeness can be largely alleviated.

Panel A

Exponential increases in COVID cases at prefecture city level after the outbreak



Panel B

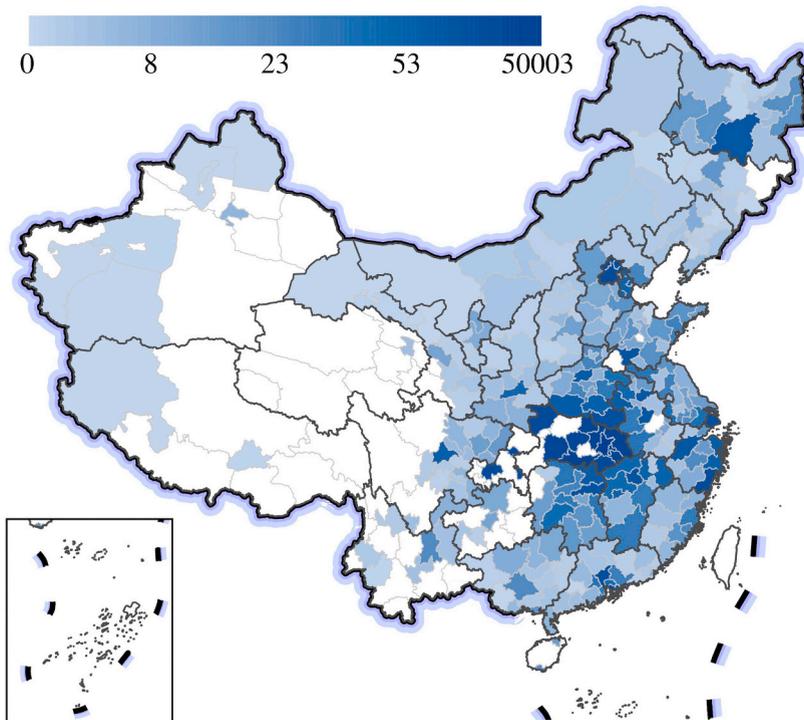


Fig. A1. The temporal and geographic variations in objective risk exposure.

Panel A: The temporal variation in COVID-19 risk exposure relative to the COVID-19 outbreak in each prefecture-level city.

Panel B: The geographic variation of COVID-19 confirmed cases at city level.

Notes: Panel A shows the temporal variation and exponential increases in the cumulative number of COVID-19 confirmed cases relative to the COVID-19 outbreak (emergence of first COVID-19 cases) for each prefecture-level city. Panel B shows the cumulative number of COVID-19 confirmed cases for each prefecture-level city (294 cities in total) by the end of the study period on Mar 16, 2020.

Table A1
Descriptive statistics by different sample periods.

Variable	N	Mean	S.D.
Before the matched outbreak dates in 2019			
#. insurance purchases	8150	229.246	555.006
#. platform visits	8150	1811.024	4080.945
#. insurance purchase per visit	8150	0.131	0.096
#. consumers	8150	107.424	266.210
#. insurance purchases per consumer	8107	2.253	0.564
After the matched outbreak dates in 2019			
#. insurance purchases	5668	200.235	563.034
#. platform visits	5668	1687.990	3700.552
#. insurance purchase per visit	5668	0.132	0.171
#. consumers	5668	98.319	334.173
#. insurance purchases per consumer	5646	2.255	0.660
Before the outbreak dates in 2020			
#. insurance purchases	8125	323.332	814.486
#. platform visits	8125	1659.114	3912.855
#. insurance purchase per visit	8125	0.206	0.113
#. consumers	8125	202.713	561.292
#. insurance purchases per consumer	8124	1.677	0.394
After the outbreak dates in 2020			
#. insurance purchases	5399	585.245	1742.932
#. platform visits	5399	2696.406	6534.541
#. insurance purchase per visit	5399	0.202	0.088
#. consumers	5399	423.955	1389.411
#. insurance purchases per consumer	5399	1.462	0.252

Table A2
Robustness of the pandemic effect to alternative DID design.

