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Risk communication clarity and insurance demand: The case of the COVID-19 pandemic[☆]

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ABSTRACT

We study how the clarity of COVID-19 risk communications affects COVID-19 insurance demand using proprietary prefecture-level insurance data from China. We find that when local disclosures of COVID-19 risk contain case origin information, local purchases of COVID-19 insurance and local Internet searches for COVID-19 information increase, even after controlling for newly confirmed local cases and new deaths. Our results are robust to using the disclosure clarity of a major neighboring city. The findings suggest that providing improved knowledge about risk to individuals lead them to engage in more risk management. Our evidence contributes to the debate over how risk communication affects individuals' risk-related behaviors.

1. Introduction

Access to relevant risk information is key to risk management decision making, and understanding how individuals react to risk information when making behavioral choices has long been of interest to academics and policymakers alike. Some researchers find that more information (or improved knowledge) about risk leads individuals to reduce risky behaviors or improve their risk management (Dupas, 2011; Stango and Zinman, 2014; Fitzsimons et al., 2016; Dupas et al., 2018).[1] Others,

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[1] Specifically, Stango and Zinman (2014) show that individuals who can see overdraft fees in advance are less likely to incur such fees. Dupas (2011) and Dupas et al. (2018) study how health risk information relates to unsafe sexual behaviors. Fitzsimons et al. (2016) find that improved nutrition knowledge improves child nutrition, household food consumption, and health.

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however, find that improved information can reduce information ambiguity[2] and subjective risk, which may reduce the perceived need for risk management (Viscusi et al., 1991; Bennear et al., 2013; Chen et al., 2013; Kerwin, 2018; Kim et al., 2019).[3] While information disclosure can be an attractive public policy tool to improve consumers' choices in many contexts, its efficacy is not widely tested in personal *financial* risk management. Handel et al. (2019) argue that many consumers in health insurance markets are subject to information frictions that affect their risk management decisions (e.g., insurance purchasing decisions) and show that disclosure intervention programs aimed at reducing consumer frictions do *not* necessarily improve personal insurance decision-making. In this paper, we contribute to the debate by examining how communications regarding a nascent but rapidly expanding risk about which the public knows very little—the COVID-19 pandemic—affect individual and household insurance decisions. The COVID-19 pandemic is a particularly interesting context, as it caused a global economic recession and reduced people's income while simultaneously increasing their protection needs.

Using proprietary nationwide insurance data obtained from the developer of a leading mobile social communication app in China with a built-in online insurance platform, we examine how the clarity of public local (prefecture-city level) disclosures of COVID-19 risk (whether the disclosure contained detailed information about case origins) affected local demand for COVID-19 insurance between January 22, 2020, which was one day after China's official designation of COVID-19 as a legally quarantinable infectious disease, and March 16, 2020, when the pandemic was declared effectively under control. March 16 is also the last day for which our sample data are available.[4]

At the beginning of the pandemic, people were aware that they risked becoming infected (the "COVID-19 infection risk") but knew little about the probability distribution of this infection risk (i.e., they faced significant ambiguity). This means that alongside the standard quantitative disclosures regarding the number of confirmed cases, qualitative disclosures such as the identification of case origins may decrease the ambiguity of COVID-19 information. These qualitative disclosures, however, may also increase the salience of infection. Therefore, the effects of COVID-19 case origin disclosures on local demand for COVID-19 insurance are unclear ex ante. On the one hand, individuals' perceptions of the risk levels to which they are exposed are greater for more ambiguously communicated risk (Viscusi et al., 1991). Ambiguity-averse people tend to make a worst-case assessment of information quality when processing ambiguous news (Epstein and Schneider, 2008) and to stay away from investments whose returns are more difficult to predict (Alary et al., 2013; Dimmock et al., 2016).[5] Information regarding case origins may help to reduce subjective risk and ambiguity in COVID-19 risk, allowing people to better assess the objective risk of infection; detailed case origin information may also signal to the public that the government authority can effectively trace and contain the spread of the virus. This could mitigate people's concern and lower the demand for insurance protection. A lack of information about case origins could also generate anxiety among local residents and increase subjective risk, as cases with unknown origins increase the difficulty of infection containment. This line of reasoning suggests a negative relationship between local disclosures of case origins and demand for COVID-19 insurance.

On the other hand, detailed information about COVID-19 cases may heighten individuals' perception of risk and increase the salience of infection, both of which would increase insurance take-up (Johnson et al., 1993). If qualitative information regarding case origins is available, people may perceive higher risk: detailed information about case origins can show that the virus is highly infectious, and such salience may result in overreactions from individuals (Bordalo et al., 2012; Dessaint and Matray, 2017). Eisenbach and Schmalz (2016) model an anxious agent who is more averse to imminent risks than to distant risks and show that such an agent may choose to buy short-term insurance coverage without much foresight (even if the insurance policy charges an expensive premium). In a pandemic setting, people may be under-informed about potential infection risks (Fetzer et al., 2021). Easley and O'Hara (2009, p. 1840) argue that for investors who care about both risk and ambiguity, "disclosure can actually exacerbate difficulties by making investors aware of obscure outcomes that they otherwise might not have thought possible." Thus, it is also possible that disclosing COVID-19 case origins increases people's perceived risk and leads them to take up more COVID-19 insurance to cover this perceived risk. We test the above predictions and find that controlling for the number of newly confirmed cases and new deaths (as proxies for risk information), public disclosure of case origins results in a higher take-up of COVID-19 insurance policies, as measured by the count of new policies and premium amounts.

A potential threat to our inference is the endogeneity of local disclosures of COVID-19 case origins, which is likely to arise from the existence of omitted variables that are correlated with both local COVID-19 disclosures and COVID-19 insurance take-up. We mitigate this concern in two ways. First, we take advantage of the time-series variation of COVID-19 disclosures and estimate *within* prefecture cities, which allows us to effectively control for the effects of omitted time-invariant prefecture-level variables. Second, we show that the local take-up of COVID-19 insurance also responds to case

[2] According to Knight (1921), risk indicates uncertainty regarding outcomes, while ambiguity indicates uncertainty regarding the probability distribution of possible outcomes. Klibanoff et al. (2005) further discuss the subtle difference between risk aversion and ambiguity aversion, arguing that people can be averse to both risk and ambiguity.

[3] Kerwin (2018) argues that a rational person may become fatalistic, meaning that rational responses to health risks are sometimes risk-seeking rather than risk-avoidant. Indeed, he finds that people who think they already have HIV or those who believe that they are doomed to contract HIV in the future choose to take more risks in sexual activities, as indicated by a positive elasticity of sexual risk-taking to high HIV risk beliefs. Bennear et al. (2013) find that providing households with more detailed information about the harm of groundwater arsenic does not increase water source switching. Kim et al. (2019) report mixed findings regarding the effects of health examination results on people's health behaviors.

[4] In the paper, the "clarity" of a COVID-19 risk communication or disclosure refers to whether or not it contains detailed information about case origins. All of the dates in the paper fall in 2020 unless stated otherwise.

[5] See Corcos et al. (2020) for a review of behavioral factors in insurance purchases.

origin disclosures coming from a major neighboring prefecture city (in provinces other than Hubei, whose prefecture cities were completely locked down to each other within the province). We find a no-result in Hubei, which shows that economic co-movements between neighboring prefectures are unlikely to be responsible for our finding in the neighboring-prefecture test. The reason for this is that while lockdowns prevent the virus from spreading between two neighboring prefectures via population migration, they should have a minimal effect on the economic co-movement between a prefecture and its major neighboring prefecture. Therefore, the positive response of COVID-19 insurance take-up to local disclosures of case origins is unlikely to be due to omitted time-variant prefecture-level variables; instead, geographical proximity to the disclosed case trajectory appears to be the most important. In another placebo test, we find that the effect of local disclosures of case origins on insurance take-up is limited to insurance policies that cover COVID-19 risk, with no such effect on other types of insurance that bear little relevance to COVID-19 exposure. Taken together, the above tests mitigate the concern that our finding is driven by the endogeneity of local disclosures of COVID-19 case origins.

Admittedly, our result is predicated on the availability of a supply of COVID-19 insurance and reflects an equilibrium of demand and supply. However, it is important to note that our result is not due to any prefecture-specific promotion efforts by insurance suppliers. We confirmed with the leading online insurance distribution platform (the data provider) that all COVID-19 insurance policies marketed through the platform were simultaneously available to all users of the popular mobile communication app nationally with the same premium rates and policy terms, which means that local prefecture governments do not have any control over the supply of local insurance. We were also informed that neither the distribution platform nor its insurance company partners engaged in location-specific promotions of this insurance, as such promotions can offset the advantages of selling insurance through the app and increase the cost to companies significantly. This enables us to carry out a cleaner study of how case origin disclosures affect insurance demand by holding insurance supply constant across different prefectures on each day. We also show that our result is not driven by the larger supply of COVID-19 insurance that was probably available in the latter part of our sample period. Overall, our result suggests that the disclosure of COVID-19 case origins heightens perceived infection risk and induces demand for protection.

Our finding is potentially consistent with an alternative interpretation. That is, in the early stages of the pandemic, detailed reporting was feasible due to a low number of cases, whereas later it was not. Those most worried about the virus may have purchased insurance early in the pandemic (and thereby satiated their demand, as coverage is for a full year). This pattern may lead to a simple correlation between local case origin disclosures and COVID-19 insurance take-up without any underlying causality.[6] Fig. 1, however, shows that at the beginning of the pandemic, the proportion of prefectures that disclosed case origins was not high even though the number of cases was low. Repeating our analysis using the second part of the sample period (from February 13, 2020 to the end of the sample period) shows similar results, suggesting that this alternative explanation is unlikely.

To understand why COVID-19 case origin disclosures increase household take-up of COVID-19 insurance, we show that upon such disclosures, the number of Internet searches for COVID-19-related keywords increases by about 9%. The effect of case origin disclosures on COVID-19 insurance take-up also increases as the proportion of vulnerable people in the population increases, but is attenuated by people's lower level of confidence in local governments.

Our study makes three contributions to the field. First, it extends the debate in the literature over how ambiguous information affects people's risk perception and how this in turn leads to differences in personal risk management. Prior studies have focused on unsafe sexual behaviors (e.g., Dupas 2011, Dupas et al. 2018, Kerwin 2018), child malnutrition (Fitzsimons et al., 2016), contaminated drinking water sources (Bennear et al. 2013), and health behaviors (e.g., Kim et al. 2019). However, with several exceptions (e.g., Stango and Zinman (2014) on checking account overdrafts, Handel et al. (2019) on health insurance), there is limited evidence in the context of personal financial management, particularly in relation to tackling a new pandemic risk. Financial decisions are more complex than the settings listed above, involve more limited information, require financial literacy, and are more affected by cognitive limitations and behavioral biases (Campbell, 2016). Our study extends this line of research by examining insurance decisions and COVID-19 disclosures during the current pandemic.

