Insuring Against the Heat

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Abstract

We examine how households respond to heat when making health insurance decisions. Using administrative data from major insurers covering 70 percent of China's health insurance market, we find that a one-degree Celsius increase in purchase-day temperature increases uptake of critical illness insurance by 0.6 percent, with demand rising by 4 percent on extreme heat days. These effects are short-lived: cancellations spike when temperatures cool during the post-purchase cooling-off period. Households are also more likely to choose single-premium contracts on hot days, consistent with a commitment motive. A series of tests point to salience bias as the primary mechanism. Heat intensifies health-related search activity, amplifies responses in physically exposed settings, and selectively increases demand for high-severity products. The effects are transitory and do not influence future claims or contract terms.

Keywords: Household Finance, Insurance, Temperature, Heat, Salience

JEL Classification: D14, G22, Q54, I13

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1. Introduction

Why do households buy health insurance? Standard economic theory predicts that demand reflects long-term risk: risk-averse households seek to smooth consumption across uncertain health states (Arrow, 1963; Rothschild and Stiglitz, 1976). However, a growing body of evidence shows that real-world insurance choices often deviate from this benchmark (Sydnor, 2010; Barseghyan et al., 2013; Handel, 2013). Many decisions appear misaligned with actuarial risk, pointing to the role of behavioral factors. This paper studies one such factor: temperature. As an immediate and salient environmental cue, heat may distort risk perception and trigger rapid financial responses, even when underlying health risks remain unchanged. Indeed, prior research has shown that heat can distort labor supply (Graff Zivin and Neidell, 2014), influence judicial decisions (Heyes and Saberian, 2019), and shift retail investors' beliefs about climate risk (Choi et al., 2022). Nonetheless, its impact on actual household-level financial decisions, particularly insurance uptake, remains largely unexplored.

In this paper, we provide direct evidence that households insure against the heat. Using detailed microdata from major Chinese insurers, we show that health insurance purchases spike on hot days, cancellations increase when temperatures fall during the post-purchase cooling-off period, and households are more likely to prepay when conditions are warmer. These behaviors are short-lived and inconsistent with forward-looking optimization. To structure our analysis, we draw on the salience framework developed by Bordalo et al. (2020, 2022), which offers a useful lens for interpreting attention-driven responses to environmental cues. We derive four testable predictions from this framework: attention should spike following a shock; responses should be strongest when exposure is direct; product choice should shift toward more emotionally vivid coverage; and effects should dissipate quickly. The data support each of these predictions, pointing to salience as the primary mechanism.

These empirical patterns also help distinguish salience from competing explanations, particularly projection bias, which implies more persistent distortions in beliefs or preferences. Both mechanisms have been used to explain related behaviors, such as car purchases following weather shocks (Busse et al., 2015) and insurance uptake during pollution events (Chang et al., 2018). However, they are rarely disentangled in high-stakes, long-term financial contexts. By leveraging the short-lived nature of temperature shocks and detailed contract-level data, we are

able to isolate salience as the dominant mechanism: households respond not to revised beliefs about underlying risk, but to the perceived immediacy of risk.

To test these ideas in a high-stakes setting, we focus on critical illness insurance, a product that pays a lump sum upon diagnosis of major health conditions. This market provides a clean environment for studying decision-making under uncertainty, as households must weigh low-probability, high-cost health risks against the upfront cost of protection. Our analysis spans the 2008-2018 period, following a major regulatory reform by the China Insurance Association that standardized the definition of covered illnesses, enhancing consistency across insurers and comparability across contracts. We examine how salience influences behavior in this context by linking rich transaction-level insurance data with high-frequency, city-level weather records.

Our empirical analysis draws on two primary datasets. The first is a comprehensive administrative dataset from eight major insurance providers, covering approximately 70 percent of the national market. It includes detailed micro-level data on 5.1 million insurance policies and more than 1 million city-day observations across 280 cities in 30 provinces. The dataset provides rich information on policy characteristics (such as purchase date, premium, and coverage), individual demographics (including age, gender, and urban or rural residency), and claims history (such as illness onset, filing dates, and payout amounts). The second dataset is the CN05 Gridded Observation Dataset, developed by the China National Climate Change Research Center. This dataset provides high-resolution daily weather data, including maximum and minimum temperatures, precipitation, and wind speed, with fine spatial and temporal detail. Our main interest is daily maximum temperature and abnormal temperature, defined as the deviation of daily maximum temperature from its historical baseline.

Linking these datasets, we construct a city-day panel that connects insurance purchases to local temperature fluctuations. Exploiting within-city daily variation and controlling for seasonality and insurer fixed effects, we seek to isolate the impact of transitory temperature shocks. We find that a one-degree Celsius increase in abnormal or maximum temperature raises the purchase rate by 0.006 policies per million residents, a 0.6% increase relative to the daily average. The effect is immediate and short-lived, confined to the purchase day. It is stronger on extreme heat days, with temperatures above the 90th percentile increasing demand by 4 percent. In contrast, extreme cold has no measurable effect. This asymmetry suggests that heat

acts as a vivid environmental cue that temporarily elevates perceived risk, consistent with a behavioral rather than forward-looking response.

While epidemiological evidence shows that cold-related mortality far exceeds heat-related deaths (Cohen and Dechezleprêtre 2022), our findings align with a broader behavioral pattern: households tend to respond most strongly to acute, physically felt environmental shocks. For instance, prior studies show spikes in the purchase of air-conditioners when temperature rises (Bonan et al., 2024) and increased investment in cooling technologies during heatwaves (Barwick et al., 2024). These responses often reflect immediate perceived threat rather than rational cost-benefit assessment. Our results are consistent with this pattern: insurance uptake rises sharply on hot days, only to reverse during the cooling-off period, evidence of behavior driven by transient salience rather than forward-looking reassessment of risk.

The effects of heat extend beyond whether households purchase insurance to how they choose to pay for it. On hotter days, we find that households are more likely to select single-premium contracts rather than spreading payments over time. This shift toward prepayment suggests a desire to lock in protection when the perceived risk is elevated, despite identical policy terms. The behavior mirrors the use of commitment devices, where individuals take costly upfront actions to secure peace of mind (Ashraf et al., 2006; Carrera et al., 2022). Nonetheless, while prepayment may provide short-term reassurance, it may also lead to financial inefficiencies if driven by momentary distortions in risk perception rather than long-run planning.

In sum, we show that temperature shocks influence not only whether households purchase insurance but also how they choose to pay for it. The evidence consistently points to salience as the underlying mechanism. Vivid and transitory cues elevate perceived risk and trigger immediate financial responses. Following Bordalo et al. (2020, 2022), we interpret these behaviors through three channels of salience: contrast, which captures how certain attributes of a product stand out when comparing to their alternatives; prominence, which reflects the overlook of hidden attributes; and surprise, which directs attention to unexpected events.

We test the predictions of this framework along four dimensions. First, we show that temperature shocks trigger immediate increases in attention to both heat and health risks. Using the Baidu Search Volume Index, we construct daily indices for heat-related and health-related terms and find that both rise sharply on hotter days, consistent with the surprise channel.

Second, we examine heterogeneity in behavioral responses and find that effects are significantly stronger when physical exposure is direct. This includes purchases made offline, in urban areas, and by outdoor workers, highlighting the role of prominence.

Third, we document selective increases in the uptake of emotionally vivid, high-severity insurance products. Using data from an insurer offering a wide product range, we find that heat raises demand for critical illness and life insurance, while routine products such as accident or medical insurance show no change. This pattern aligns with the contrast channel. Finally, we show that these effects are short-lived. Uptake spikes on the day of the shock, fades quickly, reverses during the cooling-off period, and does not affect future claims or contract terms. Collectively, these results demonstrate that salient but transient cues can meaningfully distort household financial decisions, even in settings designed to protect against long-term risk.

While our main results point to salience as a likely mechanism, it is important to consider alternative explanations that could also account for the observed patterns. In particular, three possibilities merit closer examination: rational learning, projection bias, and supply-side adjustments. Each reflects a distinct behavioral or market process. Rational learning suggests that households interpret temperature shocks as signals of long-term health risk. Projection bias implies that individuals overpredict the persistence of current conditions and the future utility derived from having an insurance contract, leading to elevated perceived risk. Supply-side adjustments, in turn, suggest that insurers may respond to weather conditions by changing product features or marketing efforts. Carefully distinguishing between these mechanisms helps to clarify the drivers of the observed behavioral response.

We assess each of these alternatives using targeted empirical tests. For rational learning, we examine whether insurance policies purchased on hotter days result in more future claims. Across multiple specifications and time horizons, we find no evidence of such a relationship. This weakens the case for a learning-based interpretation. For projection bias, we test whether behavioral responses are stronger among higher-risk individuals, whether contract durations change, and whether claims are more likely to be rejected. In each case, the data show little support for persistent belief distortions. The results instead suggest that the response to heat is short-lived and context-dependent, consistent with an attentional shift rather than a durable change in expectations.

We also examine whether the observed patterns could reflect supply-side changes. Using detailed contract-level data, we assess whether product terms (including premiums, coverage periods, and insured amounts) vary systematically with temperature. Across the board, we find no evidence of such adjustments. While we cannot fully rule out more subtle forms of insurer response, the stability of contract features strengthens the interpretation that the observed effects stem from household behavior. Taken together, these findings align more closely with a salience-based explanation. Heat appears to act as a vivid, transient cue that heightens perceived risk in the moment, shaping financial choices in ways that may not reflect long-term intentions or needs.

Our findings carry important policy implications. More broadly, they show that transitory environmental cues can distort household financial decisions, even in high-stakes settings. While our analysis focuses on critical illness insurance, the underlying mechanism likely applies to a range of contexts where households must balance long-term risk with short-term signals, including saving, investment, health spending, and disaster preparedness. Fleeting environmental conditions can divert attention and drive decisions that deviate from long-term interests. Recognizing this form of bias is crucial for designing financial products and public policies that promote stability and resilience. By establishing a clear link between environmental cues and biased decision-making, our study contributes to a deeper understanding of how cognitive distortions shape financial behavior in an increasingly uncertain climate.