	(1)	(2)	(3)	(4)	(5)
	Log (#. insurances)				
$2020 \times Post_{base}$	0.855*** (0.018)				
$2020 \times Post_{provfirstcase}$		0.817*** (0.011)			
$2020 \times Post_{wuhanlockdown}$			0.881*** (0.011)		
High risk cities $\times Post_{base}$				0.256*** (0.053)	
Wuhan vs other lock cities $\times Post_{base}$					0.340*** (0.044)
Constant	4.464*** (0.004)	4.449*** (0.003)	4.443*** (0.002)	5.012*** (0.001)	6.717*** (0.003)
Observations	27,342	27,342	27,342	13,524	368
R-squared	0.908	0.907	0.910	0.954	0.978
Prefecture FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES
Treat and Post FE	YES	YES	YES	YES	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. Column 1 replicates the baseline estimates in Table 2 column 1. In column 2, we use the emergence of the first COVID-19 cases at the provincial level as the start of the outbreak (provincial shock). In column 3, we use the Wuhan lockdown as the start of the outbreak (national shock). In columns 4 and 5, we restrict the sample to year 2020 and estimate the difference-in-differences model by using geographic variation in risk exposure (geographic DID). In column 4, we compare cities with more COVID-19 total cases (treatments) and less total cases (controls) measured at the end of the study periods; and in column 5, we compare Wuhan (treatments) and similar early-lockdown cities (controls) (H. Fang et al., 2020). The results and findings are robust to the alternative DID specifications.

Table A3
Testing the difference in pre-treatment trend between treatments and controls.

	(1)
	Log number of insurance purchases (Pre-period)
2020 × Relative Time Before the Pandemic	−0.00003 (0.00004)
Constant	4.689*** (0.001)
Observations	13,253
R-squared	0.924
Prefecture FE	YES
Date FE	YES
Treat FE	YES

Notes: The coefficient represents the estimated time trend in insurance purchases during the pre-pandemic periods in the treatments (i.e., 2019–2020) relative to controls (i.e., 2018–2019), where “Relative Time Before the Pandemic” denotes the number of days relative to the COVID-19 outbreak defined for each city. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4
Estimated pandemic effects further excluding the possible compositional shifts.

	(1)	(2)	(3)
	Excluding the periods after Spring Festival		
	Baseline	Before Lockdown	Pandemic Effect vs. Lockdown Effect
2020 × Post	0.524*** (0.017)	0.465*** (0.020)	0.465*** (0.020)
2020 × Post × After _{lock}			0.344*** (0.040)
Constant	4.585*** (0.002)	4.571*** (0.002)	4.587*** (0.002)
Observations	19,992	19,307	19,992
R-squared	0.906	0.904	0.906
Prefecture FE	YES	YES	YES
Date FE	YES	YES	YES
Treat and Post FE	YES	YES	YES
Post Lockdown FE	NO	NO	YES

Notes: Standard errors shown in parentheses are clustered at the prefecture-city level. In column 1, we rerun the baseline regression excluding periods after Spring Festival. In column 2, we exclude the periods after the lockdown or the Spring Festival to further eliminate the influence of lockdown effect. In column 3, instead of excluding post-lockdown periods, we explicitly disentangle the pandemic effect and the effect of compositional shifts (driven by lockdown and related policy restrictions) by introducing the lockdown dummy into the model, and interact it with the main DID estimate using data that only exclude periods after Spring Festival. The lockdown dates are specifically defined for each city. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5
Mediation analysis: effect of pandemic on mechanism variables.