Second, our work sheds light on how the clarity of public risk communications about a new breed of health risks affects people's insurance decisions, especially in developing countries, which typically have a lower take-up rate of commercial insurance than developed countries. Extant literature has analyzed the disclosure of private information previously unavailable to some parties in insurance transactions (De Meza et al., 2010; Abito and Salant, 2019), but few studies have examined the role of public information. Although public information disclosure is an attractive public policy tool for improving consumers' choices in many contexts, its efficacy is not widely tested in insurance settings (Handel et al., 2019). We show that in the case of pandemic risk, qualitative disclosures that include case origins improve people's risk management. This result suggests that more public information disclosures help consumers to understand risks and may result in risk mitigation behaviors. While increased personal financial risk management amid a pandemic is desirable from a societal perspective, as it partially relieves the fiscal burden on governments, it is not clear whether it is optimal for individuals. In fact, we find that heuristics (i.e., representativeness, availability, and anchoring biases (Kahneman, 2003) play a role in the interpretation of disclosed case origin information and how this interpretation feeds into insurance decisions. While our results are also consistent with the risk salience theory, data limitations (e.g., a lack of subsequent policy surrender information) preclude

[6] We thank an anonymous reviewer for suggesting this alternative explanation.

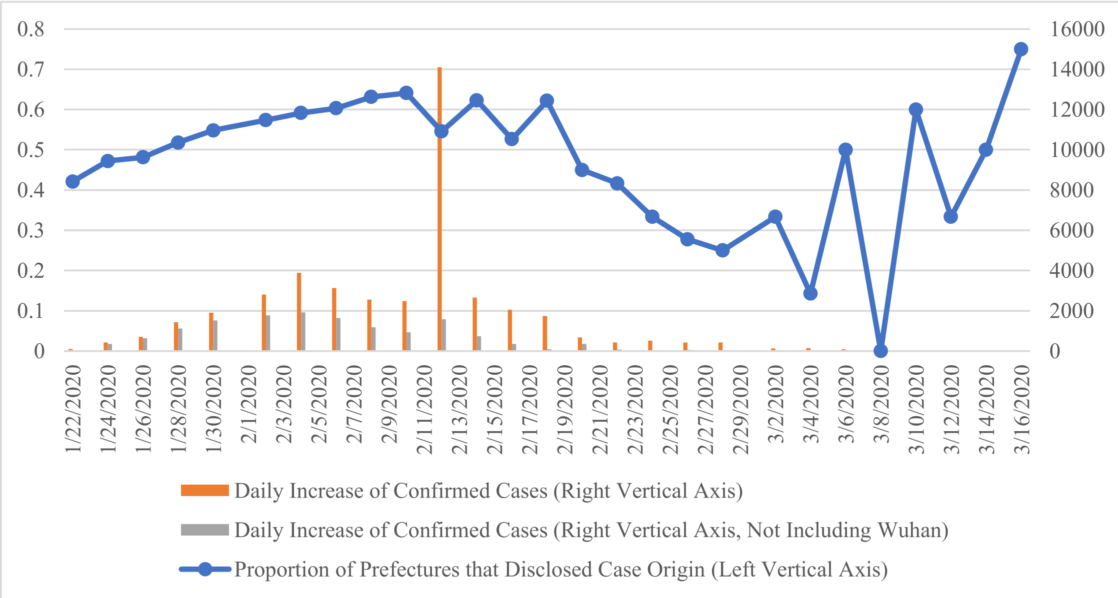

Fig. 1. Proportion of Case Origin Disclosing Prefectures among Prefectures with New Daily Confirmed Cases
Figure 1 presents the evolution of the proportion of case origin disclosing prefectures (among prefectures that reported new daily confirmed cases) over time. The left vertical axis denotes the proportion of case origin disclosing prefectures; the right vertical axis denotes the daily increase of confirmed cases; the horizontal axis presents the calendar day (on the every other day basis) in our sample period from January 22 to March 16, 2020. On February 12, 2020, Hubei province started to include the number of clinical diagnosis cases in the reported number of confirmed cases, resulting in a spike in newly confirmed cases, mainly in Wuhan. The peak in the proportion of case origin disclosing prefectures among prefectures reporting new daily confirmed cases near the end of the sample period is because there were a small number of prefectures reporting new daily confirmed cases (and hence a small denominator in calculating the proportion) on those days. For example, March 8, 2020, only has one prefecture with confirmed cases.

us from directly testing salience bias. Nevertheless, salience bias is likely to have limited economic consequences on the insured in our setting, given that COVID-19 insurance only lasts for a year and involves a moderate premium.

Third, our study joins an emerging body of literature on the economic consequences of the COVID-19 pandemic and how information about COVID-19 has affected the efficacy of policy interventions (e.g., social distancing and stay-at-home orders) during the pandemic. For example, concurrent research studies the effects of the pandemic on stock returns (e.g., Hassan et al. 2020, Ding et al. 2021), investors' expectations of future growth (e.g., Gormsen and Koijen 2020), economic anxiety (e.g., Fetzer et al. 2021), household consumption (e.g., Catherine et al. 2020), labor demand (e.g., Adams-Prassl et al. 2020), and domestic violence (e.g., Leslie and Wilson 2020), among others. Additional studies examine how differences in political beliefs affect people's compliance with social distancing and self-isolation orders (e.g., Allcott et al. 2020) and health behaviors and policy preferences (e.g., Gadarian et al. 2021). To the best of our knowledge, no prior studies have examined how individuals and households respond to COVID-19 risk via financial risk management. Using unique data from China, we fill this research gap.

Fetzer et al. (2021) find that in the U.S., individuals tend to overestimate the mortality of COVID-19 but underestimate the non-linear nature of its transmission. They argue that information and public education may play a central role in infection containment and in managing the negative economic impact of increased economic anxiety. Our evidence complements their study by showing that increasing qualitative disclosures in COVID-19 risk communications can encourage people to use financial risk management tools to tackle economic anxiety.

The remainder of this paper is organized as follows. In Section 2, we introduce the institutional background. In Section 3, we develop our hypotheses. In Section 4, we describe our data and research design. We present our empirical results in Section 5 and conclude the paper in Section 6.

2. Institutional background

2.1. The COVID-19 pandemic

On January 21, 2020, the Chinese Center for Disease Control and Prevention formally designated the novel coronavirus-infected pneumonia as a legally quarantinable infectious disease in China. The World Health Organization (WHO) declared the novel coronavirus outbreak a public health emergency of international concern (PHEIC) on January 30, 2020, named the resulting pneumonia "COVID-19" on February 11, 2020, and upgraded the outbreak to pandemic status on March 11, 2020. As of February 15, 2021, more than 109 million confirmed cases and 2.5 million deaths have been reported worldwide.[7]

2.2. The emergence of COVID-19 insurance in China

Although in China the government bears the medical expenses of confirmed COVID-19 patients and suspected patients, medical expenses that are incurred before cases are designated "confirmed" or "suspected" according to the medical diagnosis criteria need to be borne by individuals and/or their commercial medical insurance providers.[8] For patients who have similar symptoms but are not officially suspected or confirmed cases, the cost of medical treatment is first covered by government-provided basic medical insurance (albeit with a rather low cap) and then by commercial medical insurance (if any) or the patients themselves. In addition to treatment costs, COVID-19 policies also provide coverage for deaths related to COVID-19, while the basic government medical insurance scheme does not. COVID-19 therefore gives rise to individual and household demand for financial protection, and this is often insufficiently funded by the government.

Against this backdrop, commercial insurance providers in China quickly responded by expanding the scope of their existing medical insurance policy coverage or launching new COVID-19 insurance policies specifically targeting COVID-19 risk. The developer of the mobile communication app in China that we contacted has played a dominant role in distributing COVID-19 policies since January 22, 2020 through the online insurance platform that is built into its app.[9] Given the online platform's dominant position in mobile communication apps and the disrupted offline sales channels of insurance during our sample period (January 22 to March 16, 2020), online distribution through the platform was the primary way insurance companies offered COVID-19 insurance. Once a COVID-19 insurance policy entered the platform, the policy was simultaneously available to all mobile app users throughout the country with the same policy rates and terms. We confirmed with our data provider that neither the platform nor its business partners engaged in area-specific promotion or advertising activities. This feature of the insurance supply is important, as it enables us to conduct a cleaner study of how case origin disclosure affects insurance demand by holding insurance supply constant across prefectures on each day of the sample period.

A typical COVID-19 policy in China provides coverage ranging from RMB100K to 200 K (about USD15,384 to 30,768, using the exchange rate as of December 31, 2020) with a duration of 1 year. The policy can cover related hospitalization expenses and include a lump-sum benefit when the insured is diagnosed as being in a serious condition or in the event of death or disability. The insurance policy takes effect the day after sign-up, but is subject to a 1-week waiting period to mitigate adverse selection.

The online insurance platform also distributed some free COVID-19 policies on behalf of insurance companies that require users to sign up through the mobile phone app.[10] The insurance companies awarded these free COVID-19 policies for several reasons: to demonstrate good corporate social responsibility, as an advertisement, and as a way to attract new customers and expand their customer base.

2.3. Prefecture-level COVID-19 disclosures

In China, local Health Commissions are part of local governments and are the only official sources of local COVID-19 information. Daily public disclosures of COVID-19 information are administered at different layers of government, including the national, province, and prefecture/city levels. All of the prefectures adhere to a daily zero reporting system, under which daily reporting is still needed even if there are no newly confirmed cases. During the sample period, these local COVID-19 disclosures differed in terms of whether they contained case origin information. For instance, on February 5, 2020, Chengdu city in Sichuan province disclosed not only quantity information about new and cumulative confirmed cases and deaths, but also detailed origin information for each of the five newly confirmed cases (see Appendix 1 for details). However, Shanghai's January 24 disclosure contained no case origin information and was limited to quantity information in the form of case numbers (Appendix 1).

The COVID-19 risk disclosures of prefectures exhibit time-series variations. For instance, Chengdu reported the origins of newly confirmed cases from January 21 to 23, but such case origin information was absent the following week (January 24–31, 2020) despite the reporting of confirmed cases over that period. In the data, 44% of the prefecture cities examined had at least one change in the disclosure of case origins, and within this group, 63% had multiple changes. Importantly, such within-prefecture time-series variations enable us to identify the effects of risk communication clarity on local demand for COVID-19 insurance.

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[7] Source: https://www.worldometers.info/coronavirus/.

[8] "Suspected cases" need to meet certain medical diagnosis criteria with regard to testing and/or X-ray evidence. See http://www.nhc.gov.cn/yzygj/s7653p/202001/f492c9153ea9437bb587ce2ffcbee1fa.shtml.

[9] We are required to maintain the anonymity of the data provider.