Related Literature. This paper contributes to several strands of research. First, we add to the literature on the economic effects of temperature, particularly its influence on decision-making. Earlier studies show that heat can influence labor supply (Graff Zivin and Neidell, 2014), judicial rulings (Heyes and Saberian, 2019), and financial behavior (Cao and Wei, 2005; Choi et al., 2022). More recent work documents firm-level consequences, including declines in revenue and operating income (Pankratz et al., 2023). At the macro level, temperature shocks reduce productivity and increase mortality (Barreca et al., 2016; Agarwal et al., 2021). We extend this literature by examining how heat shapes individual financial decisions in the context of health insurance. While existing studies have not directly examined this setting, Chen et al. (2024) study group insurance uptake during extreme temperatures and find that heat increases enrollment. However, group insurance is typically provided as an employee benefit,

with premiums paid by employers. Our focus differs in both scope and mechanism, as we study voluntary, individual-level decisions that are more sensitive to momentary perceptions of risk.

Next, we contribute to the literature on behavioral frictions in insurance markets. Prior work has highlighted systematic deviations from optimal coverage, including preferences for low deductibles (Sydnor, 2010), inertia in plan selection (Handel, 2013), and heterogeneity in risk preferences (Barseghyan et al., 2013). Our closest reference point is Chang et al. (2018), who find that air pollution increases insurance uptake, with some reversal in the short term. We extend this line of inquiry by focusing on temperature as a salient environmental cue and by using additional contract-level and claims data to probe the underlying mechanism.

Finally, our analysis contributes to the literature on behavioral biases in economic decision-making, with a focus on salience and projection (DellaVigna, 2009). Projection bias suggests that individuals overweight current conditions when forming expectations about the future (Loewenstein et al., 2003), whereas salience theory holds that vivid or extreme stimuli disproportionately capture attention and influence behavior (Bordalo et al., 2013, 2020, 2022). Empirical work has documented the effects of these biases across various domains, including education choices (Simonsohn, 2010) and tax compliance (Chetty et al., 2009). Related studies have also linked heat and pollution exposure to short-term spikes in car purchases (Busse et al., 2015) and insurance uptake (Chang et al., 2018), but rarely disentangle the underlying mechanisms in high-stakes, long-horizon financial contexts. Our results suggest that salience is more consistent with the observed patterns than projection. We combine search behavior, contract structure, and claims outcomes to assess these channels.

The paper proceeds as follows. Section 2 describes the data and variables. Section 3 presents the empirical results. Section 4 explores the underlying mechanisms. Section 5 considers alternative explanations and robustness checks. Section 6 concludes.

2. Data

In this section, we describe the datasets used in our analysis. Our study draws on two primary sources: industry-wide health insurance data and high-frequency meteorological data. The health insurance dataset offers rich micro-level information, including individual contract details, demographic characteristics, and claims records across multiple insurance providers.

To capture environmental exposure, we link this with detailed weather data that record daily temperature conditions. By combining the two datasets, we can exploit how variations in short-term temperature fluctuations could impact insurance purchasing behavior.

2.1 Industry Insurance Data

The nationwide insurance dataset used in this study is drawn from eight major insurance providers in China, including seven domestic firms and one international company. Collectively, these insurers account for approximately 70 percent of the national health insurance market, providing a robust and representative foundation for empirical analysis. In all, the dataset comprises a sample of 5.1 million insurance policies spanning 280 cities across 30 provinces in mainland China, excluding Xizang. Its broad geographic scope captures variation in climate, income, and urbanization, allowing us to identify heterogeneous responses to temperature shocks and isolate the role of environmental salience in insurance behavior.

We focus on critical illness insurance, a widely used product that provides a lump-sum payout upon diagnosis of specified severe health conditions. The product features large, infrequent payouts tied to clearly defined events, making it well suited for studying household responses to risk. Although first introduced in 1995, the market remained fragmented until 2007, when the China Insurance Association issued the *Specification for Illness Definitions in Critical Illness Insurance*. This reform standardized product definitions by requiring coverage for a core set of six illnesses within a broader list of twenty-five, while allowing additional conditions under uniform criteria. [1] The resulting standardization created a more transparent and comparable product landscape across insurers and overtime.

Our analysis focuses on the post-reform period from 2008 to 2018. Over this decade, health insurance premiums rose sharply from 58.6 billion CNY to 544.8 billion CNY[2]. In 2018 alone, critical illness insurance premiums reached 317.5 billion CNY, with new policy premiums exceeding 100 billion CNY. Since the introduction of the first critical illness product in 1995, a total of 360 million policies had been sold by 2018. Of these, 220 million remained active,

[1] The six core diseases are malignant tumors, acute myocardial infarction, sequelae of cerebrovascular accidents, major organ or hematopoietic stem cell transplants, coronary artery bypass surgery, and end-stage renal disease.

[2] Based on average exchange rates in 2018, 1 Chinese yuan (CNY) was approximately equal to 0.15 USD, making 544.8 billion CNY equivalent to roughly 81.72 billion USD.

covering more than 170 million individuals. This represents approximately 12.1 percent of the population with the financial capacity to purchase insurance. The figures reflect significant market penetration among insured households and underscore the growing role of critical illness insurance in China's health financing system.

Our dataset comprises two main components: underwriting data and claims records. The underwriting data provides detailed information on policy characteristics, including purchase date, observation end date (defined as policy lapse, claim settlement, or contract expiration), premium amount, and coverage amount. It also includes individual attributes such as gender, age at purchase, health classification, region code, residency, and occupation. Claims data complement these records with post-purchase outcomes, including illness onset, filing and settlement dates, disease codes, and payout amounts.

To assess the representativeness of our dataset, we compare it with publicly available industry statistics from the China Banking and Insurance Regulatory Commission. As shown in Figure A1 of the online appendix, our sample closely follows national patterns in premium growth, coverage levels, and the demographic distribution of policyholders. This alignment supports the generalizability of our findings. Table 1 summarizes key features of the data used in our empirical analysis.

[Insert Table 1]

Panel A of Table 1 provides a detailed overview of the demographic and policy-specific characteristics of the insurance contracts at the individual level. The dataset includes 5,159,181 insurance policies and 1,125,037 city-daily observations. Gender distribution is nearly equal. The average age is 26 years, with a wide range spanning newborns to the elderly. On average, 0.3% of policyholders are categorized as sub-standard risk, and 66.9% reside in urban areas, reflecting a significant urban presence in the dataset. The financial attributes of the policies show an average premium amount of 1,635 CNY and an insured amount of 124,303 CNY. Policy cancellations during the cooling-off period are virtually non-existent, while 14.8% of contracts are terminated early without a claim. The overall claim rate is low, averaging 0.8%.

For our benchmark analysis, we construct a balanced panel of daily observations at the city level. A policy is considered valid based on its recorded start and end dates in the underwriting

data. Cities with missing permanent resident population records during observation periods are excluded. This results in a final sample of 280 cities across 30 provinces in mainland China (excluding Xizang Autonomous Region). Our main outcome variable is the purchase rate, which captures the intensity of new insurance uptake. Specifically, it is defined as the number of new critical illness insurance policies issued in a given city on a given day, divided by the city's total population. It is then scaled to reflect the number of new policies per 1,000,000 residents. The average purchase rate across the sample is 0.942, with values ranging from 0 to 10.864, indicating meaningful variation across both time and geography.

2.2 Meteorological Data

To measure local weather conditions, we use high-frequency data from the CN05 Gridded Observation Dataset, developed by the China National Climate Change Research Center. This dataset compiles daily meteorological records from over 2,400 stations across China, starting in 1961. It includes key variables such as maximum, minimum, and mean temperature, wind speed, and precipitation, recorded at a spatial resolution of 0.25 by 0.25 degrees. The dataset is constructed using the anomaly approach developed by Xu et al. (2009), which interpolates climatology and anomaly fields separately from station-level data. Its accuracy has been validated in independent studies, including Wu and Gao (2013). For our analysis, we aggregate the gridded data to the city level by averaging values within each city's administrative boundary. This yields daily measures that align with our insurance dataset.

Our analysis focuses on two key temperature measures. The first is maximum temperature (*Max temp*), defined as the highest observed temperature in a city on a given day. The second is abnormal temperature (*Abnormal temp*), which captures the deviation of the daily maximum from its historical norm. To construct this measure, we calculate the baseline as the average daily maximum temperature for each calendar day over the 1961 to 1990 period, using a centered 10-day moving window. For example, the baseline for December 15 is based on data from December 10 to 20. Abnormal temperature reflects short-term departures from expected seasonal patterns and serves as our main measure of transitory heat shocks.

To identify extreme weather events, we construct two binary indicators. An extreme hot day is defined as a day when the maximum temperature exceeds the 90th percentile of its historical distribution for that specific calendar date. An extreme cold day is defined as a day when the minimum temperature falls below the 10th percentile of its historical counterpart. For

robustness, we also test alternative thresholds based on percentile cutoffs from the empirical sample distribution. These definitions align with international climate classification standards, including those used by the Intergovernmental Panel on Climate Change (IPCC), the Expert Team on Climate Change Detection and Indices (ETCCDI), and recent empirical studies such as Pankratz et al. (2023).

Table 1 Panel B summarizes the city-day level variables used in our analysis. These measures form the basis for linking transitory weather fluctuations to insurance behavior. The daily absolute maximum temperature (*Max temp*) averages 19.11 degrees Celsius, with values ranging from -30.75 to 41.56 degrees Celsius. In contrast, the abnormal maximum temperature (*Abnormal temp*), which captures deviations from historical norms, has a mean of 0.82 degrees Celsius and a standard deviation of 3.99 degrees Celsius, indicating frequent and sizable temperature shocks. Precipitation (Rain) is coded as a binary variable equal to one if any rainfall is recorded within the city. Its mean of 0.966 reflects a high frequency of rainy days, though most events are mild. Wind speed averages 2.18 meters per second, capturing further variation in daily weather conditions.

To illustrate spatial heterogeneity, Figure A2 in the online appendix maps the geographic distribution of extreme temperatures across China. Although most provinces are exposed to both extreme heat and cold, the frequency, intensity, and persistence of these events vary substantially across regions. This heterogeneity underscores the importance of distinguishing between distinct dimensions of thermal exposure. Thus, it is of interest to separately account for absolute temperature levels and localized deviations from historical norms. Failing to do so risks conflating physical risk with psychological salience, obscuring the interpretation of behavioral responses to environmental shocks.

3. Empirical Results

We now present our main findings. Section 3.1 examines how temperature affects insurance purchase rates. Section 3.2 investigates whether temperature influences cancellation behavior. Section 3.3 explores whether consumers adjust premium payments in response to temperature variation.