	(1)	(2)	(3)
	Log (#. confirmed cases)	Negative Emotions	Insurance Awareness
2020 × Post	2.947*** (0.074)	0.253*** (0.026)	0.610*** (0.047)
Constant	0.004 (0.015)	0.014*** (0.005)	3.123*** (0.009)
Observations	27,342	26,877	26,877
R-squared	0.816	0.105	0.481
Prefecture FE	YES	YES	YES
Date FE	YES	YES	YES
Treat and Post FE	YES	YES	YES

Notes: This table reports the DID estimates of the mechanism variables (i.e., effect of the COVID-19 outbreak on the mechanism variables/mediators), which is the first-step of the mediation type of analyses. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6

The effects of the COVID-19 pandemic on the number of purchased insurance policies for each types of insurance.

	(1)	(2)	(3)
Dep. var.: Log (#. insurance purchases)	Health	Life	Others
2020 × Post	0.512*** (0.084)	0.072*** (0.009)	-0.306*** (0.037)
Constant	2.025*** (0.005)	0.195*** (0.002)	4.327*** (0.003)
Observations	27,342	27,342	27,342
R-squared	0.897	0.593	0.892
Prefecture FE	YES	YES	YES
Date FE	YES	YES	YES
Treat and Post FE	YES	YES	YES

Notes: This table reports the regression results in Fig. 3 Panel A. In all columns, we include fixed effects to account for the potential effects of the liability changes of various types of insurance. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7

The effects of the COVID-19 pandemic on the number of consumers for different age groups.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Log (#. consumers)	<16	16–20	21–25	26–30	31–35	36–40
2020 × Post	-0.001 (0.001)	0.590*** (0.026)	0.787*** (0.022)	0.844*** (0.019)	0.939*** (0.019)	0.959*** (0.019)
Constant	0.004*** (0.000)	0.876*** (0.005)	1.483*** (0.004)	2.028*** (0.004)	2.035*** (0.004)	1.812*** (0.004)
Observations	27,342	27,342	27,342	27,342	27,342	27,342
R-squared	0.044	0.750	0.832	0.868	0.871	0.858
Prefecture FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Treat and Post FE	YES	YES	YES	YES	YES	YES
	(8)	(9)	(10)	(11)	(12)	(13)
	41–45	46–50	51–55	56–60	61–65	>65
2020 × Post	0.979*** (0.018)	0.972*** (0.019)	0.941*** (0.020)	0.789*** (0.022)	0.514*** (0.020)	0.042*** (0.008)
Constant	1.572*** (0.004)	1.405*** (0.004)	0.948*** (0.004)	0.524*** (0.004)	0.280*** (0.004)	0.121*** (0.002)
Observations	27,342	27,342	27,342	27,342	27,342	27,342
R-squared	0.827	0.809	0.765	0.706	0.605	0.467
Prefecture FE	YES	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES	YES
Treat and Post FE	YES	YES	YES	YES	YES	YES

Notes: This table reports the regression results of Fig. 3 Panel B. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8

The effects of the COVID-19 pandemic on the number of consumers by genders and insurance beneficiaries.

	(1)	(2)	(3)	(4)
Dep. var.: Log (#. consumers)	Male	Female	For others	For oneself
2020 × Post	0.901*** (0.015)	1.173*** (0.020)	0.956*** (0.020)	0.959*** (0.017)
Constant	3.537*** (0.003)	2.530*** (0.004)	1.173*** (0.004)	3.799*** (0.003)
Observations	27,342	27,342	27,342	27,342
R-squared	0.910	0.887	0.836	0.914
Prefecture FE	YES	YES	YES	YES
Date FE	YES	YES	YES	YES
Treat and Post FE	YES	YES	YES	YES

Notes: Columns 1 and 2 report regression results of Fig. 3 Panel C; while columns 3 and 4 report the results of Fig. 3 Panel D. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9
Information exposure and the consistency of insurance purchases with objective risks.