[10] Free COVID-19 policies could be received by 18- to 65-year-olds who had not been designated as "confirmed" or "suspected" COVID-19 cases. The total proportion of free policies awarded by the online distribution platform was approximately 20% of the total count of COVID-19 policies distributed via the platform. Neither the free policy offerings nor the advertising of COVID-19 insurance varied across cities.

3. The effects of risk communication clarity on local demand for COVID-19 insurance

Complete information is needed for optimal choices at the individual level and the broader achievement of market efficiency (Stigler, 1961; Hirshleifer, 1971; Grossman and Stiglitz, 1976). However, imperfect information is the norm, especially in healthcare and insurance markets (Arrow, 1963). Increasing recognition of the problems associated with imperfect information has led to the promotion of policies that encourage the disclosure of relevant information. For example, efforts have been made to include additional information that helps to increase the clarity of the disclosure. In the case of insurance transactions, such additional information can include an insurer's loss ratio, the sales agent's commission rate (De Meza et al., 2010), the true probability of loss, the contract's expected loss, or the insurer's expected profit from the transaction (Abito and Salant, 2019; Ragin et al., 2021). Based on the expectation that providing such *private* information helps to mitigate information asymmetry and achieve efficient quality outcomes, information disclosure in general is desirable.

In recent years, an increasing number of information programs that aim to disclose *public* information have been implemented. These programs are designed to encourage social and behavioral changes, especially in developing countries, under the belief that consumers may not be fully informed and cannot make optimal decisions with this limited information (Kling et al., 2012). In health insurance markets, the goal of regulatory interventions is to establish an environment in which consumers can efficiently purchase insurance for risk protection and health care purposes. Public information disclosures can help consumers recognize potential risk and encourage risk mitigation behaviors that help consumers to protect themselves against potential hazards such as pollution and diseases. Disclosures are shown to affect people's behavior in a variety of settings, including HIV infection (Dupas, 2011), drinking water contamination (Bennear et al., 2013), and child malnutrition (Fitzsimons et al., 2016). Insurance decisions are informationally sensitive, and distorted consumer beliefs often affect the demand for insurance (Barseghyan et al., 2013). Public disclosures of pandemic information can therefore be valuable in encouraging personal financial risk management via insurance. While public information disclosures are an attractive public policy tool, the efficacy of this tool in improving consumers' choices is not widely tested in insurance settings (Handel et al., 2019).

The effect of COVID-19 case origin disclosures on the local take-up of COVID-19 insurance is unclear ex ante. On the one hand, individuals' perceptions of the risk levels to which they are exposed are heightened for more ambiguously communicated risk (Viscusi et al., 1991). Ambiguity-averse people tend to make a worst-case assessment of information quality when processing ambiguous news (Epstein and Schneider, 2008) and to stay away from investments whose returns are more difficult to predict (Alary et al., 2013; Dimmock et al., 2016). Information regarding case origins may help to reduce the ambiguity of COVID-19 risk, allowing people to better assess the risk of infection. Detailed case origin information also signals to the public that the government can effectively trace and respond to the spread of the virus, which may also mitigate people's concern over COVID-19 risk and lower the demand for insurance protection. Therefore, a public policy that provides more information may reduce the impact of information friction and decrease insurance demand. Indeed, reported infection cases with *unknown* sources can generate anxiety among local residents, as cases with unknown origins add to the difficulty of infection containment, thereby increasing subjective risk.[11] Taken together, the above reasoning predicts a negative relationship between local disclosures of case origins and the demand for COVID-19 insurance.

On the other hand, individuals' perceptions of the risk levels to which they are exposed may be heightened by more detailed COVID-19 information (Johnson et al., 1993). If qualitative information about case origins is available, there is more clarity in risk communications, and people may perceive more risk because the infection trajectory shows that the virus is highly contagious—i.e., case origin disclosures may increase the salience of infection risk. Since the seminal work of Bordalo et al. (2012), a growing number of studies have shown that individuals and company managers may overreact to salient risk (e.g., Dessaint and Matray 2017). Eisenbach and Schmalz's (2016) model shows that an anxious agent who is sensitive to imminent risks may choose to buy short-term insurance coverage without much foresight (even if the insurance policy charges an expensive premium). Chang et al. (2018) find that negative transitory health shocks, such as a sudden increase in air pollution, may increase the demand for health insurance because people are affected by salience bias. Indeed, in the setting of the COVID-19 pandemic, people may be under-informed about potential infection risks (Fetzer et al., 2021). It is likely that an information policy increases insurance demand when people are under-informed about potential infection risks. The same view is also shared by Easley and O'Hara (2009, p. 1840), who argue that investors care about both risk and ambiguity, so "disclosure can actually exacerbate difficulties by making investors aware of obscure outcomes that they otherwise might not have thought possible." Therefore, COVID-19 case origin disclosures may increase people's perceived risk and thus their demand for COVID-19 insurance.

Overall, the effect of case origin disclosures on local demand for COVID-19 insurance is an empirical issue, and we examine it empirically below.

[11] Bloomberg, Unknown origin of HK's rising local cases sparks resurgence fears, July 9, 2020. (https://www.chinadailyhk.com/article/136274#Unknown-origin-of-HK's-rising-local-cases-sparks-resurgence-fears.)

4. Research design

4.1. Data and descriptive statistics

To test the effects of the clarity of COVID-19 risk communications on insurance demand, we use several data sources, as discussed below.

4.1.1. Insurance take-up information at the prefecture level

We obtain aggregate insurance take-up data at the prefecture level for the period from January 22 to March 16, 2020 from a leading online insurance distribution platform. This platform has more than 100 million users and has distributed over 30 million policies in China. COVID-19 was formally designated as a legally quarantinable infectious disease in China on January 21, 2020, and the insurance distribution platform began providing COVID-19 insurance on January 22. Our data period ends on March 16, 2020, when the Central Government COVID-19 Response Leading Working Group announced that the spread of the virus was under control. The insurance data cover 9150 prefecture-day observations, collected every other day, for 339 prefectures in China between January 22, 2020 and March 16, 2020.[12] For each prefecture-day for which data are available, we have information on the count of insurance policies and the aggregate premiums for different lines of insurance, which include COVID-19 insurance, serious illness insurance, medical insurance, life insurance, small business insurance, accident insurance, and travel insurance. While unique, these proprietary insurance data have several limitations. First, we do not have access to individual-level insurance data, or subsequent surrender or claim information. However, given that the COVID-19 policy of interest is short-term (1 year) in nature and that premiums are automatically deducted from a mobile wallet on a monthly basis, policy surrender is uncommon. Second, to preserve confidentiality, the data we obtain are not raw data; instead, they are premium amounts and policy counts that have been scaled using an unknown constant by the data providers. This unknown constant has been applied to all of the insurance data (i.e., across all policy types) we obtain. While this affects the economic magnitude of the estimated regression coefficients, this scaling should not affect our inferences about the direction and significance of the relationship between local public disclosures of case origins and COVID-19 insurance purchases. Third, the count of insurance policies in the data includes the free COVID-19 policies that were given out by the insurance platform. However, we would argue that because these free insurance policies needed to be signed up via mobile apps, the count of free policies also measures risk awareness and insurance demand to some extent. The premium amounts do not reflect the free policies, as they only capture the demand for insurance that involves a premium. This measure may, therefore, understate the demand for COVID-19 protection.

4.1.2. COVID-19 cases and the clarity of risk communications

We manually collect the daily reported number of newly confirmed COVID-19 cases and new COVID-19 deaths from each prefecture's health commission. We also collect information about the clarity of daily COVID-19 disclosures—i.e., whether they contained detailed information about the origins of newly confirmed cases (*Disclose*) on a day. Having such qualitative case origin information increases the clarity of COVID-19 disclosures and the saliency of infection risk. The case origin disclosure information is available for each day of the data collection period. As Table 1 shows, around 12% of the disclosure observations contain case origin information. We also examine the spatial distribution of the average likelihood that case origins are disclosed when there are newly confirmed cases and find that the eastern provinces appear to be more likely to disclose case origins than the western and northeastern provinces. This difference in the disclosure of case origins seems to imply a positive relationship between the level of a province's economic development and the clarity of its local COVID-19 risk communications, probably because more human and financial resources are needed to trace case origins. To prevent these inter-region differences from affecting our inferences, we include prefecture fixed effects in the baseline model specification, which allows us to compare insurance purchases for days with and without case origin disclosures within the same prefecture. This is possible because, as we show in Section 2, there are variations in the clarity of COVID-19 risk communications even within the same prefecture.

4.2. Baseline regression model

We test the effects of the clarity of prefecture-level COVID-19 risk communications on the local take-up of COVID-19 insurance by estimating the following baseline ordinary least squares (OLS) model:

$$Demand_{it} = \alpha + \beta Disclose_{i,t-1} + \gamma lnConfirmed_{i,t-1} + \delta lnDead_{i,t-1} + \theta lnProvConfirmed_{i,t-1} + \zeta_t + \eta_i + \varepsilon_{it} \tag{1}$$

We use logged policy counts ($lnPolicies_{it}$) and logged premium amounts ($lnPremium_{it}$) as proxies for insurance demand ($Demand_{it}$) in prefecture i on day t. The variable of interest, $Disclose_{i,t-1}$, indicates qualitative information disclosure, a dummy variable that equals 1 if the local disclosure of COVID-19 in prefecture i on day $t-1$ contains details about case origins. As discussed, on the one hand, this qualitative disclosure may reduce the ambiguity of COVID-19 infection risk; on the other hand, it may increase the saliency of COVID-19 infection risk.

[12] Our insurance data provider was only willing to provide us with data at the frequency of every 2 days.

Table 1
Summary Statistics
This table reports the summary statistics for the variables used in the analysis. Please refer to Appendix 2 for Harris and Tzavalis's (1999) test of non-stationarity in the insurance demand and COVID-19 case variables and Appendix 3 for detailed variable definitions.