3.1 Baseline Results

We begin by testing whether daily temperature shocks influence insurance demand. Specifically, we estimate the effect of temperature on policy uptake using the following city-day level regression:

$$Purchase\ Rate_{i,t} = \alpha + \beta_1\ Temp_{i,t} + \ \beta_2 Rain_{i,t} + \beta_3 Wind_{i,t} + v_{i,t} + \lambda_t + \mu_t + \epsilon \quad (1)$$

Here, the dependent variable, $\text{Purchase Rate}_{i,t}$ measures the number of critical illness insurance policies purchased per 1,000,000 residents in city i on day t. The main explanatory variable, $\text{Temp}_{i,t}$, is defined either as abnormal maximum temperature (*Abnormal temp*) or absolute maximum temperature (*Max temp*). As defined earlier, the abnormal maximum temperature reflects the deviation of the actual daily maximum temperature from its baseline, calculated using the 10-day moving window of historical data. Absolute maximum temperature is the raw daily high. We also control for other weather conditions. $\text{Rain}_{i,t}$ is a binary indicator for any recorded precipitation, while $\text{Wind}_{i,t}$ captures daily wind speed. To control for unobserved heterogeneity, the model includes city-year-month fixed effects ($v_{i,t}$), day of week fixed effects (λ_t) and holiday fixed effects (μ_t). Standard errors are clustered at the city and date levels.

Table 2 presents the regression result, with separate panels for each temperature measure. Panel A highlights the effect of abnormal maximum temperature, while Panel B focuses on absolute maximum temperature.

[Insert Table 2]

In Panel A, we find that a 1-degree Celsius deviation from the historical norm increases the purchase rate by 0.006 policies per 1,000,000 residents on the purchase day (Column 1), statistically significant at the 1% level. The effect persists over a two-day window (Column 2; 0.0061) and rises slightly over three- and five-day averages (Columns 3-4; 0.0064 and 0.0077), remaining statistically significant at the 5% level. However, the effect fades in the ten-day average model (Column 5) and becomes statistically insignificant, underscoring the short-lived nature of the response. To rule out the possibility that this reflects intertemporal substitution, Column 6 introduces a 30-day lag structure while isolating the purchase-day effect. The

coefficient remains stable at 0.006 and statistically significant at the 1% level, confirming that the response is not simply a temporal shift in planned purchases. Relative to the mean daily purchase rate of 0.942, this implies an increase of 0.6 percent.

While small in magnitude, the estimated effect is statistically precise and indicative of a meaningful behavioral response - one that becomes even more pronounced during episodes of extreme heat, as we demonstrate later. To test the robustness of this finding, we evaluate a range of alternative definitions for abnormal temperature. Table A1 in the online appendix reports results using: (i) a 5-day moving window, (ii) a 15-day moving window, (iii) alternative baseline periods from 1971–2000 and 1985–2005, and (iv) abnormal average temperature (based on daily mean rather than maximum). Across all specifications, the estimated effects remain stable and statistically significant, reinforcing the conclusion that short-term heat shocks systematically increase insurance uptake.

Panel B yields similar findings for absolute maximum temperature. A one-degree Celsius increase in absolute temperature raises the purchase rate by 0.0059 (Column 1), again statistically significant at the 1% level. The effect remains stable over short windows (Columns 2–4), but weakens in the ten-day average and becomes insignificant. In the 30-day lag model (Column 6), the coefficient remains at 0.0058, corresponding to the same 0.6% increase as in Panel A. Put together, Table 2 demonstrates that both abnormal and absolute temperature increases significantly raise insurance purchase rates, particularly over short time horizons. The effects are strongest on the purchase day and taper off over longer windows, consistent with a behavioral response to immediate environmental cues rather than sustained shifts in perceived risk. These results align with the hypothesis that transitory heat shocks trigger rapid, attention-driven changes in financial decision-making.

To visualize these dynamics, Figure 1 plots the cumulative impact of temperature shocks on insurance uptake. Panel A shows the response to abnormal temperature deviations, while Panel B presents results for absolute maximum temperature. In both cases, the cumulative effects peak shortly after the temperature change and gradually decline, becoming statistically insignificant over time. This temporal pattern reinforces the interpretation that temperature shocks operate through short-lived effects rather than forward-looking risk assessments.

[Insert Figure 1]

Nonlinear Responses to Temperature. To explore potential nonlinearities, we categorize temperatures into different bins. Building on Equation (1), we re-estimate the model by substituting the temperature variable with its corresponding temperature bin rather than continuous variables. This allows us to examine how purchase behavior varies across the full temperature distribution. Figure 2 presents the regression coefficients, illustrating how purchase behavior changes across different temperature ranges, with 95% confidence intervals provided for each estimate.

[Insert Figure 2]

Panel A plots the coefficients of abnormal temperature quantiles, dividing the data into 10 bins based on relative temperature rankings within the sample. The median temperature serves as the omitted reference group. We find that the lowest quantiles, corresponding to large temperature drops, show small and statistically insignificant coefficients. As temperatures increase, the coefficients turn positive and grow in magnitude, becoming statistically significant in the upper quantiles. Thus, insurance purchases respond primarily to unusually warm days, rather than to cold ones.

Panel B illustrates the same analysis for absolute temperature quantiles. Here, the temperature range is divided into 10 bins, spanning from extreme cold (below -10 degrees Celsius) to extreme heat (30 degrees Celsius and above). Coefficients for lower temperature bins are negative or near zero. As the temperature increases, the coefficients become more positive, indicating a growing positive association between moderate to high temperatures, and insurance purchases. Just like Panel A, Panel B points to a strong, nonlinear relationship between heat and insurance purchases. The pattern is especially pronounced for extreme heat, consistent with the idea that temperature shocks act as salient cues, prompting precautionary behavior. Cold weather, in contrast, does not elicit a comparable response.

Effects of Extreme Temperature. We now formally test the impact of extreme temperatures using the following specification:

$$Purchase\ Rate_{i,t} = \alpha + \beta_1\ Ext\ Hot_{i,t} + \beta_2 Ext\ Cold_{i,t} + v_{i,t} + \lambda_t + \mu_t + \epsilon \quad (2)$$

As in Equation (1), the dependent variable is the number of critical illness insurance policies purchased per 1,000,000 residents in city i on day t. The key difference is that we now focus on binary indicators for extreme hot days ($Ext\ Hot_{i,t}$) and extreme cold days ($Ext\ Cold_{i,t}$). All other controls and fixed effects remain unchanged. Results are reported in Table 3.

[Insert Table 3]

We test two alternative definitions of extreme temperature. In Column 1, extreme hot days and extreme cold days are defined relative to the historical temperature distribution (1961–1990). Specifically, extreme hot days occur if the daily maximum temperature exceeds the 90th percentile of the historical distribution, and extreme cold days occur if the daily minimum temperature falls below the 10th percentile. The results show a significant positive effect of extreme heat: on such days, the purchase rate rises by 0.0376 policies per 1,000,000 residents, statistically significant at the 5% level. This translates to a 4 percent increase relative to the daily average. In contrast, extreme cold days are associated with a negative value (-0.0147), but the effect is not statistically significant.

Column 2 re-estimates the model using sample-based percentiles instead of historical benchmarks. The results remain consistent. Extreme hot days again increase the purchase rate by 0.0376, statistically significant at the 10% level. Extreme cold days continue to show no statistically significant effect. This asymmetry reinforces the interpretation that heat (rather than temperature extremes per se) drives insurance uptake. The evidence points to a salience-driven mechanism, where elevated discomfort or perceived vulnerability during hot spells heightens risk awareness and prompts immediate financial action. In contrast, cold weather conditions appear less behaviourally salient, eliciting limited urgency or demand for protection..

3.2 Cancellations During the Cooling-Off Period

To further test whether temperature drives insurance behavior, we examine its effect on policy cancellations during the cooling-off period (CoP). In China, insurance buyers can cancel their contracts at no cost within 10 days of purchase. If temperature influences perceived risk, we expect higher cancellation rates when conditions become cooler during the CoP, particularly relative to the purchase date. We test this prediction using the following individual-contract level specifications:

$$Cancel_{j,t} = \alpha + \beta_1\, Dif\ Temp_{j,t} + X_j + Z_{j,t} + v_{i,t} + \lambda_t + \mu_t + \gamma_{k,t} + \epsilon \quad (3)$$

Here, the dependent variable, $Cancel_{j,t}$ is a dummy variable equals 1 if an insurance contract is canceled during the CoP (excluding cancellations on the purchase date), by individual j at time period t. In addition, our primary variable of interest, $Dif\ Temp_{j,t}$ captures differences in temperature conditions during the cooling off period. We test three sets of specifications, using both abnormal and absolute temperature measures, as detailed below.

First, we examine the average temperature during the cooling-off period. For abnormal temperature deviations, we use *CoP abnormal temp*, defined as the mean deviation from the historical maximum temperature during the cooling-off period. Its absolute counterpart, *CoP max temp*, is the average maximum temperature over the same period. Second, we compare cooling-off period temperatures to purchase-day temperatures to capture relative changes in perceived conditions. The abnormal version is *Relative purchase-date abnormal temp*, while the absolute version is *Relative purchase-date max temp.* Third, to complement these continuous measures, we construct binary indicators that capture the *direction* of temperature change during the cooling-off period. Specifically, we define *1(CoP abnormal temp<purchase-date abnormal temp)* and *1(CoP max temp<purchase-date max temp)* to indicate whether conditions cooled relative to the purchase day. These indicators help isolate directional shifts in perceived temperature, which are critical in triggering reversal behaviors such as cancellations.

In addition, the control variables include both time-invariant and time-varying factors. Time invariant control variables (X_j) refer to individual characteristics such as gender, age, residential location and risk type. Time varying control variables ($Z_{j,t}$) include changes in weather conditions like wind and rain that individuals in different cities are exposed to. Like before, we account for city-year-month fixed effects ($v_{i,t}$), day of week fixed effects (λ_t), holiday fixed effect (μ_t), and insurance company-year fixed effects ($\gamma_{k,t}$). Standard errors are clustered by city and date. Table 4 presents our results.

[Insert Table 4]

Panels A and B consistently show that temperature fluctuations during the cooling-off period influence insurance cancellations, with both abnormal deviations and absolute temperature levels affecting consumer decisions. In Column 1 of both panels, lower average temperatures during the CoP are associated with higher cancellation rates. The coefficient of approximately -0.00005 (significant at the 5% level) implies that a 1°C decrease raises cancellations by 0.005 percentage points. Column 2 compares cooling-off period temperatures to those on the purchase date. A one-degree drop relative to the purchase day increases cancellation rates by 0.008 percentage points, highlighting that even modest changes in perceived conditions can trigger behavioral reversal. Column 3 reinforces this result using a binary indicator for whether the CoP was colder than the purchase date. Here, cancellations rise by 0.029 and 0.036 percentage points for abnormal and absolute temperature measures, respectively.