	(1)	(2)	% Risk Effect	(3)	(4)	% Risk Effect	P-value
Dep. var.: Log (#. insurance purchases)	Hubei	Hubei		Other prov.	Other prov.		
Panel A. Magnitude of Info. Exposure							
2020 × Post	1.208*** (0.049)	0.481 (0.542)	60.2%	0.841*** (0.018)	0.663*** (0.036)	21.2%	<0.001
Objective Risks	NO	YES		NO	YES		
Observations	1023	1023		26,319	26,319		
R-squared	0.910 (5)	0.914 (6)	% Risk Effect	0.909 (7)	0.909 (8)	% Risk Effect	P-value
	More info.	More info.		Less info.	Less info.		
Panel A. Magnitude of Info. Exposure							
2020 × Post	0.862*** (0.023)	0.640*** (0.048)	25.8%	0.850*** (0.028)	0.667*** (0.053)	21.5%	0.171
Objective Risks	NO	YES		NO	YES		
Observations	12,741	12,741		14,601	14,601		
R-squared	0.916 (9)	0.917 (10)	% Risk Effect	0.899 (11)	0.900 (12)	% Risk Effect	P-value
	More popular science	More popular science		Less popular science	Less popular science		
Panel B. Quality of Info. Exposure							
2020 × Post	0.864*** (0.022)	0.652*** (0.044)	24.5%	0.847*** (0.029)	0.669*** (0.058)	21.0%	0.282
Objective Risks	NO	YES		NO	YES		
Observations	13,578	13,578		13,764	13,764		
R-squared	0.910 (13)	0.911 (14)	% Risk Effect	0.904 (15)	0.905 (16)	% Risk Effect	P-value
	More COVID-19 stat.	More COVID-19 stat.		Less COVID-19 stat.	Less COVID-19 stat.		
Panel B. Quality of Info. Exposure							
2020 × Post	0.869*** (0.022)	0.590*** (0.054)	32.1%	0.847*** (0.028)	0.697*** (0.050)	17.7%	<0.001
Objective Risks	NO	YES		NO	YES		
Observations	12,648	12,648		14,694	14,694		
R-squared	0.918 (17)	0.919 (18)	% Risk Effect	0.899 (19)	0.900 (20)	% Risk Effect	P-value
	More SARS cases	More SARS cases		Less SARS cases	Less SARS cases		
Panel C. Past Pandemic Experience							
2020 × Post	0.884*** (0.020)	0.677*** (0.042)	23.5%	0.813*** (0.033)	0.634*** (0.064)	22.0%	0.656
Objective Risks	NO	YES		NO	YES		
Observations	16,461	16,461		10,881	10,881		
R-squared	0.913 (21)	0.914 (22)	% Risk Effect	0.901 (23)	0.902 (24)	% Risk Effect	P-value
	More H1N1 cases	More H1N1 cases		Less H1N1 cases	Less H1N1 cases		
Panel C. Past Pandemic Experience							
2020 × Post	0.863*** (0.027)	0.641*** (0.051)	25.7%	0.844*** (0.023)	0.695*** (0.049)	17.7%	0.014
Objective Risks	NO	YES		NO	YES		
Observations	15,345	15,345		11,997	11,997		
R-squared	0.911	0.912		0.904	0.904		
Prefecture FE	YES	YES		YES	YES		
Date FE	YES	YES		YES	YES		
Treat and Post FE	YES	YES		YES	YES		

Notes: This table reports the regression results illustrated in Fig. 4. The odds columns (e.g., columns 1 and 3) present the regression estimates without controlling for objective risks, while the even columns (e.g., columns 2 and 4) present the estimates after controlling for objective risks. “% Risk

Effect” represents the estimated proportion of pandemic effect that is explained by objective risks (i.e., risk effects) for each subsample, which is calculated as $(\beta_1 - \beta'_1)/\beta_1 \times 100\%$, where β_1 is the coefficient estimate of pandemic effects (Eq. (1)) without any mechanisms being controlled, while β'_1 is the coefficient estimate of pandemic effects controlling for objective risks. The p-values presented at the right of each panel denote the statistical significance of the difference in estimated risk effects (%) between each pair of subgroups. Prefecture fixed-effects, date fixed-effects, and the treat and post dummies are included in all regressions. Standard errors shown in parentheses are clustered at the prefecture-city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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