Variable	Obs	Mean	Std. Dev.	p25	p50	p75
Disclose (t-1)	9150	0.118	0.322	0	0	0
Confirmed (t-1)	9150	3.744	63.787	0	0	0
Dead (t-1)	9150	0.170	3.085	0	0	0
ProvConfirmed (t-1)	9150	57.227	337.695	0	1	11
Disclose_Neighbor (t-1)	9148	0.131	0.338	0	0	1
Confirmed_Neighbor (t-1)	9148	5.938	89.472	0	0	0
Dead_Neighbor (t-1)	9148	0.300	4.346	0	0	0
lnPolicies						
COVID-19	9150	0.163	0.322	0.019	0.050	0.153
Medical Treatment	9150	0.018	0.044	0.001	0.006	0.014
Serious Illness	9150	0.004	0.012	0	0.001	0.003
Life	9150	0.000	0.002	0	0	0
Small Business	9150	0.036	0.086	0.003	0.009	0.028
Accident	9150	0.002	0.010	0	0	0
Travel	9150	0.000	0.002	0	0	0
lnPremiums						
COVID-19	9150	2.690	1.464	1.739	2.661	3.589
Medical Treatment	9150	1.582	1.269	0.560	1.481	2.340
Serious Illness	9150	0.778	1.081	0	0.115	1.352
Life	9150	0.206	0.637	0	0	0
Small Business	9150	0.707	1.058	0.002	0.071	1.292
Accident	9150	0.139	0.411	0	0	0
Travel	9150	0.007	0.068	0	0	0
Baidu Search Index						
With Search Keyword 1	9150	2927.714	5084.925	855	1244	2789
With Search Keywords 2	9150	3536.961	5452.059	1233	1794	3439
Ratio of New Users Above 60	9006	0.018	0.036	0	0.010	1
Ratio of New Female Users	9006	0.324	0.145	0	0.322	1
MobilePhone	7882	1.163	0.747	0.807	0.974	1.270
InternetAccess	7828	0.310	0.178	0.192	0.260	0.349
High Above 65 Ratio	9150	0.534	0.499	0	1	1
High Old Dependency Ratio	9150	0.584	0.493	0	1	1
Distrust	8556	2.408	0.217	2.332	2.425	2.595

To isolate the effect of the clarity of risk communications, we control for the severity of the pandemic situation in each prefecture on the disclosure day, as proxied by the number of cases: the natural logarithm of 1 plus the number of newly confirmed cases and the natural logarithm of 1 plus the number of new deaths in prefecture i on day $t-1$. As both a prefectural government's COVID-19 disclosure and the demand for insurance may be affected by the pandemic situation in the province concerned, we also control for the logged number of newly confirmed cases on day $t-1$ in the province (excluding the prefecture concerned).[13] These case quantity variables help to capture the effects of risk information that are unrelated to ambiguity.

ζ_t indicates calendar day fixed effects (FEs) that capture any time trend that affects all of the prefectures, such as national policies or the launch of new insurance products. It is also important to note that the inclusion of calendar day fixed effects helps to control for the likely time trend in the number of newly confirmed cases. η_i indicates prefecture FEs that capture time-invariant prefectural characteristics, such as culture,[14] distance from Wuhan city, medical care infrastructure, and level of economic development at the onset of the pandemic. The inclusion of η_i enables us to identify the effect of case origin disclosures on local insurance take-up by exploiting time-series variations in COVID-19 disclosures within the same prefecture, which avoids the confounding effects of any prefecture-level time-invariant omitted variables. ε_{it} is the error term. Robust standard errors are clustered at the prefecture level. Each observation represents a prefecture-day combination.

If information about case origins helps to lower people's perceived infection risk (Viscusi et al., 1991), the coefficient of $Disclose_{i,t-1}$ should be negative and significant. If case origin disclosures raise the salience of infection risk and people are generally under-informed about this risk (Johnson et al., 1993; Dessaint and Matray, 2017), the coefficient of $Disclose_{i,t-1}$ is expected to be positive and significant.

[13] We do not further control for the number of new deaths in the province due to its strong correlation (over 0.60) with the number of newly confirmed cases in the province on the same day.

[14] Zhong et al. (2015) report that regional culture has an impact on insurance consumption in China, but supply factors (such as market completion and foreign insurer participation) do not.

Table 2
COVID-19 Case Origin Disclosure and Insurance Take-up
This table reports how the take-up of COVID-19 insurance responds to local public disclosure of case origins. In all tables, all controls are lagged by one day relative to the measurement of the dependent variable. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A, $Y =$	(1) *lnPolicies*	(2)	(3)	(4)	(5)
Disclose (t-1)	**0.140***** **(0.042)**	**0.102***** **(0.017)**	**0.042***** **(0.015)**	**0.043***** **(0.014)**	**0.043***** **(0.014)**
lnConfirmed (t-1)	0.133*** (0.025)	0.087*** (0.011)	0.048*** (0.010)	0.046*** (0.009)	0.046*** (0.010)
lnDead (t-1)				0.023 (0.043)	0.023 (0.042)
lnProvConfirmed (t-1)					−0.001 (0.006)
Prefecture FEs		Y	Y	Y	Y
Day FEs			Y	Y	Y
Observations	9150	9150	9150	9150	9150
Adjusted R-squared	0.162	0.579	0.755	0.755	0.755
Panel B, $Y=$	*lnPremiums*				
Disclose (t-1)	**0.576***** **(0.126)**	**0.245***** **(0.032)**	**0.074***** **(0.017)**	**0.073***** **(0.017)**	**0.073***** **(0.017)**
lnConfirmed (t-1)	0.516*** (0.071)	0.230*** (0.021)	−0.020** (0.010)	−0.019* (0.010)	−0.025** (0.010)
lnDead (t-1)				−0.013 (0.034)	−0.027 (0.035)
lnProvConfirmed (t-1)					0.020** (0.010)
Prefecture FEs		Y	Y	Y	Y
Day FEs			Y	Y	Y
Observations	9150	9150	9150	9150	9150
Adjusted R-squared	0.121	0.795	0.887	0.887	0.887

5. Empirical results

5.1. Summary statistics

Table 1 reports the summary statistics for the major variables in this analysis. In our sample, COVID-19 case disclosures include information about case origins on approximately 12% of the prefecture-days, and the incidence of case origin disclosures in a prefecture-city's major neighboring city is similar (13%). It is also evident in our sample period when the pandemic was heightened in China, new insurance purchases were dominated by COVID-19 insurance coverage, an observation based on the means of the logged count of insurance policies and the logged premium amounts across different types of insurance. This suggests that COVID-19 insurance coverage is a major personal financial risk management decision in the pandemic period.

In principle, variables such as insurance purchases, number of cases, and number of deaths are likely to be non-stationary and to exhibit some sort of persistent relationship that may cause our estimated regression coefficients to be spurious. This is less of a concern for our logged count of insurance policies, logged premium amounts, and logged number of COVID-19 cases, which are measured as daily *new* figures rather than as cumulative numbers. Nevertheless, we conduct the Harris and Tzavalis test (1999) to check whether the variables using panel data are stationary. The null hypothesis is that the panel data set for each variable contains a unit root. The results of the Harris and Tzavalis test are shown in Appendix 2. We are able to reject the null hypothesis on the existence of a unit root in the five continuous variables relating to insurance demand and COVID-19 cases. There is therefore no evidence that the insurance variables and the COVID-19 case variables are non-stationary.

5.2. Baseline results

To test how local demand for COVID-19 insurance responds to public disclosures of case origins, we estimate Eq. (1), reporting the results in Table 2. Panel A presents the results for the count of COVID-19 insurance policies and Panel B presents the results for the size of insurance premiums. It is worth mentioning that, as discussed in Section 4.1.1, to preserve confidentiality, all of the insurance data (e.g., count of policies and premium amounts across different types of policies) were scaled by the data providers using an unknown constant. This is why, when analyzing the regression results, we only discuss the direction and significance of the coefficients that are not affected by scaling.

In Column (1) of Panel A, we only include *Disclose* and ln*Confirmed*. The estimates, which are based on both time-series and cross-sectional variations, show that the coefficient of *Disclose* is positive and significant at the 1% level, suggesting that people respond to the clarity of risk information by taking up more COVID-19 insurance policies. This is consistent with the notion that people are usually under-informed about pandemic risk (Fetzer et al., 2021) and that detailed risk information increases individuals' perceived risk (Johnson et al., 1993). The coefficient of ln*Confirmed* is also positive and significant, suggesting that the daily number of newly confirmed cases captures the risk of infection. In Column (2), we add prefecture FEs to mitigate the effects of omitted time-invariant prefecture characteristics, finding that the coefficient of *Disclose* remains positive and significant (albeit smaller, understandably, as the inference is based on within-prefecture time-series variations). In Column (3), we further control for day FEs to capture the effect of any calendar day-specific national pandemic developments on the public's sentiment and any national launches of new insurance products, and the coefficient of *Disclose* becomes smaller but remains positive and significant. In the following two columns of Panel A, we further control for new deaths in the prefecture and newly confirmed cases in the province, finding that adding these two variables has little effect on the result of *Disclose*; in fact, these two additional control variables are not loaded. The lack of significance of the effect of new local deaths is perhaps due to the perceived low death rate of COVID-19 infection in China, as the people who died of the infection during that period were reported to be mainly old people with chronic illnesses.

Note that the variable for the count of COVID-19 policies also includes the free COVID-19 policies that were given away by the online insurance distribution platform that needs users to sign up through a mobile app. While the local sign-up count for free COVID-19 policies also reflects an increase in local COVID-19 insurance demand, it is natural to examine how insurance premiums respond to local disclosures of COVID-19 case origins. As the premium data per se do not include free policies, the premium amounts reflect the demand related to COVID-19 that extends beyond sign-ups for free policies. In the results reported in Panel B, we also find that COVID-19 insurance premiums increase with increased disclosure of COVID-19 case origins.

lnConfirmed is positively related to the count of COVID-19 policies but negatively related to the logged premium amounts, as shown in Columns (3)–(5) of Panel B when day FEs are controlled for. The reason may be that when the number of newly confirmed cases is higher, more people are incentivized by the increase in cases to sign up for the free COVID-19 policies provided by the insurance distribution platform.

5.3. The response of local insurance demand to the COVID-19 disclosures of a major neighboring prefecture

In this section, we link local insurance take-up to the COVID-19 case origin disclosures of a major neighboring prefecture with which the focal prefecture shares an extensive border. This approach helps to mitigate concern over the endogeneity of local COVID-19 disclosures arising from the existence of omitted time-varying variables.

We conduct the test separately for Hubei province and other provinces. Hubei (including its capital city Wuhan) was the province most badly hit by COVID-19, and its prefecture cities were locked down to each other from January 23–27 onward. This inter-city lockdown lasted until March 25, when all of the prefectures in Hubei other than Wuhan lifted their lockdowns. During the lockdown period that almost coincides with our sample period, the virus could not spread further in Hubei because people could not move between its prefectures. This was not the case in other provinces. If what matters for our baseline finding is the geographical proximity between people and the infection trajectory of the virus, we should observe a positive and significant response in local demand for COVID-19 insurance to the case origin disclosures of a major neighboring prefecture in the sample, excluding Hubei. This is what we observe in Columns (1) and (3) of Table 3. It is also reassuring that the coefficients of *Disclose_Neighbor* are smaller than those of *Disclose* (reported in Table 2), especially in the premium model.