Although the magnitude may seem modest, it is substantial relative to the baseline cancellation rate, which is close to zero. This indicates a pronounced behavioral response to even small shifts in temperature. The above findings emphasize the importance of considering contextual factors and behavioral biases to better understand consumer behavior in insurance decisions. Specifically, we observe that the cancellation effect is negatively related to the temperature during the CoP and is driven by changes in temperature relative to the level at the time of purchase. Thus, cooler temperatures during the CoP may create a sense of comfort or reduced urgency, leading to an increased likelihood of contract cancellations.

3.3 Insurance Premium Payment Mode

Next, we examine whether temperature influences how households pay for health insurance, focusing on the choice between single-premium and regular-premium modes. To do so, we estimate the following contract-level regression across different payment types:

$$Y_j = \alpha + \beta_1 Temp_{j,t} + \beta_2 Rain_{j,t} + \beta_3 Wind_{j,t} + v_{i,t} + \lambda_t + \mu_t + \gamma_{k,t} + X_j + Z_{j,t} + \epsilon \quad (4)$$

Here, the dependent variable Y_j are a set of indicator variables for insurance premium payment mode. We define five binary variables: *Single* equals 1 if the premium of the contract is paid in a lump-sum; *Annual* equals 1 if paid in annual instalments; *Semiannual*, *Quarterly*, and

Monthly are defined analogously. As before, the main variable of interest, $Temp_{j,t}$ captures either abnormal or daily maximum temperature at the time of purchase. All regressions control for precipitation, wind, and fixed effects as in prior specifications, with standard errors clustered by city and date.

Table 5 presents the results. Column 1 reports results for single-premium contracts, Column 2 for annual installments, and Columns 3 to 5 for semiannual, quarterly, and monthly payment modes, respectively.

[Insert Table 5]

We find that higher temperatures significantly increase the likelihood of selecting a single-premium contract (Column 1) and reduce the likelihood of choosing annual installment plans (Column 2). Specifically, a one-degree Celsius increase in abnormal temperature raises the probability of paying in full by 0.000070 (significant at the 1% level) and lowers the likelihood of selecting an annual plan by 0.000063 (significant at the 5% level). These effects may seem small in absolute terms, but they are substantial relative to baseline frequencies: single-premium contracts make up just 0.29% of all policies, while annual plans account for more than 97%. A shift of even 0.01 percentage points represents a nontrivial change in behavior.

In contrast, we find no statistically significant effects in Columns 3 to 5, which correspond to semiannual, quarterly, and monthly payment plans. These less common options jointly account for less than 2% of total contracts, and their selection appears largely unresponsive to temperature. This pattern suggests that heat influences behavior primarily at the salient margin between full prepayment and the dominant annual installment structure. Further supporting this interpretation, we show in Table A2 (online appendix) that higher temperatures are associated with shorter payment horizons overall. Households are more likely to commit upfront rather than delay payment, consistent with a salience-based mechanism in which hot conditions heighten perceived urgency and drive more decisive financial behavior.

Our findings can be interpreted through the lens of commitment bias in household insurance decisions. When confronted with salient environmental cues like heat, households are more likely to prepay, locking in their choices rather than deferring payments through installment

plans. This mirrors findings from Ashraf et al. (2006), who show that individuals voluntarily adopt commitment devices to overcome self-control problems in savings decisions. It also reflects broader patterns documented by Carrera et al. (2022), where individuals constrain future flexibility in response to immediate cues. In our context, the choice to prepay may offer psychological reassurance in the face of heightened perceived risk, even if it does not reflect long-term financial optimization.

The shift toward full upfront payment thus reveals more than a change in contract preference. It reflects how transitory environmental shocks can distort the timing and structure of household financial decisions. While this behavior may offer psychological comfort in the short term, it highlights the broader role of salience in shaping economic choices that carry long-term consequences.

4. Mechanism: The Role of Salience

Having documented the effects of temperature on insurance uptake, we now turn to the underlying mechanism. Rather than reflecting updated assessments of long-term health risk, households appear to respond to how risk feels in the moment. This behavior is consistent with salience bias, wherein vivid and immediate cues distort attention, shifting decisions toward what is psychologically prominent. To formalize this idea, we draw on the framework developed by Bordalo et al. (2020, 2022), which outlines three distinct channels through which salience shapes attention: surprise, contrast, and prominence.

The surprise channel posits those unexpected fluctuations (such as a sudden spike in temperature), trigger comparisons with recent experiences. This resulted in heightened attention to what has changed. The contrast channel suggests that decision-makers focus on attributes that stand out relative to other options, making certain risks or features more psychologically salient. The prominence channel emphasizes that decision-makers concentrate on features that are most visible and immediate at the time of choice, while overlooking less salient but potentially more relevant dimensions.

In our context, each channel maps onto a distinct behavioral margin in the context of health insurance. To further disentangle their roles, we derive four empirical predictions from this framework. First, consistent with surprise, attention should spike following a temperature

shock. Second, in line with prominence, behavioral responses should be strongest when physical exposure is direct and intense. Third, reflecting contrast, individuals should shift toward insurance products that are emotionally vivid and associated with catastrophic risks. Fourth, the effects should fade quickly, consistent with a temporary reallocation of attention rather than a persistent change in underlying beliefs. We test each of these predictions in turn.

4.1 Online Search

We begin with the first empirical prediction, which posits that temperature shocks heighten attention through the surprise channel. Our baseline findings already support this mechanism. Insurance uptake responds systematically to deviations from historical temperature norms, even though the underlying contract terms remain unchanged. This suggests that behavior is not driven by changes in product attributes, but by how unexpected conditions make the risks feel more immediate. In this sense, the salience of insurance arises not from its content, but from the context in which it is evaluated.

To investigate this mechanism more directly, we analyze online search behavior as a real-time, high-frequency proxy for household attention. The underlying intuition is straightforward. When individuals experience an unexpected temperature spike, they often seek information about both the external conditions and the health risks they might face. This reallocation of attention toward newly salient threats is exactly what the surprise channel predicts. Online search data allow us to observe this process directly, capturing how external shocks reshape perceived risk. Since our analysis focuses on China, we measure attention using Baidu's Search Volume Index (SVI), which tracks daily search activity across 280 cities.

We construct two indices from the SVI. The first, which we refer to as heat-related searches, aggregates terms such as "hot," "high temperature," "heat wave," and "high-temperature weather," capturing attention to the immediate sensory experience of heat. The second, health-related searches, includes terms such as "heat stroke," "cardiovascular diseases," and "cardio-cerebrovascular diseases," reflecting concern with heat-induced illness. Both indices are log-transformed and set to zero on days with no relevant search activity. Collectively, these measures capture two facets of salience: the physical prominence of heat and the associative salience of its health consequences.

We then merge these indices with daily temperature data from 2011 to 2018 and re-estimate Equation (1), using each search index as the outcome. The key explanatory variables are the temperature measures defined earlier. Panel A of Table 6 uses abnormal temperature; Panel B uses absolute maximum temperature. All specifications include fixed effects for city-by-year-month, day-of-week, and holidays, and control for 30-day lagged temperature. Standard errors are clustered by city and date.

[Insert Table 6]

Our results provide strong evidence for the surprise channel. A one-degree Celsius increase in abnormal temperature leads to a 2.3 percent increase in heat-related searches and a 0.3 percent increase in health-related searches, both statistically significant at the 1% level. These effects are similar when using absolute maximum temperature in Panel B. Evidently, the rise in heat-related searches shows that even modest temperature shocks can trigger widespread sensory awareness. The increase in health-related searches, though smaller, reveals that this attentional shift also encompasses heightened concern about personal risk. Put together, these findings confirm that the observed spike in search activity is not merely seasonal or coincidental but reflects a behavioral response to salience induced by temperature.

It is important to point out that we cannot determine whether these searches precede or follow insurance purchases. However, either interpretation is consistent with salience-based behavior. Some individuals may search before purchasing, prompted by the shock itself. Others may search after purchasing, to better understand the risk they have just acted on. In both cases, the behavior reflects a momentary reorientation of attention in response to a vivid and unexpected cue. The search response thus provides a behavioral signature of salience in action. It confirms a central implication of salience theory: that emotionally charged, attention-grabbing environmental shocks distort how risk is perceived and drive decision-making in the moment.

4.2 Physical Exposure

Having shown that temperature shocks reallocate attention in real time, we next examine whether direct physical exposure strengthens the behavioral response. For salience to operate through the prominence channel, individuals would need to physically experience the heat and recognize changes in it over time. If perceived risk is shaped by what is most vivid at the time

of decision, then insurance uptake should be more sensitive to temperature shocks in contexts where heat is directly and physically experienced.

We focus on two key dimensions of physical exposure: the sales channel and the residential environment. The first captures the setting in which the transaction occurs. Offline purchases involve face-to-face interactions, often in heat-exposed environments such as offices, or kiosks where ambient temperature is directly felt. In contrast, online purchases are typically made in climate-controlled indoor settings that shield individuals from external conditions. If salience relies on physical prominence, then temperature shocks should exert a stronger influence on offline transactions, where heat is more immediately noticeable at the point of decision.

The second dimension relates to baseline thermal exposure in daily life. Urban areas are consistently hotter due to the urban heat island effect, leading to more frequent and prolonged exposure to elevated temperatures. If the experience of heat amplifies salience, then households in urban environments should display stronger behavioral responses to temperature shocks. Table A3 in the Online Appendix supports this logic, showing that urban residents face systematically higher temperatures, both in absolute terms and relative to local historical norms. This reinforces the idea that environmental context plays a critical role in heightening the salience of heat.

To test these hypotheses, we apply the same contract-level regression as in Equation (4) to examine whether temperature shocks are associated with differences in the setting of insurance purchases. Specifically, whether contracts are sold through in-person channels (*Offline Sales)* or purchased by urban residents (*Urban)*.

Table 7 presents the results. Column 1 shows that higher temperatures significantly increase the probability of offline purchases, consistent with the idea that direct physical exposure heightens perceived risk. Column 2 reveals a similarly strong effect for urban residents, suggesting that individuals in persistently hotter environments are more responsive to temperature shocks. These patterns provide direct support for the prominence mechanism, in which environmental salience when heat is both present and felt, amplifies behavioral responses.

[Insert Table 7]

To explore how context further shapes salience, we extend the analysis with interaction terms and subgroup comparisons. Specifically, we re-estimate the regression using urban residency as the outcome and examine how temperature effects vary by sales channel and occupational setting. This allows us to test whether salience intensifies when multiple sources of physical exposure align.

[Insert Table 8]

Columns 1 and 2 of Table 8 show that higher temperatures significantly predict urban purchases, but only in offline settings. This interaction suggests that the combination of face-to-face transactions and ambient heat makes risk more prominent, increasing behavioral sensitivity to temperature shocks. In contrast, online sales show no such effect, consistent with the idea that digital environments dilute physical cues and weaken salience. Subsequently, Columns 3 and 4 examine differences by occupation. Among outdoor workers, who are regularly exposed to heat, we find a strong positive relationship between temperature and urban purchases. For indoor workers, who experience less direct exposure, the effect is negligible.

To rule out alternative explanations based on risk preferences or demographics, we conduct additional robustness checks using individual characteristics as outcomes. Specifically, we re-estimate Equation (4) with the following variables: *Male* indicates if the policyholder is male; *Sub-Standard Risk* identifies individuals flagged by the insurer as having elevated health risk; and *Age* is included as a continuous variable. Columns 3 to 5 of Table 7 show that none of these characteristics significantly respond to temperature shocks. The coefficients for gender and age are small and statistically insignificant, while the effect on Sub-Standard Risk is directionally positive but not significant. This suggests that the behavioral response is not driven by demographic or health-based selection but instead reflects differences in physical exposure.

For further robustness, we re-estimate our main specification (Equation 1) across a wide range of subsamples. The Online Appendix reports results by age group (Table A4), gender (Table A5), risk profile (Table A6), urban vs. rural location (Table A7), and city tier (Table A8). Across all dimensions, our core findings remain stable and statistically significant. Taken together, these results highlight the critical role of context in shaping the salience of risk. Temperature shocks exert the greatest behavioral influence when individuals are physically

exposed. These patterns reinforce the prominence channel as a key mechanism behind insurance uptake and clarify the environmental conditions under which temperature shocks are most behaviorally consequential.

4.3 Product Type

We have shown that temperature shocks trigger immediate shifts in attention and intensify behavioral responses when physically experienced. We now ask whether salience also distorts what individuals focus on. Put differently, we are interested in not just whether or when they respond, but which risks they choose to insure. This question corresponds to the third mechanism in the salience framework: contrast, which posits that attention is drawn to attributes that stand out relative to others in a given choice set.

In our setting, the contrast channel predicts that temperature-induced salience should not increase insurance demand uniformly. Instead, it should shift attention toward products that are more emotionally vivid or cognitively prominent. Specifically, we expect a greater uptake of policies linked to severe, long-horizon risks, such as critical illness or life insurance. More routine products, such as medical or accident coverage, should see little change. If temperature shocks simply heightened general precaution or risk aversion, we expect comparable increases across all product types. A selective response, by contrast, would indicate that contrast-based salience is shaping the composition of demand.

To test this prediction, we draw on a complementary dataset from a major Chinese insurer, which records over eight million policy purchases between 2009 and 2017. While the data originates from a single firm, the insurer operated nationally and accounted for approximately six percent of the market during the sample period. Crucially, the dataset includes detailed information on four distinct product categories: critical illness, medical, life, and accident insurance. These products vary in payout structure, coverage horizon, and perceived severity, making them well suited to test whether temperature shocks shift demand toward risk categories that are more psychologically salient.

We adopt the same empirical strategy as in earlier sections, re-estimating Equation (1) separately for each product category. The outcome variable is the number of policies purchased per million residents for a given product type. The key independent variables are abnormal

temperature (Panel A) and absolute maximum temperature (Panel B). All regressions include city-by-year-month, day-of-week, and holiday fixed effects, and control for 30-day lagged temperature. Standard errors are clustered by city and date. Table 9 summarizes the results.

[Insert Table 9]

The findings reveal a clear pattern of selective responsiveness. In Panel A, we find that a one-degree Celsius increase in abnormal temperature increases purchases of critical illness and life insurance, by 0.0195 and 0.0255 policies per million residents, respectively. Both effects are statistically significant at the one percent level. These effects represent substantial increases relative to baseline purchase rates for these products. In contrast, there is no statistically significant change in the uptake of medical or accident insurance. Panel B, which uses absolute temperature, shows similar patterns, although the coefficients are slightly smaller.

These results strengthen the case for contrast as a key salience channel. Households are most responsive to products that align with the psychological profile of salient risk. Those that are emotionally intense, associated with rare but catastrophic events, and cognitively prominent in moments of perceived vulnerability. More routine insurance types, which are less vivid and carry weaker emotional associations, remain unaffected. Combined with earlier evidence on timing and physical exposure, our findings show that temperature shocks influence not only whether and when insurance is purchased, but also which risks feel most urgent to insure.

4.4 Temporal Dynamics

Beyond the three channels discussed above, the final implication of salience relates to timing. Salience influences behavior through short-lived shifts in attention. Once the triggering stimulus fades, the behavioral response should dissipate as well. To test this prediction, we examine whether the effects of temperature shocks persist or quickly fade as conditions normalize.

Our baseline estimates already suggest a rapid decline. Earlier, Table 2 showed that a one-degree Celsius increase in temperature raises insurance uptake on the same day. When we re-estimate the regression using multi-day average temperatures, the effect remains positive for two to five days but decreases in magnitude. By the ten-day window, the effect is no longer

statistically significant. This pattern is consistent across both abnormal and absolute temperature measures. Our previous findings from Figure 2 and Table 3 further reinforce this result. Uptake rises sharply during extreme heat days but remains flat during cooler or more moderate periods. The behavior appears to be triggered by short-lived peaks in perceived risk rather than ongoing exposure.

To support this interpretation directly, we examine whether temperature shocks produce real but temporary health consequences. Using detailed insurance claims data, we estimate the relationship between temperature and illness, focusing on cardiovascular diseases (CVDs), which are known to be highly sensitive to heat. Following the benchmark regression in Equation (1), we replace the outcome variable with the number of CVD claims per 1,000 active contracts and conduct city-date level regressions. Results are reported in Table 10.

[Insert Table 10]

Panel A presents results using abnormal temperature. Column 1 shows that a one-degree Celsius increase on the illness day is associated with 0.000013 additional claims per 1,000 contracts, significant at the 1% level. Columns 2 through 5 show weaker and inconsistent effects over longer exposure windows. Column 6 includes controls for lagged temperature and yields a slightly stronger same-day effect of 0.000016. Panel B, which uses absolute temperature, shows similar but somewhat weaker results. These findings confirm that heat exposure elevates immediate health risk, but the effect fades quickly. This supports the idea that individuals are responding to genuine physical strain, though the urgency they experience is shaped by the intensity of the present moment rather than by expectations about the future.

Additional support comes from post-purchase behavior. Table 4 shows that insurance cancellations increase when temperatures fall during the cooling-off period. This suggests that once the salient conditions dissipate, the perceived need for insurance declines. Households that purchased coverage during a heat event are more likely to reverse that decision once the sense of urgency fades. Table 5 shows a similar pattern in payment behavior. Higher temperatures increase the likelihood of selecting single-premium contracts, which involve an upfront and irreversible commitment. However, this effect is limited to the day of purchase and does not influence other contract features such as duration or coverage scope. These results

suggest that households are motivated to act immediately, responding to how risk feels in the moment rather than reassessing long-term exposure.

Consequently, the evidence confirms that the behavioral response to temperature shocks is immediate, short-lived, and closely tied to present conditions. The effects appear and fade quickly, mirror the short-term nature of heat-related health risks, and reverse once the triggering stimulus disappears. These patterns align with salience theory, which emphasizes the role of vivid and transient environmental cues in shaping financial decisions.

5. Alternative Mechanism

To assess the robustness of the salience interpretation, we consider three leading alternative explanations: rational learning, projection bias, and supply-side adjustment. Rational learning suggests that households treat temperature shocks as informative signals about long-term health risk and adjust their insurance choices accordingly. Projection bias posits that individuals mispredict their future utility from insurance or incorrectly believe that temporary conditions will persist, even if their beliefs about future states are otherwise accurate. Supply-side adjustment proposes that insurers may respond to weather fluctuations by altering product offerings or marketing intensity, thereby influencing observed demand patterns.

In the subsections that follow, we examine each of these mechanisms in turn. We first test the predictions of rational learning, then evaluate evidence for projection bias, and finally assess the possibility of supply-driven changes. Across all three cases, we find limited empirical support. The patterns in the data continue to align most closely with salience bias, in which vivid and transitory cues distort attention and shape perceived vulnerability in the moment.

5.1 Rational Learning

Rational learning provides a natural benchmark against which to evaluate behavioral explanations. If households face uncertainty about future health risks, high temperatures may be interpreted as informative signals. Under this view, increased insurance uptake reflects forward-looking, risk-sensitive behavior. This is observationally similar to salience: both predict increased purchases following heat exposure. However, the underlying mechanism differs. Rational learning predicts persistent behavioral changes and higher subsequent claim rates, while salience implies short-lived, attention-driven responses unrelated to actual risk.

To distinguish between these explanations, we test whether purchase-day temperature predicts future claims. If households purchase insurance in response to meaningful increases in risk, policies bought on hotter days should be more likely to result in claims. If not, the response is more likely driven by distorted attention, consistent with salience bias. Here, we estimate contract-level regression of realized claims on purchase-day temperature, following the specification in Equation (4). Table 11 reports the results.

[Insert Table 11]

For each policy, we track whether a claim is filed post-purchase. Column 1 considers all claims within the sample period. Columns 2-4 break the analysis into three different time horizons: within two years, between two and five years, and beyond five years. Like before, Panel A reports the impact of abnormal temperature, while Panel B analyzes the role of absolute maximum temperature. Across all specifications, we find that the temperature on the day of purchase is unrelated to future claims. Coefficients are small and statistically insignificant, regardless of the time window or temperature measure.

To validate these results further, Table A9 disaggregates claims into four categories: cancer, cardiovascular diseases, other illness-related claims, and non-disease-related death. Across all categories, we find no economically and statistically significant relationship between purchase-day temperature and claim likelihood. These null results suggest that heat-induced purchases do not reflect better forecasting of long-term health risks, undermining the rational learning hypothesis.

5.2 Projection Bias

The lack of a link between temperature and future claims rules out rational belief updating. We next consider whether projection bias could explain the observed behavior. Projection bias occurs when individuals mispredict their future preferences or mistakenly expect temporary states to persist.