Due to the complete lockdown of Hubei province, we do not expect insurance demand in the prefectures of Hubei province to respond to the case origin disclosures of their major neighboring prefectures. That is, the tests using the Hubei sample serve as a placebo test of our hypotheses, and the no-results in Columns (2) and (4) are consistent with our arguments. One threat to the inference in Columns (1) and (3) is that the response of the focal prefecture's COVID-19 insurance take-up to the disclosure of case origins in a major neighboring prefecture might be an artifact of the close economic co-movement between the two cities (which may change people's income expectations and therefore their demand for insurance). The no-results in Hubei reported in Columns (2) and (4), however, suggest that economic co-movements between neighboring prefectures are unlikely to be responsible for our findings in Columns (1) and (3). This is because the lockdowns prevent the virus from spreading between the two neighboring prefectures but should have a minimal effect on the economic co-movements between a prefecture and its major neighboring prefecture. Overall, the neighborhood tests based on Hubei versus non-Hubei provinces lend further support to our inferences.

5.4. Alternative interpretations

5.4.1. Is the result due to demographic differences in the user base of the social media app in different prefectures?

One concern is that our baseline finding may reflect demographic differences in the user base of the social media app in different prefectures. We do not have data regarding the total number of users in different age groups, although we do have age data for the newly registered users of the app in different prefectures during our sample period. Note that our regression model controls for prefecture FEs, which means that the differences in the user base of different prefectures

Table 3
Neighborhood COVID-19 Case Origin Disclosure and COVID-19 Insurance Take-up
This table examines whether the demand for COVID-19 insurance in a prefecture city responds to public disclosure of the case origins in its major neighboring city (*Disclose_Neighbor (t-1)*, a dummy that equals one for having such origin disclosure), which shares the most of the border with the focal prefecture. Hubei province is the most badly hit province in which cities are completely locked down to each other. The no-result in Hubei shows that economic co-movements between neighboring prefectures are unlikely to be responsible for our finding in Columns (1) and (3) because lockdowns only prevent the virus from spreading between the two neighboring cities but should have a minimum effect on the economic co-movements between a prefecture and its major neighboring prefecture. Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Y=	(1) Provincesother than Hubei *lnPolicies*	(2) Hubei	(3) Provincesother than Hubei *lnPremiums*	(4) Hubei
Disclose_Neighbor (t-1)	**0.042***** **(0.015)**	**0.014** **(0.035)**	**0.037*** **(0.022)**	**−0.033** **(0.078)**
lnConfirmed_Neighbor (t-1)	0.005 (0.008)	−0.002 (0.012)	−0.005 (0.013)	−0.020 (0.025)
lnDead_Neighbor (t-1)	−0.016 (0.017)	0.028 (0.033)	−0.029 (0.068)	0.079 (0.050)
lnProvConfirmed (t-1)	0.009 (0.008)	0.129*** (0.011)	0.033*** (0.011)	0.030 (0.024)
Prefecture FEs	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y
Observations	8693	455	8693	455
Adjusted R-squared	0.747	0.769	0.888	0.879

Table 4
COVID-19 Case Origin Disclosure and Insurance Take-up Incorporating Demographic Differences
This table examines whether the impact of case origin disclosure on insurance take-up is due to the demographic differences of the user base of the social media app among prefectures. *Ratio of New Users Above 60* and *Ratio of New Female Users* capture the proportion of daily newly registered users above 60 and the proportion of daily newly registered female users in a prefecture city. *Disclose (t-1)* continues to have a significant impact on insurance take-up when demographic differences are controlled for. Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Y=	(1) *lnPolicies*	(2) *lnPremiums*	(3) *ln(Premium Per Policy)*
Disclose (t-1)	**0.043***** **(0.014)**	**0.069***** **(0.017)**	**−0.018** **(0.026)**
lnConfirmed (t-1)	0.045*** (0.010)	−0.033*** (0.010)	−0.057*** (0.015)
lnDead (t-1)	0.024 (0.042)	−0.019 (0.034)	0.087 (0.054)
lnProvConfirmed (t-1)	−0.001 (0.006)	0.015 (0.009)	−0.073*** (0.022)
Ratio of New Users Above 60	0.034 (0.025)	0.988*** (0.283)	1.141 (1.137)
Ratio of New Female Users	0.086*** (0.015)	0.502*** (0.075)	−0.574** (0.246)
Prefecture FEs	Y	Y	Y
Day FEs	Y	Y	Y
Observations	9003	9003	8895
Adjusted R-squared	0.756	0.885	0.516

at the beginning of the sample period become a time-invariant factor that is accounted for by prefecture FEs. To evaluate whether our results are due to demographic differences in the new users of the social media app in different prefectures, we include two variables in the model (*Ratio of New Users Above 60* and *Ratio of New Female Users*) that capture the daily proportion of newly registered users above 60 and the daily proportion of newly registered female users in a prefecture city, respectively. People aged 60 or above are more vulnerable to COVID-19 than other age groups, and women may be more risk-averse than men—an increase in both of these groups is likely to lead to more purchases of COVID-19 insurance policies. The results reported in Columns (1) and (2) of Table 4 are qualitatively similar to the results reported in Table 2. In addition, the positive coefficients of *Ratio of New Users Above 60* and *Ratio of New Female Users* in Column (2) are driven by these population groups' higher demand for insurance, not by a higher price for older people and women. This finding is shown in Column (3), which reports the factors influencing the average price proxied by the logarithm of premiums divided by the count of policies in a city.

Table 5
COVID-19 Case Origin Disclosure and Insurance Take-up before and after February 12
This table reports how the take-up of COVID-19 insurance responds to local public disclosure of case origins using the period between January 22 and February 11 in which the increase in the supply of COVID-19 insurance is less dramatic, and after February 12 as robustness checks. February 12 is not included in either sub-period because there was a structural change in the case reporting criteria in Hubei province on that day. Thus, February 12 was a reporting regime transition day. All controls are lagged by one day relative to the measurement of the dependent variable. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Before February 12	(2)	(3) After February 12	(4)
Y =	*lnPolicies*	*lnPremiums*	*lnPolicies*	*lnPremiums*
Disclose (t-1)	**0.038****	**0.048****	**0.055*****	**0.065***
	(0.015)	**(0.022)**	**(0.017)**	**(0.035)**
lnConfirmed (t-1)	0.032***	−0.025*	0.027**	−0.018
	(0.010)	(0.014)	(0.011)	(0.022)
lnDead (t-1)	0.088	0.071*	0.020	−0.038
	(0.076)	(0.042)	(0.024)	(0.055)
lnProvConfirmed (t-1)	−0.006	0.007	−0.003	−0.012
	(0.009)	(0.015)	(0.004)	(0.014)
Prefecture FEs	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y
Observations	3390	3390	5421	5421
Adjusted R-squared	0.712	0.921	0.838	0.857

5.4.2. Is the result driven by an increase in the supply of COVID-19 insurance?

As discussed earlier, the sale of COVID-19 insurance policies was essentially online during the sample period, given the largely halted offline business activities during the Chinese New Year break and the following pandemic period in the first quarter of 2020. The online insurance distribution platform that provided us with the insurance data played a dominant role in distributing the COVID-19 policies of different insurers, given the popularity of its mobile app. Once a COVID-19 insurance policy enters this platform, it is instantly available to all mobile app users throughout the country with the same policy rates and terms. Clearly, this process means that the supply of insurance is beyond the control of local prefectural governments. We confirmed with our data provider that neither the platform nor its business partners engaged in geography-specific promotional or advertising activities. This feature of the insurance supply means that we can hold insurance supply constant across different prefectures on each day in our analysis. In addition, local governments were the only official source to release local information regarding COVID-19 cases during the sample period, and the online insurance distribution platform did not have the authority to obtain local case origin information in advance. Therefore, our result is not due to varying efforts in the promotion of COVID-19 insurance across different prefectures.

However, one possible concern may be that our observed results are due to the increased supply of COVID-19 insurance over time. To address this concern, we first note that our regression specification controls for calendar day fixed effects, which capture any day-specific national-level increase in insurance supply. A news search shows that the insurance industry regulator, the China Insurance Regulatory Commission (CIRC), played a role in increasing the supply of insurance covering COVID-19. Between February 3 and February 11 of 2020, for example, the CIRC issued three guidance documents encouraging the extension of existing health insurance policy coverage to include COVID-19 infection and the launch of new COVID-19 insurance policies, requiring fair and efficient claim handling as well as insurance agents' adherence to certain codes of conduct, and regulating free insurance provided to the public, among other things.[15] Therefore, we expect to find a more pronounced increase in the supply of COVID-19 insurance from February 12, 2020 onward. In this section, we split the sample period at February 12, 2020 and repeat our baseline analysis separately for the sub-periods before and after February 12 as a robustness check. The results using this short window of analysis are reported in Columns (1) and (2) of Table 5, and they are qualitatively similar to the results reported in Table 2. Overall, therefore, our result is unlikely to be an artifact of an increase in the supply of COVID-19 insurance over time.

5.4.3. Is the result due to the lower number of infected cases in the early stages of the sample period?

Our baseline finding of a positive relationship between local public disclosures of case origins and local residents' insurance demand is potentially amenable to an alternative explanation: it could be that in the early stages of the pandemic, detailed reporting was feasible due to the low number of cases, whereas later it was not. Those most worried about the virus may also have purchased insurance early in the pandemic (and thereby satiated their demand, as coverage is for a full year). This may lead to the observed positive relationship between the two variables without any underlying causality. To

[15] We also conduct a comprehensive news search in the WISE news database (which covers more than 2000 media sources) with a keyword in Chinese equivalent to "COVID insurance" to look for evidence regarding whether local governments promoted the purchase of COVID-19 insurance in our sample period. We are only able to identify eight news articles mentioning COVID-19 insurance in our sample period, and none mentioning local governments promoting the purchase of COVID-19 insurance.