In our setting, two forms of projection bias are relevant. Projection of state implies that households misinterpret short-lived heat as a signal of sustained risk. Projection of utility means individuals misjudge how much value they will place on being insured in the future,

given how urgent risk feels in the moment. Both forms predict increased insurance uptake during heat shocks. However, they differ from salience in one critical respect. While salience reflects a momentary distortion in attention toward immediately visible risks, projection bias involves a misperception about the future: either in beliefs about risk or in expectations of future utility.

The existing evidence already casts doubt on projection bias as the dominant explanation. Salience theory predicts that behavioral responses should be most pronounced when risk is felt vividly and immediately. For example, in offline sales settings or in urban environments where physical exposure to heat is greater. Consistent with this, we observe substantial heterogeneity in insurance uptake across these contexts. Projection bias, in contrast, implies a more generalized shift in beliefs. If individuals misperceive future risk due to current conditions, we expect more uniform responses across settings, regardless of how or where the insurance is purchased.

To evaluate the projection bias hypothesis more directly, we test three empirical predictions associated with projection of state. First, if individuals with higher baseline health risks are more prone to projecting current conditions forward, the response to heat should be stronger among older adults, males, and those flagged by insurers as sub-standard risk. Second, if heat exposure leads households to anticipate sustained health threats, they should opt for contract features that offer longer-term protection, such as extended policy durations. Third, if projection bias results in distorted expectations, we should observe higher rejection rates, as households submit claims that fall outside policy coverage or eligibility criteria.

We begin with risk heterogeneity. As shown earlier in Table 7, temperature-induced demand is not disproportionately driven by individuals with higher health risk. Older adults, males, and sub-standard risk individuals do not respond more strongly to heat shocks. This contradicts projection bias, which predicts heightened responses among those with greater vulnerability. Instead, the broad-based nature of the response aligns with salience, which operates through context and immediacy, not underlying risk. Next, we examine contract design. If individuals believe health risk will remain elevated, they should opt for longer-duration policies on hot days. We find no such pattern. Table A10 shows that policy duration remains unchanged. This supports the interpretation that behavior reflects immediate concern, not long-run belief updating.

Last, we assess whether projection bias leads to exaggerated or mistaken claims. If households misjudge future risk and act on distorted beliefs, insurers should reject more claims from policies purchased during heat events. Table A11 reports no increase in claim denials. Rejection rates remain stable regardless of purchase-day temperature, indicating that policyholders do not file ineligible or unsupported claims based on heat-driven misperceptions. Taken together, these findings provide little support for projection bias of states. We find no evidence of stronger effects among higher-risk groups, no shift in contract duration, and no rise in rejected claims. Households respond to extreme heat not because they expect it to persist, but because it makes risk feel immediate and pressing.

5.3 Supply Channel

A final possibility is that the observed behavior is driven not by household demand, but by supply-side responses. If insurers systematically change premiums, coverage, or sales strategies based on weather, the observed relationship between temperature and uptake may reflect supply conditions rather than behavioral shifts.

To assess this possibility, we test whether key contract features (including the sum insured, premium amount, coverage period, and expiry age) systematically vary with temperature at the time of purchase. Table A10 and A12 in the online appendix show no evidence of such adjustments. Premiums remain stable across temperature ranges. The sum insured does not vary with weather conditions, and neither the coverage period nor the expiry age shows any systematic relationship with temperature. These results rule out supply-side confounders and support the interpretation that the observed temperature effects reflect changes in household demand. Households appear to respond to vivid environmental cues rather than to changes in product design or pricing.

Viewed alongside the preceding results, these findings reinforce a broader conclusion. Transient and salient risks can shift perceived urgency and influence financial decision-making, even when objective risk remains constant. The context in which decisions are made is therefore central to how individuals respond. This mechanism helps explain why environmental shocks may distort attention and lead to suboptimal choices, even in high-stakes settings such as insurance. Recognizing these dynamics is important for designing policies that support better household decision-making under environmental stress.

6. Conclusion

In sum, this paper shows that brief temperature shocks lead to sharp, short-lived increases in household insurance demand. Using administrative data linked to high-frequency weather records, we find that a one-degree Celsius rise on the purchase day significantly increases same-day policy uptake. These effects are most pronounced in settings where heat is directly experienced, such as offline purchases, urban areas, and outdoor occupations.

Our contribution is both empirical and conceptual. We provide systematic evidence for all three channels of salience outlined by Bordalo et al. (2020, 2022). Surprise captures the abrupt rise in attention following unexpected temperature spikes. Prominence explains why behavioral responses are stronger when physical exposure makes the risk more immediately felt. Contrast accounts for selective increases in the uptake of emotionally vivid products such as life and critical illness insurance. While each channel has been examined in isolation, our setting allows us to study them jointly within a unified framework.

We also assess alternative mechanisms. There is limited support for rational learning, projection bias, or supply-side responses. Temperature on the purchase day does not predict future claims or influence contract features, suggesting that observed behavior reflects temporary shifts in attention rather than updated expectations or strategic supply-side changes.

Put together, these findings deepen our understanding of how environmental shocks shape household decisions. The results highlight the role of context in mediating behavioral responses and underscore how salient but temporary experiences can distort perceptions of risk. As climate volatility intensifies, mitigating salience-driven behavior will be increasingly important for supporting household resilience and promoting stable financial choices. Clear risk communication, longer-term planning tools, and better product framing may help steer households toward decisions more closely aligned with underlying risk.

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Table 1. Summary Statistics

Var	Def.	Obs	Mean	Sd	Min	Max
Panel A: Contract Level						
Male	1= Male, 0= Female	5,192,260	0.494	0.500	0	1
Age	Age when buy insurance	5,192,260	25.769	16.643	0	75
Subrisk	1= Sub-standard Risk 0= standard Risk	5,192,260	0.003	0.054	0	1
Urban	1= urban, 0= Suburb	5,192,260	0.668	0.471	0	1
Offline sales	1 = agent sales& broker sales& bancassurance 0 = telephone sales& internet sales	5,192,260	0.987	0.111	0	1
City_tier	Tier 1-5	5,192,260	2.760	1.224	0	5
Premium		5,192,260	1632.847	2025.156	1.000	537200
Amount insured	amount insured (in thousands of yuan)	5,192,260	124.179	114.473	0.058	6000
Cancel	1 = contract canceled during the Cooling Off Period, 0 = else	5,192,260	0.006	0.080	0	1
Early termination	1= contract end before expiration date for non-claim reasons, 0 = else	5,192,260	0.147	0.354	0	1
Claim	1= contract having claim record, 0= else	5,192,260	0.008	0.091	0	1
Panel B: City-Daily Level						
Purchase rate	Number of critical illness insurance purchased per 1,000,000 residents	1,125,037	0.942	1.460	0.000	10.864
Max temp	Daily maximum temperature	1,125,037	19.111	11.153	-30.749	41.560
Abnormal temp	Abnormal daily maximum temperature	1,125,037	0.823	3.991	-17.332	20.462
Rain	1 = precipitation>0 0 = precipitation=0	1,125,037	0.966	0.182	0.000	1.000
Wind	wind speed	1,125,037	2.183	0.995	0.000	12.523

Notes. This table presents the summary statistics used in our sample. The sample period is from 2008 to 2018, covering 280 cities across 30 provinces in China (except Tibet). Panel A presents the results at the policy level, while Panel B presents the results at the city-daily- level.

Table 2. Impact of temperature on insurance purchase rate (city-daily level)

Dependent variable: Purchase rate						
	(1)	(2)	(3)	(4)	(5)	(6)
	Purchase day	Last 2 days	Last 3 days	Last 5 days	Last 10 days	Purchase day
Panel A: Abnormal temperature						
Abnormal temp	0.0060***	0.0061***	0.0064**	0.0077**	0.0068	0.0060***
	(0.0020)	(0.0023)	(0.0026)	(0.0031)	(0.0047)	(0.0021)
Rain	-0.0128	-0.0154	-0.0172	-0.0188	-0.0210	0.0055
	(0.0206)	(0.0207)	(0.0208)	(0.0209)	(0.0211)	(0.0202)
Wind	-0.0185**	-0.0221***	-0.0237***	-0.0251***	-0.0239***	-0.0175**
	(0.0073)	(0.0076)	(0.0079)	(0.0080)	(0.0082)	(0.0077)
Panel B: Absolute temperature						
Max temp	0.0059***	0.0058**	0.0060**	0.0068**	0.0068	0.0058***
	(0.0022)	(0.0025)	(0.0029)	(0.0034)	(0.0049)	(0.0019)
Rain	-0.0133	-0.0160	-0.0178	-0.0193	-0.0212	0.0021
	(0.0211)	(0.0211)	(0.0211)	(0.0211)	(0.0211)	(0.0197)
Wind	-0.0184**	-0.0219***	-0.0234***	-0.0245***	-0.0237***	-0.0167**
	(0.0073)	(0.0076)	(0.0078)	(0.0080)	(0.0081)	(0.0076)
30-day-lag	No	No	No	No	No	Yes
City-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1125037	1124754	1124471	1123905	1122490	1116267
R^2	0.443	0.443	0.443	0.443	0.443	0.445

Notes. This table presents the impact of temperature on insurance purchase rate based on city-daily level data. The dependent variable *Purchase rate* is the number of insurance policy sold per 1,000,000 residents. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. *Max temp* is the maximum temperature on the purchase date. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. In panel A, 30-day-lag represents the abnormal temperature of the past 30 days, whereas in Panel B, it represents the maximum temperature of the past 30 days. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Insurance purchase rate in extreme hot days and cold days (city-daily level)

	Dependent variable: Purchase rate	
	(1)	(2)
	10th/90th of historical calendar day	10th/90th of sample
Extreme Hot days	0.0376**	0.0376*
	(0.0175)	(0.0203)
Extreme Cold days	-0.0147	-0.0340
	(0.0154)	(0.0361)
Control	Yes	Yes
City-year-month FE	Yes	Yes
Day of week FE	Yes	Yes
Holiday FE	Yes	Yes
N	1125037	1125037
R^2	0.443	0.443

Notes. This table presents the impact of temperature on insurance purchase rate by extreme hot days and cold days, based on city-daily level data. The dependent variable *Purchase Rate* is the number of insurance policy sold per 1,000,000 residents. In Column 1, *Extreme Hot Days* equals to 1 if the maximum temperature is greater than the 90th percentile of the historic (1961–1990) distribution of maximum temperatures, and 0 otherwise. *Extreme Cold Days* equals to 1 if the maximum temperature is less than the 10th percentile of the historic (1961–1990) distribution of maximum temperatures, and 0 otherwise. In Column 2, *Extreme Hot Days* equals to 1 if the maximum temperature is greater than the 90th percentile of maximum temperatures of the sample, and 0 otherwise. *Extreme Cold Days* equals to 1 if the maximum temperature is less than 10th percentile of maximum temperatures of the sample, and 0 otherwise. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Impact of temperature on insurance cancellation (contract level)

Dependent variable: 1 (contract has been cancelled during the CoP)			
	(1)	(2)	(3)
Panel A: Abnormal temperature			
CoP abnormal temp	-0.000049**		
	(0.000021)		
Relative purchase-date abnormal temp		-0.000076**	
		(0.000032)	
1(CoP abnormal temp<purchase-date Abnormal temp)			0.000286*
			(0.000152)
Purchase-date abnormal temp		0.000043*	0.000010
		(0.000022)	(0.000022)
Control	Yes	Yes	Yes
Panel B: Absolute temperature			
CoP max temp	-0.000048**		
	(0.000021)		
Relative purchase-date max temp		-0.000083**	
		(0.000040)	
1(CoP max temp< purchase-date max temp)			0.000358**
			(0.000165)
Purchase-date max temp		0.000041**	-0.000006
		(0.000020)	(0.000022)
Control	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes
N	5192260	5192260	5192260
R^2	0.033	0.033	0.033

Notes. This table presents the impact of temperature on insurance cancellation, based on contract level data. The independent variable is a dummy variable that equals to 1 if the insurance contract has been cancelled within 10 days of purchase. This is defined as the Cooling-off Period (CoP). Contracts that are cancelled at purchase date are excluded. Following Chang, Huang and Wang (2018), *Relative purchase-date max temp* is the average maximum temperature during the CoP minus the order date maximum temperature. *CoP max temp* is the average maximum temperature during the CoP. 1(CoP abnormal temp< purchase-date *temp*) is an indicator variable when the maximum temperature during the CoP is lower than the order date maximum temperature. All columns control for city-year-month fixed effects, day-of-week effects, holiday fixed effects and insurance company-year fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Impact of temperature on insurance contract premium payment mode (contract level)

Dependent variable: 𝟙(specific payment mode categories)					
	(1)	(2)	(3)	(4)	(5)
	Single	Annual	Semiannual	Quarterly	Monthly
	0.29%	97.47%	0.15%	0.51%	1.57%
Panel A: Abnormal temperature					
Abnormal temp	0.000070***	-0.000063**	0.000005	0.000006	-0.000018
	(0.000024)	(0.000028)	(0.000004)	(0.000011)	(0.000020)
Control	Yes	Yes	Yes	Yes	Yes
Panel B: Absolute temperature					
Max temp	0.000043***	-0.000034	0.000004	-0.000007	-0.000031
	(0.000016)	(0.000027)	(0.000004)	(0.000011)	(0.000030)
Control	Yes	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes	Yes	Yes
N	5192260	5192260	5192260	5192260	5192260
R^2	0.089	0.386	0.021	0.119	0.055

Notes. This table presents the impact of temperature on insurance contract premium payment mode based on contract level data. The dependent variable is the indicator of specific payment mode categories, including single payment, annual payment, semiannual payment, quarterly payment and monthly payment. The first row of the table specifies the payment mode, and the second row of the table is the mean values of payment mode indicators. *Max temp* is the maximum temperature on the purchase date (in thousands of yuan). *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Impact of temperature on Baidu Search Volume Index

	(1)	(3)
	Heat-Related Searches	Health-Related Searches
Panel A: Abnormal temperature		
Abnormal temp	0.0232***	0.0034***
	(0.0015)	(0.0011)
Wind	0.0183***	-0.0008
	(0.0049)	(0.0053)
Rain	0.0334***	0.0080
	(0.0128)	(0.0124)
Panel B: Absolute temperature		
Max temp	0.0238***	0.0041***
	(0.0015)	(0.0011)
Wind	0.0168***	-0.0019
	(0.0049)	(0.0053)
Rain	0.0273**	0.0036
	(0.0126)	(0.0122)
30-day-lag	Yes	Yes
City-year-month FE	Yes	Yes
Day of week FE	Yes	Yes
Holiday FE	Yes	Yes
N	809387	809387
R^2	0.517	0.487

Notes. This table presents the impact of temperature on Baidu Search Volume Index. The sample period is from 2011 to 2018, as Baidu Index records start from January 1, 2011. The sample covers 280 cities, consistent with the benchmark regression. *Heat Related Searches* is the natural logarithm of the sum of Baidu Search Volume Index of *"热" ("hot"), "高温" ("high temperature")*, *"热浪" ("heat wave")* and *"高温天气" ("high-temperature weather")* if the sum is greater than zero; otherwise 0. *Health Related Searches* is the natural logarithm of the sum of Baidu Search Volume Index of *"热射病" ("heat stroke")*, *"心血管疾病" ("cardiovascular diseases")* and *"心脑血管疾病" ("cardio-cerebrovascular diseases")* if the sum is greater than zero; otherwise 0.In Panel A, the main dependent variable *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. In Panel B, the main dependent variable *Max temp* is the maximum temperature of purchase date. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. 30-day-lag represents the maximum temperature of the past 30 days. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 7. Impact of temperature on insurance contract characteristics (contract level)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Offline sales	Urban	Male	Age	Sub-standard risk
Panel A: Abnormal temperature					
Purchase-date abnormal temp	0.000085**	0.000179**	-0.000030	0.001457	0.000004
	(0.000035)	(0.000078)	(0.000071)	(0.006432)	(0.000008)
Rain	-0.000478	0.000251	0.002179*	-0.046410	0.000051
	(0.000387)	(0.001260)	(0.001125)	(0.068823)	(0.000139)
Wind	0.000055	-0.000034	-0.000246	0.006505	0.000000
	(0.000130)	(0.000425)	(0.000327)	(0.023956)	(0.000040)
Panel B: Absolute temperature					
Purchase-date max temp	0.000040	0.000231***	-0.000040	0.002150	0.000003
	(0.000032)	(0.000075)	(0.000064)	(0.006648)	(0.000008)
Rain	-0.000547	0.000276	0.002174*	-0.045895	0.000050
	(0.000385)	(0.001259)	(0.001123)	(0.069171)	(0.000140)
Wind	0.000041	0.000009	-0.000254	0.006990	0.000000
	(0.000130)	(0.000426)	(0.000327)	(0.023732)	(0.000040)
City-year-month FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes	Yes	Yes
N	5192260	5192260	5192260	5192260	5192260
R^2	0.085	0.356	0.013	0.067	0.011

Notes. This table presents the impact of temperature on insurance contract characteristics based on contract level data. The first row of the table specifies the characteristics. *Max temp* is the maximum temperature on the purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Impact of temperature on urban and suburb residents' insurance purchase (contract level)

Dependent variable: *Urban*				
	Sales channel		Occupation	
	(1)	(2)	(3)	(4)
	Offline sales	Online sales	Outdoor	Indoor
Panel A: Abnormal temperature				
Purchase-date abnormal temp	0.000180**	-0.000004	0.000206*	0.000110
	(0.000078)	(0.000106)	(0.000107)	(0.000087)
Rain	0.000281	-0.001851	-0.001600	0.000494
	(0.001289)	(0.001253)	(0.001975)	(0.001451)
Wind	-0.000007	0.000126	-0.000448	0.000048
	(0.000427)	(0.000742)	(0.000683)	(0.000427)
Panel B: Absolute temperature				
Purchase-date max temp	0.000229***	-0.000006	0.000177*	0.000105
	(0.000076)	(0.000103)	(0.000100)	(0.000090)
Rain	0.000303	-0.001853	-0.001689	0.001453
	(0.001289)	(0.001255)	(0.001963)	(0.001565)
Wind	0.000035	0.000125	-0.000441	0.000353
	(0.000428)	(0.000737)	(0.000682)	(0.000462)
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes	Yes
N	5127173	60713	1194945	3996020
R^2	0.355	0.547	0.421	0.328

Notes. This table presents heterogeneity of the impact of purchase-date temperature on whether the insured persons live in urban areas, based on contract level data. Columns 1 and 2 refer to heterogeneity by sales channels. Columns 3 and 4 refer to heterogeneity by the insured occupation. We exclude samples of the insured, who are minors. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

T-test

	Urban=0	Urban=1	Diff
Offline sale	0.999	0.982	0.017***
Outdoor occupation	0.344	0.173	0.171***

Table 9. Impact of temperature on insurance purchase rate across different types of insurance products

Dependent variable: Purchase Rate				
	(1)	(2)	(3)	(4)
Insurance categories:	Critical Illness Insurance	Medical Insurance	Life Insurance	Accident Insurance
Mean Value	1.234	0.822	2.252	0.370
Panel A: Abnormal temperature				
Abnormal temp	0.0195***	0.0036	0.0255***	0.0011
	(0.0062)	(0.0024)	(0.0093)	(0.0011)
rain	-0.0777	-0.0427**	0.0107	-0.0211**
	(0.0469)	(0.0204)	(0.0701)	(0.0095)
wind	-0.0712**	-0.0169	-0.0921**	-0.0047
	(0.0303)	(0.0105)	(0.0396)	(0.0043)
Panel B: Absolute temperature				
Max temp	0.0118**	0.0022	0.0206**	0.0006
	(0.0053)	(0.0022)	(0.0081)	(0.0010)
rain	-0.0872*	-0.0441**	-0.0119	-0.0213**
	(0.0455)	(0.0199)	(0.0668)	(0.0093)
wind	-0.0596**	-0.0147	-0.0829**	-0.0038
	(0.0300)	(0.0105)	(0.0389)	(0.0043)
30-day-lag	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
N	334976	334976	334976	334976
R^2	0.544	0.707	0.604	0.707

Notes. This table presents the impact of temperature on insurance purchase rate based on a single insurance company's full sample data. The sample period is from 2008 to 2017, covering 155 cities across 18 provinces in China. In Columns 1 to 4, the dependent variables are the purchase rates of critical illness insurance, medical insurance, life insurance, and accident insurance, respectively, each measured by the ratio of the number of purchases to the total population. per 1,000,000 residents. *Mean Value* represent the mean of the respective purchase rates of each type of insurance. In Panel A, the main dependent variable *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. In Panel B, the main dependent variable *Max temp*is the maximum temperature of purchase date. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. 30-day-lag represents the maximum temperature of the past 30 days. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Table 10. Impact of temperature on city-daily insurance claim rate (city-daily level)