Table 6
COVID-19 Case Origin Disclosure and the Take-up of Insurance of Various Types
This table provides a placebo test by examining whether the higher take-up of COVID-19 insurance is indeed due to people's specific concern over COVID-19 infection risk, and if so, the response of insurance demand to local public disclosure of case origins (*Disclose (t-1)*, a dummy that equals one for having case origin disclosure) should not extend to other types of insurance that provide little coverage against COVID-19 risk. Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel A, *Y*=	(1) COVID-19 *lnPolicies*	(2) Medical Treatment	(3) Serious Illness	(4) Life	(5) Small Business	(6) Accident	(7) Travel
Disclose (t-1)	**0.043*****	**0.002***	**−0.000**	**−0.000**	**0.001**	**−0.001**	**−0.000**
	(0.014)	**(0.001)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.001)**	**(0.000)**
lnConfirmed (t-1)	0.046***	−0.000	0.001***	0.000**	−0.005**	0.003***	0.000
	(0.010)	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)
lnDead (t-1)	0.023	−0.001	−0.001**	−0.000	0.000	−0.004**	−0.000
	(0.042)	(0.003)	(0.000)	(0.000)	(0.004)	(0.002)	(0.000)
lnProvConfirmed (t-1)	−0.001	−0.000	−0.000	−0.000	0.001	−0.001	0.000
	(0.006)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Prefecture FEs	Y	Y	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y	Y
Observations	9150	9150	9150	9150	9150	9150	9150
Adjusted R-squared	0.755	0.917	0.914	0.666	0.896	0.357	0.186
Panel B, *Y*=	**COVID-19 *lnPremiums***	**Medical Treatment**	**Serious Illness**	**Life**	**Small Business**	**Accident**	**Travel**
Disclose (t-1)	**0.073*****	**0.050****	**0.012**	**0.005**	**−0.019**	**−0.025**	**−0.007**
	(0.017)	**(0.022)**	**(0.026)**	**(0.024)**	**(0.030)**	**(0.030)**	**(0.005)**
lnConfirmed (t-1)	−0.025**	−0.040***	0.008	0.036**	−0.046***	0.113***	0.007
	(0.010)	(0.013)	(0.016)	(0.015)	(0.017)	(0.025)	(0.005)
lnDead (t-1)	−0.027	0.062	0.013	0.016	0.003	−0.150**	0.003
	(0.035)	(0.061)	(0.068)	(0.034)	(0.055)	(0.065)	(0.010)
lnProvConfirmed (t-1)	0.020**	−0.009	0.008	−0.009	−0.035***	−0.003	−0.002
	(0.010)	(0.009)	(0.009)	(0.008)	(0.013)	(0.013)	(0.002)
Prefecture FEs	Y	Y	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y	Y	Y
Observations	9150	9150	9150	9150	9150	9150	9150
Adjusted R-squared	0.887	0.821	0.693	0.471	0.688	0.460	0.265

determine whether this alternative explanation is indeed responsible for our findings, we first examine the evolution of the proportion of origin-disclosing prefectures (of all of the prefectures that reported daily new confirmed cases) over time. As Fig. 1 shows, at the beginning of the pandemic, the proportion of prefectures that disclosed information about case origins was not high, although the number of cases was low. We repeat our baseline analysis using the latter part of our sample period (i.e., from February 13, 2020 to the end of the sample period). The results are reported in Columns (3) and (4) of Table 5 and demonstrate that our findings are not consistent with this alternative explanation.

5.5. Evidence for the drivers of insurance take-up

5.5.1. Placebo test

In this section, we describe a placebo test that examines whether the higher take-up of COVID-19 insurance in response to the disclosure of COVID-19 case origins is indeed due to people's concern about infection risk. If it is, the response of local insurance demand to the disclosure of case origins should be limited to insurance that covers COVID-19 risk and should not extend to other types of insurance that provide little COVID-19 coverage. To test this, we regress local demand for COVID-19 insurance, medical treatment insurance, serious illness insurance, life insurance, small business insurance, accident insurance, and travel insurance on *Disclose*, separately. The results of this test, which are reported in Table 6, show that in addition to COVID-19 insurance, the take-up of medical treatment insurance responds to case origin disclosure, albeit to a lesser extent. As discussed in Section 2, some insurers also extended the coverage of existing medical treatment policies to COVID-19 infection. As expected, the demand for other types of insurance is not sensitive to local case origin disclosure.

5.5.2. Evidence from local internet searches for COVID-19 information

Next, we use the Baidu Internet search index on COVID-19-related keywords in each prefecture on each day to examine whether the search responds to local disclosures of COVID-19 case origins.[16] We look at keywords including the Chinese equivalents of "Coronavirus" (*xinxing guanzhuang bingdu* or *xinguan bingdu*), "Corona-pneumonia" (*xinxing guanzhuang feiyan* or *xinguan feiyan*), and "Corona" (*xinguan*). Note that the search statistics include searches initiated from both mobile phones

[16] Baidu is equivalent to China's Google (Google does not operate in China).

Table 7
COVID-19 Case Origin Disclosure and Internet Search Index of COVID-19
This table reports results from examining how local public disclosure of case origins (*Disclose (t-1)*, a dummy that equals one for having such origin disclosure) affects local people' search for COVID-19 related information. Search Keyword 1 refers to the Chinese equivalent of "Coronavirus", Search Keywords 2 include the Chinese equivalent of "Coronavirus", "Corona-pneumonia", "Corona". Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) Y= ln(Baidu search index)	(2)
	With Search Keyword 1	With Search Keywords 2
Disclose (t-1)	**0.097***** **(0.015)**	**0.088***** **(0.015)**
lnConfirmed (t-1)	−0.000 (0.011)	0.006 (0.011)
lnDead (t-1)	−0.063*** (0.020)	−0.063*** (0.021)
lnProvConfirmed (t-1)	0.022*** (0.006)	0.023*** (0.006)
Prefecture FEs	Y	Y
Day FEs	Y	Y
Observations	9150	9150
Adjusted R-squared	0.979	0.973

Table 8
COVID-19 Case Origin Disclosure and Insurance Take-up: The Moderating Role of Communication Penetration
This table reports the results on the role of different communication channels (mobile phone and internet access) in affecting how the take-up of COVID-19 insurance responds to local public disclosure of case origins (*Disclose (t-1)*, a dummy that equals one for having such origin disclosure). Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *lnMobilePhone* and *lnInternetAccess* are the natural logarithms of the number of mobile phone users and internet subscribers scaled by local population in the prefectural city in 2018, and the two variables per se are absorbed by prefecture dummies.

Y =	(1) *lnPolicies*	(2)	(3) *lnPremiums*	(4)
Disclose (t-1)	0.017 (0.014)	0.259*** (0.039)	0.066*** (0.018)	0.053* (0.032)
Disclose (t-1) × lnMobilePhone	**0.203***** **(0.025)**		**−0.000** **(0.026)**	
Disclose (t-1) × lnInternetAccess		**0.178***** **(0.025)**		**−0.010** **(0.025)**
lnConfirmed (t-1)	0.043*** (0.010)	0.044*** (0.010)	−0.038*** (0.010)	−0.038*** (0.010)
lnDead (t-1)	0.027 (0.044)	0.029 (0.044)	0.002 (0.035)	0.002 (0.035)
lnProvConfirmed (t-1)	0.002 (0.006)	−0.001 (0.006)	0.022** (0.010)	0.023** (0.010)
Prefecture FEs	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y
Observations	7882	7828	7882	7828
Adjusted R-squared	0.778	0.776	0.886	0.886

and computer devices. The results, reported in Table 7 based on two slightly different sets of keywords, are positive: the disclosure of case origins increases Baidu COVID-19 searches by 9%, which is consistent with the argument that case origin disclosures heighten the perceived risk of COVID-19 infection (Johnson et al., 1993).[17]

5.5.3. Tests of the information dissemination medium

Thus far, we have shown that heightened concern over COVID-19 following local disclosures of case origins is the driver of the higher take-up of COVID-19 protection. As COVID-19 disclosures were disseminated locally through a variety of communication channels (mobile phone, Internet, and television, among others) during the pandemic period, a higher penetration of mobile phones and Internet should amplify the effect of COVID-19 case origin disclosures on insurance take-up.[18] In Table 8, $lnMobilePhone_i$ and $lnInternetAccess_i$ are the natural logarithm of mobile phones and Internet penetration (the number of mobile phone users and Internet subscribers, scaled according to local population) in prefecture i in 2018 (the

[17] Unreported regressions show that Baidu COVID-19 searches on day t do not predict local disclosures of case origins the next day, suggesting that case origin disclosures are not driven by public demand for transparency.
[18] There is little variation in the number of television channels at the prefecture level.

most recent year for which data are available). These data are sourced from the *China City Statistical Yearbook* (2018). We interact each variable with *Disclose*, and the two penetration variables per se are absorbed by prefecture FEs. The results, reported in Table 8, show that the effect of local public disclosures of case origins on the take-up of COVID-19 insurance increases with mobile phones and Internet penetration when the demand is measured by the count of COVID-19 policies, but not when the demand is measured by insurance premium amounts. These different results may reflect the effect of the free policies.

Taken together, the tests in this section show that local disclosures of case origins heighten perceived infection risk and induce demand for COVID-19 protection.

5.6. The moderating effect of heuristics in the relationship between case origin disclosures and insurance purchases

In the previous sections, we have shown that concern about COVID-19 and information dissemination are channels through which case origin disclosures affect insurance demand. Psychological research shows that people often use simple and efficient strategies, i.e., *heuristics*, to form judgments and make decisions, and that this may lead to errors (Tversky and Kahneman, 1974). Kahneman (2003) reviews three major types of heuristics—*representativeness, availability*, and *anchoring*—that can explain biases in judgment in the context of uncertainty. In this section, we examine how these three heuristics can help people interpret case origin disclosures and therefore moderate the effect of origin disclosures on insurance decisions.[19]

5.6.1. The representativeness heuristic

Kahneman and Tversky (1973) show that people tend to substitute a judgment of similarity, namely representativeness, for a judgment of probability. In the setting of the COVID-19 pandemic, people may judge the risk of getting infected based on how widely the pandemic has spread among the local population due to the representativeness heuristic. To test this, we use the cumulative number of confirmed cases, scaled by the local population, to capture people's perceptions of the virus. If the proportion of cumulative confirmed cases in the local population exceeds a certain level, people may view COVID-19 risk as high based on the representativeness heuristic. We scale the number of cumulative confirmed cases by the prefectural population and generate a dummy variable (*Scaled-Cumulative Confirmed (t-1)* $>$ *0.05*) indicating whether the scaled number of cumulative confirmed cases is greater than 0.05 per 10,000 people.[20] In Panel A of Table 9, we interact this dummy variable with *Disclose*. The results show that the COVID-19 insurance purchase response (measured by the logged count of policies) to case origin disclosure is stronger when the ratio of cumulative confirmed cases to the local population is above 0.05. However, this result does not hold for insurance premium amounts, possibly due to the previously discussed confounding effect of the free policies. Therefore, there is some evidence that the representativeness heuristic plays a role in shaping how insurance demand responds to local case origin disclosures.

5.6.2. The availability heuristic

When people use the availability heuristic, they evaluate the probability of events using the ease with which relevant instances come to mind (Tversky and Kahneman, 1973). If the availability heuristic applies in our context, people who have experienced a similar epidemic are likely to use the availability heuristic and will therefore react more to case origin disclosures. In 2003, the epidemic of severe acute respiratory syndrome coronavirus (SARS) occurred in China. People who witnessed severe SARS infections tend to have easy access to memories of that earlier pandemic. We therefore interact *Disclose* with the dummy variable *SARS Cases Above 1000*, which equals 1 if a province had more than 1000 confirmed cases in the 2003 SARS pandemic. According to the results reported in Column (1) of Panel B in Table 9, people in provinces that were more severely affected by SARS appear to respond more strongly to COVID-19 case origin disclosures in their take-up of COVID-19 insurance policies.[21] When insurance demand is measured by premiums, however, the coefficient of the interaction term unexpectedly turns negative and significant, possibly due to the confounding effects of the free policies.

5.6.3. The anchoring heuristic

According to Tversky and Kahneman (1974), anchoring occurs when people use a reference point as an anchor for their decisions. In the setting of the COVID-19 pandemic, when the cumulative number of confirmed cases reaches a milestone, people may regard this number as an "anchor" that reflects a high risk of becoming infected. In our sample, fewer than 10% of the prefecture-day observations involve over 200 cumulative confirmed cases, suggesting that the milestone of 200 cases is a salient event. We therefore define the dummy variable *Milestone200*, which equals 1 when the cumulative number of confirmed cases in a prefecture has reached 200 cases and 0 otherwise. Panel C of Table 9 shows that after the cumulative number of confirmed cases exceeds 200, the impact of case origin disclosures on insurance demand is significantly higher when demand is measured by the logged count of COVID-19 policies, suggesting that the anchoring heuristic may amplify the effects of case origin disclosures.

[19] Again we thank an anonymous reviewer for suggesting the test on heuristics.

[20] 0.05 is close to the median of the scaled number of cumulative confirmed cases (person per 10,000 people).

[21] Note that the sample size in Panel B is larger than that in Panel A of Table 9 because the populations of some prefecture cities are missing, resulting in missing values for *Scaled-Cumulative Confirmed* (t − 1) in Panel A.

Table 9
COVID-19 Case Origin Disclosure and Insurance Take-up: The Moderating Role of Heuristics
This table reports the results on the role of heuristics in affecting how the take-up of COVID-19 insurance responds to local public disclosure of the case origins (*Disclose (t-1)*, a dummy that equals one for having such origin disclosure). Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Control variables in Table 2 are also controlled, but are not tabulated. *Scaled-Cumulative Confirmed* is prefectural cumulative confirmed cases scaled by local population in the prefecture city in 2018. *Scaled-Cumulative Confirmed (t-1) > 0.05* is a dummy set to 1 if the scaled-cumulative number of confirmed cases in prefecture i in day t-1 is larger than 0.05 person per 10 thousand people, and 0 otherwise. *SARS Cases Above 1000* is a dummy set to 1 if a province's confirmed cases in the SARS pandemic in 2003 exceeded 1000, and 0 otherwise. *SARS Cases Above 1000* per se is absorbed by prefecture fixed effects. *Milestone200 (t-1)* is a dummy set to 1 if the cumulative confirmed cases in prefecture i in day t-1 has reached 200 cases, and 0 otherwise.

Panel A, *Y*=	(1) *lnPolicies*	(2) *lnPremiums*
Disclose (t-1)	0.001	0.082***
	(0.013)	(0.022)
Scaled-Cumulative Confirmed (t-1) > 0.05	−0.002	−0.026
	(0.010)	(0.028)
Disclose (t-1) × Scaled-Cumulative Confirmed (t-1) > 0.05	**0.076*** **	**−0.042**
	(0.028)	**(0.030)**
Control variables in Table 2	Y	Y
Prefecture & Day FEs	Y	Y
Observations	7882	7882
Adjusted R-squared	0.770	0.886
Panel B, *Y*=	*lnPolicies*	*lnPremiums*
Disclose (t-1)	0.027*	0.078***
	(0.014)	(0.018)
Disclose (t-1) × SARS Cases Above 1000	**0.151*** **	**−0.053***
	(0.042)	**(0.031)**
Control variables in Table 2	Y	Y
Prefecture & Day FEs	Y	Y
Observations	9150	9150
Adjusted R-squared	0.757	0.887
Panel C, Y=	*lnPolicies*	*lnPremiums*
Disclose (t-1)	0.028*	0.068***
	(0.016)	(0.017)
Milestone200 (t-1)	0.086**	0.066
	(0.042)	(0.047)
Disclose (t-1) × Milestone200 (t-1)	**0.360*** **	**0.051**
	(0.129)	**(0.037)**
Control variables in Table 2	Y	Y
Prefecture & Day FEs	Y	Y
Observations	9150	9150
Adjusted R-squared	0.761	0.887

To summarize, we find some evidence that heuristics play a role in shaping how people interpret COVID-19 case information and how they respond to local case origin disclosures with insurance decisions. Due to the limitations of our datasets, we are unable to test for other biases. For example, a full test of salience bias would also require data that capture subsequent cancellations of COVID-19 policies, which we do not have. In addition, while we are unable to show whether the insurance purchases were optimal, we believe that the wealth implications of the COVID-19 insurance decisions we examine should be rather limited, as the policies were limited to 1 year and generally involved moderate premiums.

5.7. Heterogeneity in the effects of local disclosure of COVID-19 case origins

5.7.1. The moderating effects of local population characteristics

Old people are the most vulnerable group to COVID-19: once infected, it is difficult for them to recover, and the mortality rate is high because such people often have other chronic illnesses. As COVID-19 poses a higher risk to old people, we examine the moderating effects of local population characteristics on the insurance response to local disclosures of case origins. We look at two population characteristics (the proportion of old adults and the old-age dependency ratio—i.e., the population over 65 divided by the working population). These two variables are only available at the province level for 2018. *High Above 65 Ratio* (*High Senior Dependency Ratio*) is a dummy variable that equals 1 if the proportion of people over 65 (the old-age dependency ratio) is higher than the median of the province-level variable in 2018. We separately interact these dummy variables with *Disclosure* to capture the moderating effects of population characteristics. We also interact them with the control variables such as newly confirmed cases and deaths to account for the potential moderating effects on those variables. As shown in Columns (2)–(4) of Table 10, the interaction terms between *Disclosure* and the two dummy variables

Table 10
COVID-19 Case Origin Disclosure and Insurance Take-up: The Moderating Role of Population Characteristics
This table examines the moderating effect of the local population characteristics on the response of the take-up of COVID-19 insurance to local public disclosure of case origins (*Disclose (t-1)*, a dummy that equals one for having such origin disclosure). Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at prefecture cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Control variables in Table 2 are also included but not tabulated. Population characteristics are only available at the province level in 2018. A *High Ratio* is a dummy variable that equals one if the variable is higher than the median of the province-level variable in 2018.

Y =	(1) *lnPolicies*	(2)	(3) *lnPremiums*	(4)
Disclose (t-1) (b1)	0.013	−0.005	0.011	0.014
	(0.020)	(0.026)	(0.031)	(0.032)
Disclose (t-1)* × *High Above 65 Ratio (b2)	**0.037**		**0.091****	
	(0.028)		**(0.038)**	
Disclose (t-1)* × *High Senior Dependency Ratio (b2)		**0.051***		**0.078****
		(0.031)		**(0.039)**
Control variables in Table 2	Y	Y	Y	Y
Controls × *High Above 65 Ratio*	Y		Y	
Controls × *High Old Dependency Ratio*		Y		Y
Prefecture & Day FEs	Y	Y	Y	Y
b1 + b2	0.050***	0.046***	0.102***	0.092***
P-value of testing (b1+b2)	0.008	0.004	0.000	0.000
Observations	9150	9150	9150	9150
Adjusted R-squared	0.756	0.757	0.887	0.887

Table 11
COVID-19 Case Origin Disclosure and Insurance Take-up: The Moderating Role of Confidence in Local Government
This table reports the results on the role of confidence in local governments in affecting how the take-up of COVID-19 insurance responds to local public disclosure of case origins (*Disclose (t-1)*, a dummy that equals one for having such origin disclosure). Each observation refers to a prefecture-day combination. Robust standard errors in parentheses are clustered at cities. All regression models include a constant and its estimates are not tabulated for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Distrust* is the average level of people's lack of confidence in local governments (measured at the province level) in 2012, and *Distrust* is absorbed by prefecture dummies. *Distrust* ranks from 1 (complete trust) to 4 (complete distrust). The number of observations drops because *Distrust* in the 2012 CGSS survey does not cover Hainan province and Tibet, which caused a loss of observations in this test. Columns (1) and (3) are restricted to the observations whose *Distrust* is available.

Y =	(1) *lnPolicies*	(2)	(3) *lnPremium*	(4)
Disclose (t-1)	0.043***	0.007	0.072***	0.422**
	(0.014)	(0.173)	(0.017)	(0.175)
Disclose (t-1)* × *Distrust		**0.015**		**−0.143****
		(0.071)		**(0.071)**
lnConfirmed (t-1)	0.044***	0.044***	−0.036***	−0.035***
	(0.010)	(0.010)	(0.009)	(0.010)
lnDead (t-1)	0.025	0.026	−0.014	−0.016
	(0.043)	(0.043)	(0.036)	(0.036)
lnProvConfirmed (t-1)	−0.005	−0.005	0.015	0.017*
	(0.006)	(0.006)	(0.010)	(0.010)
Prefecture FEs	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y
Observations	8556	8556	8556	8556
Adjusted R-squared	0.764	0.764	0.879	0.879

have positive and statistically significant coefficients. The results therefore show that the effect of case origin disclosures on the demand for COVID-19 insurance is more pronounced when there is a higher (than the sample median) proportion of old adults or a high old-age dependency ratio.

5.7.2. The moderating effects of confidence in local governments

As case origin information is disclosed by local governments, a low level of confidence in the local government should weaken the effect of COVID-19 case origin disclosures on insurance demand. We draw on data capturing people's confidence in their local governments from the *Chinese General Social Survey* (CGSS, 2012).[22] This scale ranges between 1 and 4, with 1 denoting complete confidence and 4 denoting least confidence.[23] In Table 11, we show the interaction of $Distrust_i$, the

[22] The CGSS is a comprehensive national longitudinal survey. The survey covers issues including values, attitudes, health, family, and education. In 2013, the CGSS stopped reporting people's confidence in local governments, so the 2012 data are the most up-to-date data available. However, as confidence tends to change slowly, we believe that using the 2012 data point will not unduly bias our results.

[23] The corresponding survey question is "Do you think the local government is trustworthy?" On the scale, 1 indicates "completely trustworthy," 2 indicates "likely to be trustworthy," 3 indicates "likely to be untrustworthy," and 4 indicates "completely untrustworthy."

average level of lack of confidence in local government in a province, with *Disclose*. $Distrust_i$ is absorbed by prefecture FEs.[24] As the sample with corresponding confidence data is smaller than that in the baseline analysis reported in Table 2, we first repeat the baseline analysis with the smaller sample in Columns (1) and (3) of Table 11, finding that the results are robust. We then conduct an interaction analysis, shown in Columns (2) and (4). The results show that the response of the demand for COVID-19 insurance (measured by premium amounts) to case origin disclosures is attenuated when local citizens report a lower level of confidence in local governments (we do not find this effect when demand is measured by the count of COVID-19 policies, perhaps due to the effects of the free policies). If the average level of the confidence variable in a province is "likely to be untrustworthy" or "completely untrustworthy," the disclosure of case origins has no positive effect on people's demand for insurance, as in this case the combined coefficient of *Disclose* in Column (4) would become negative.

6. Conclusion

Access to relevant risk information is key to risk management decision-making. However, the literature does not agree on how risk communication and improved knowledge about risk affect individuals' risk-taking and risk management behaviors. In particular, although public information disclosure is an attractive public policy tool for improving consumers' choices in many contexts, its efficacy is not widely tested, at least in insurance settings (Handel et al., 2019). We extend the understanding of people's risk behaviors during the COVID-19 pandemic—a new but rapidly expanding health risk—by studying how the clarity of public risk communications affects people's take-up of COVID-19 insurance. Using proprietary prefecture-day-level insurance data provided by a leading online insurance distribution platform in China, we find that more clarity in risk communications, proxied by local disclosures of COVID-19 case origins, leads people to search for more COVID-19-related information and purchase more COVID-19 insurance (measured in terms of both the count of new insurance policies and the amount of policy premiums. The results are consistent with the argument that increased public information disclosures help consumers to recognize potential risks and engage in risk mitigation.

This effect is robust to using the disclosure of COVID-19 case origins in a major neighboring prefecture city (in provinces other than Hubei, in which cities were completely locked down to one another). In particular, the no-results in Hubei show that economic co-movements between neighboring prefectures are unlikely to be responsible for our finding in the neighboring-city test: lockdowns prevent the virus from spreading between two neighboring cities, but they should have a minimal effect on two cities' economic co-movements. A test using neighboring prefectures further suggests that geographical proximity between people and infected cases matters. Our result is limited to insurance that covers COVID-19 exposure; it does not hold for other types of insurance. We also find some evidence that three major types of heuristics—*representativeness, availability*, and *anchoring*—appear to moderate the effects of origin disclosures on insurance decisions. The effects of local COVID-19 case origin disclosures are stronger in places in which a higher proportion of the population is vulnerable and weaker in places in which people have less confidence in their local governments.

One limitation of our study is that data limitations (e.g., the lack of policy surrender and claim information) preclude us from testing whether insurance purchases are an overreaction to salient risk. However, any salience bias is likely to have limited economic consequences on the insured, given that COVID-19 insurance only lasts for a year and involves moderate premiums.

Our results are relevant to the debate regarding whether to publicly disclose detailed COVID-19 information in the event of a pandemic. Assuming that a higher commercial insurance take-up rate is desirable in a pandemic that may easily exhaust government fiscal resources and overwhelm public hospitals, one policy implication of this finding is that providing more qualitative information to the public can help to raise people's awareness of risk management. Of course, providing more detailed risk information could also exacerbate adverse selection and lead to market unraveling.

Data availability

The data that has been used is confidential.

Appendix 1. Sample local public COVID-19 disclosures

*Some sample local public disclosures without case origin information (*i.e., *Disclosure = 0)*

Sample 1: COVID-19 disclosure by Shanghai on January 24, 2020:

"Between 12am and 11:59pm of January 24, Shanghai reported 13 newly confirmed cases. So far there are 33 cumulative confirmed cases; of which, 30 cases are in a stable condition, 2 cases are in critical condition, and 1 case has been discharged from hospital after treatment. In addition, there are 72 suspected cases."

[24] Level of confidence in local government can only be measured at the province level. We do not have confidence data for Hainan province or Tibet.

Sample 2: COVID-19 disclosure by Tieling city on January 27, 2020:

"Till 5pm of January 27, Tieling reported two cumulative confirmed cases, both of which are imported cases. One is in Xifeng and the other is in Diaobingshan. The two cases are under isolated treatment in designated medical institutions. There is no newly confirmed case. So far there are 66 cumulative close contacts under medical observation."

Some sample local public disclosures with case origin information **(i.e.,** ***Disclosure =1)***

Sample 3: COVID-19 disclosure by Chengdu City in Sichuan province on February 5, 2020:

"There were 5 newly confirmed cases; two patients were healed and discharged from the hospital; cumulatively there were 97 confirmed cases, 19 discharged cases, and one death; 975 people having close contact with confirmed cases were put under medical observation. Below is information about the 5 newly confirmed cases:

Case 1: Female, 43 years old, resident of Gaoxin District in Chengdu. From January 22 to February 3, she travelled with her family to Kunming and Laos. On January 28, she began to have diarrhea. On February 4, she went to a hospital and was transferred to a COVID-19 designated hospital for isolation treatment.

Case 2: Female, 64 years old, resident of Gaoxin District in Chengdu, is the accompanying mother of the patient in Case 1. She began to have diarrhea on January 28. On February 4, she went to a hospital and was transferred to a COVID-19 designated hospital for isolation treatment.

Case 3: Male, 55 years old, resident of Sichuan Mianyang City, travelled to Chengdu by taxi on January 21, 2020. He showed the cold symptom on January 30, 2020, went to a hospital on February 2, and then was transferred to a COVID-19 designated hospital for isolation treatment.

Case 4: Male, 51 years old, resident of Jinniu District of Chengdu city, drove to Hubei hometown between January 21–25, 2020. He showed the fever symptom on January 30, 2020, and was then transferred to a COVID-19 designated hospital for isolation treatment.

Case 5: Female, 47 years old, resident of Wuhou District of Chengdu city, is a family member of a case confirmed on February 2. She was put under central quarantine on February 3, 2020, showed symptom of coughing on February 4, and was then transferred to a COVID-19 designated hospital for isolation treatment."

Sample 4: COVID-19 disclosure by Zhangzhou city in Fujian province on January 26, 2020:

"By 10pm of January 26, our city had one new imported confirmed case. The patient (resident of Yunxiao County) is a female and 37 years old. She came to Zhangzhou from Wuhan on January 19, went to a COVID-19 designated hospital on January 23 and was put under isolation treatment with a stable condition. During her stay in Zhangzhou, she has closely contacted 11 people including family members, friends, and restaurant waitress, and all of them are now under medical watch."

Appendix 2. Harris and Tzavalis's (1999) Test of Non-stationarity

This table conducts Harris and Tzavalis's (1999) test of non-stationarity in the insurance demand and COVID-19 case variables.

	Statistic	z	*p*-value
lnPolicies	0.493	−27.919	0.000
lnPremiums	0.082	−74.115	0.000
lnConfirmed (t-1)	0.456	−31.981	0.000
lnDead (t-1)	0.346	−44.323	0.000
lnProvConfirmed (t-1)	0.601	−15.743	0.000

Appendix 3. Variable definitions

Variable	Definitions
Disclose (t-1)	A dummy variable that equals 1 if the local government of prefecture *i* discloses the origins of confirmed cases on day *t*-1, and 0 otherwise.
lnConfirmed (t-1)	Log(1+newly confirmed cases) in prefecture *i* on day *t*-1.
lnDead (t-1)	Log(1+new deaths) in prefecture *i* on day *t*-1.
lnProvConfirmed (t-1)	Log(1+newly confirmed cases in the province where prefecture *i* locates on day *t*-1, but excluding the prefecture concerned)
Disclose_Neighbor (t-1)	A dummy variable that equals 1 if the major neighboring prefecture of prefecture *i* discloses the origins of confirmed cases on day *t*-1, and 0 otherwise.
lnConfirmed_Neighbor (t-1)	Log(1+newly confirmed cases in a major neighboring prefecture city of prefecture *i* on day *t*-1).
lnDead_Neighbor (t-1)	Log(1+new deaths in a major neighboring prefecture city of prefecture *i* on day *t*-1).
lnPolicies	
COVID-19	Log(1+ count of new COVID-19 insurance policies) in prefecture *i* on day *t*.
Medical Treatment	Log(1+ count of new medical treatment insurance policies) in prefecture *i* on day *t*.
Serious Illness	Log(1+ count of new serious illness insurance policies) in prefecture *i* on day *t*.
Life	Log(1+ count of new life insurance policies) in prefecture *i* on day *t*.
Small Business	Log(1+ count of new small business insurance policies) in prefecture *i* on day *t*.
Accident	Log(1+ count of new accident insurance policies) in prefecture *i* on day *t*.
Travel	Log(1+ count of new travel insurance policies) in prefecture *i* on day *t*.
lnPremiums	
COVID-19	Log(1+ new COVID-19 insurance premiums) in prefecture *i* on day *t*.
Medical Treatment	Log(1+ new medical treatment insurance premiums) in prefecture *i* on day *t*.
Serious Illness	Log(1+ new serious illness insurance premiums) in prefecture *i* on day *t*.
Life	Log(1+ new life insurance premiums) in prefecture *i* on day *t*.
Small Business	Log(1+ new small business insurance premiums) in prefecture *i* on day *t*.
Accident	Log(1+ new accident insurance premiums) in prefecture *i* on day *t*.
Travel	Log(1+ new travel insurance premiums) in prefecture *i* on day *t*.
lnBaiduSearchIndex	
Search Keyword 1	Log(1+ Baidu search index using keyword representing the Chinese equivalent of "Coronavirus" (*xinxing guanzhuang bingdu*)) in prefecture *i* on day *t*.
Search Keywords 2	Log(1+ Baidu search index for keywords representing the Chinese equivalent of "Coronavirus" (*xinxing guanzhuang bingdu* or *xin guan bingdu*), "Corona-pneumonia" (*xinxing guanzhuang feiyan* or *xinguan feiyan*), and "Corona" (*xinguan*)) in prefecture *i* on day *t*.
Ratio of New Users Above 60	Proportion of newly registered users above 60 in prefecture *i* on day *t*.
Ratio of New Female Users	Proportion of newly registered female users in prefecture *i* on day *t*.
lnMobilePhone	Log(the number of mobile phone users scaled by local population) in prefectural *i* in 2018.
lnInternetAccess	Log(the number of Internet subscribers scaled by local population) in prefecture *i* in 2018.
Scaled-Cumulative Confirmed (t-1) > 0.05	A dummy variable that equals 1 if the cumulative confirmed cases in prefecture *i* on day *t*-1 scaled by prefectural population in 2018 is higher than 0.05 person per 10 thousand persons, and 0 otherwise.
SARS Cases Above 1000	A dummy variable that equals 1 if the provincial confirmed cases in 2003 SARS pandemic were more than 1000 cases, and 0 otherwise.
Milestone200 (t-1)	A dummy variable that equals 1 if the cumulative confirmed cases in prefecture *i* on day *t*-1 has reached 200 cases, and 0 otherwise.
High Above 65 Ratio	A dummy variable that equals 1 if the provincial ratio of population above 65 years old is higher than the median of the province-level variable in 2018, and 0 otherwise.
High Old Dependency Ratio	A dummy variable that equals 1 if the provincial old dependency ratio (population above 65 over working population) is higher than the median of the province-level variable in 2018, and 0 otherwise.
Distrust	Average province-level lack of confidence in local government in 2012, which takes a value between 1 and 4, with 1 as completely trustworthy and 4 as completely untrustworthy.

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