Dependent variable: Claim Rate (Numbers of Claim per 1,000 insurance contracts)						
	(1)	(2)	(3)	(4)	(5)	(6)
	Purchase day	Last 2 days	Last 3 days	Last 5 days	Last 10 days	Purchase day
Panel A: Abnormal temperature						
Disease-occur-date abnormal temp	0.000013**	0.000012*	0.000011	0.000010	0.000012*	0.000016**
	(0.000006)	(0.000006)	(0.000007)	(0.000008)	(0.000006)	(0.000008)
Rain	-0.000125	-0.000131	-0.000138	-0.000135	-0.000142	-0.000122
	(0.000123)	(0.000123)	(0.000123)	(0.000121)	(0.000122)	(0.000120)
Wind	0.000067**	0.000060*	0.000058*	0.000057*	0.000066**	0.000054
	(0.000031)	(0.000031)	(0.000031)	(0.000031)	(0.000031)	(0.000034)
Panel B: Absolute temperature						
Disease-occur-date max temp	0.000009*	0.000008	0.000007	0.000005	-0.000010	0.000014*
	(0.000005)	(0.000006)	(0.000007)	(0.000008)	(0.000010)	(0.000008)
Rain	-0.000142	-0.000150	-0.000153	-0.000149	-0.000148	-0.000130
	(0.000129)	(0.000130)	(0.000130)	(0.000128)	(0.000129)	(0.000123)
Wind	0.000069**	0.000064**	0.000063*	0.000063*	0.000069**	0.000054
	(0.000033)	(0.000032)	(0.000032)	(0.000032)	(0.000033)	(0.000037)
30-day-lag	No	No	No	No	No	Yes
City-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
N	776816	776581	776345	775870	774680	785284
R^2	0.034	0.034	0.034	0.034	0.034	0.034

Notes. This table presents the impact of temperature on insurance claim rate based on city-daily level data. The dependent variable *claim rate* is the number of claims related to cardiovascular and cerebrovascular diseases per 1000 valid insurance contracts. In panel A, 30-day-lag represents the abnormal temperature of the past 30 days, whereas in Panel B, it represents the maximum temperature of the past 30 days. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

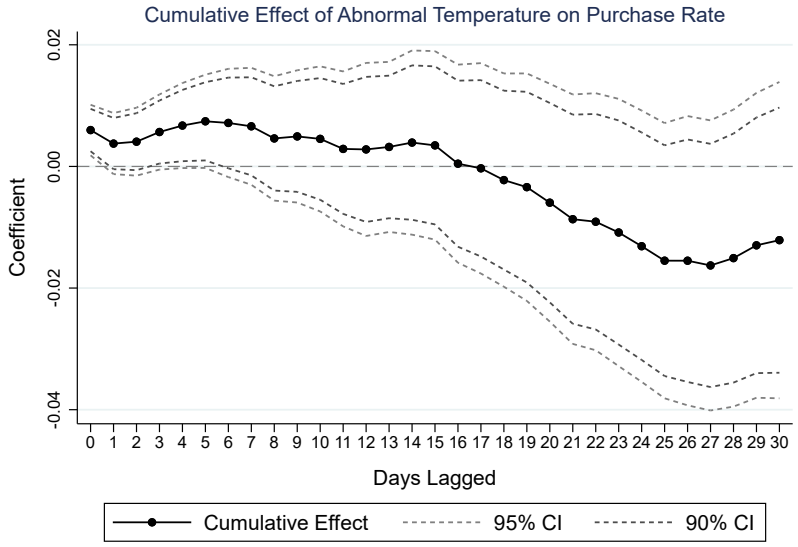
Table 11. Impact of purchase date temperature on claim in the future (contract level)

Dependent variable: 𝟙 (contract with claim filed)				
	(1) Claim during sample period	(2) Claim within 2 years	(3) Claim within 2 -5 years	(4) Claim after 5 years
Panel A: Abnormal temperature				
Purchase-date abnormal temp	0.000010	0.000008	0.000020	-0.000010
	(0.000013)	(0.000012)	(0.000021)	(0.000020)
Male	0.001143***	0.000706***	0.000949***	0.000701***
	(0.000174)	(0.000119)	(0.000168)	(0.000166)
Age	0.000429***	0.000247***	0.000308***	0.000281***
	(0.000018)	(0.000008)	(0.000009)	(0.000009)
Urban	-0.001304***	-0.001003***	-0.000448**	-0.000190
	(0.000209)	(0.000150)	(0.000185)	(0.000189)
Substd	0.012590***	0.009830***	0.004553***	0.005176***
	(0.001609)	(0.001410)	(0.001654)	(0.001899)
Offline sale	0.004185***	0.002093***	0.002843***	0.001478***
	(0.000341)	(0.000299)	(0.000426)	(0.000293)
Rain	0.000200	0.000413**	0.000439	0.000048
	(0.000213)	(0.000194)	(0.000356)	(0.000382)
Wind	-0.000089	-0.000051	-0.000026	-0.000093
	(0.000065)	(0.000069)	(0.000120)	(0.000097)
Panel B: Absolute temperature				
Purchase-date max temp	0.000007	0.000012	0.000014	-0.000004
	(0.000012)	(0.000012)	(0.000020)	(0.000018)
Male	0.001143***	0.000706***	0.000949***	0.000701***
	(0.000174)	(0.000119)	(0.000168)	(0.000166)
Age	0.000429***	0.000247***	0.000308***	0.000281***
	(0.000018)	(0.000008)	(0.000009)	(0.000009)
Urban	-0.001304***	-0.001003***	-0.000448**	-0.000190
	(0.000209)	(0.000150)	(0.000185)	(0.000189)
Substd	0.012590***	0.009830***	0.004555***	0.005175***
	(0.001609)	(0.001410)	(0.001654)	(0.001899)
Offline sale	0.004186***	0.002092***	0.002843***	0.001478***
	(0.000341)	(0.000299)	(0.000426)	(0.000293)
Rain	0.000194	0.000416**	0.000430	0.000055
	(0.000213)	(0.000193)	(0.000355)	(0.000382)
Wind	-0.000090	-0.000048	-0.000028	-0.000091
	(0.000065)	(0.000069)	(0.000120)	(0.000098)
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes	Yes
N	5192260	3092474	1388771	1384466
R^2	0.023	0.276	0.352	0.023

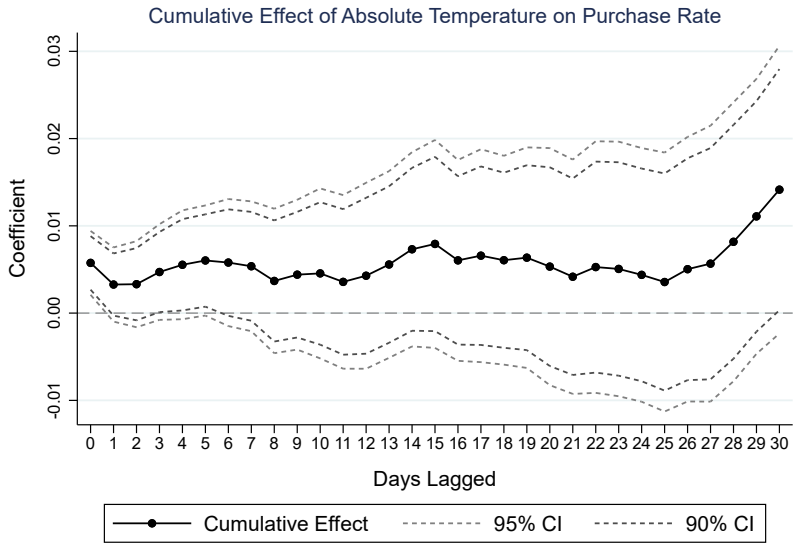
Notes. This table examines whether purchase-date temperature can predict claims using contract level data. The first row of the table specifies the claim time windows. The dependent variable in Column 1 is a dummy variable that equals to 1 if the insurance contract filed claims during 2008-2018, that is our sample periods. and 0 otherwise. The dependent variable in Column 2 equals to 1 if the insurance contract claim occurs within 2 years following the purchase date, and 0 otherwise. Insurance contracts purchased on or after 2017 with no claims recorded by 2018 are excluded. The dependent variable in Column 3 equals to 1 if the insurance contract claim occurs within 2 to 5 years after the purchase date, and 0 otherwise. Insurance contracts purchased on or after 2014 with no claims recorded by 2018 are excluded. The dependent variable in Column 4 equals to 1 if the insurance contract claim occurs after 5 years from the purchase date, and 0 otherwise. Insurance contracts purchased on or after 2014 with no claims recorded by 2018 are excluded. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Figure 1. Cumulative effect of temperature on purchase rate (city-daily level)

Panel A: Abnormal Temperature



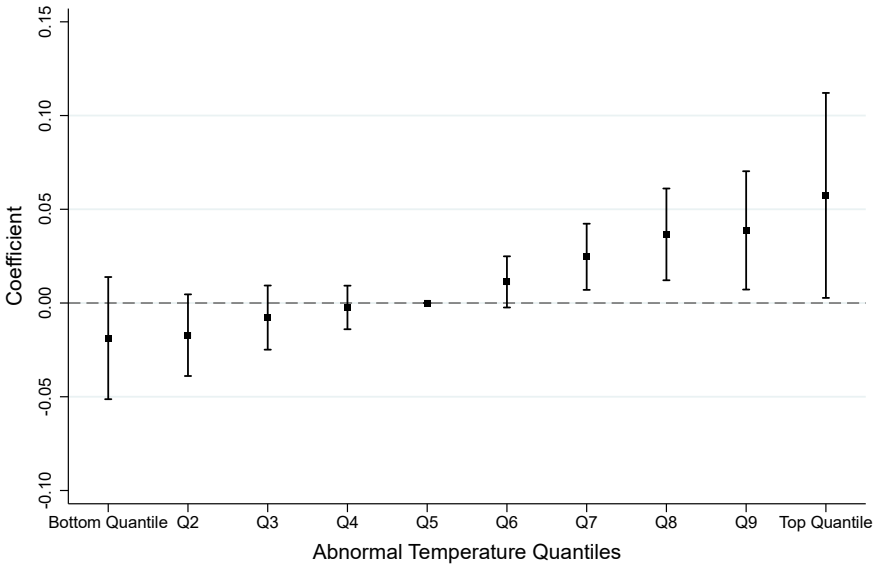
Panel B: Absolute Temperature



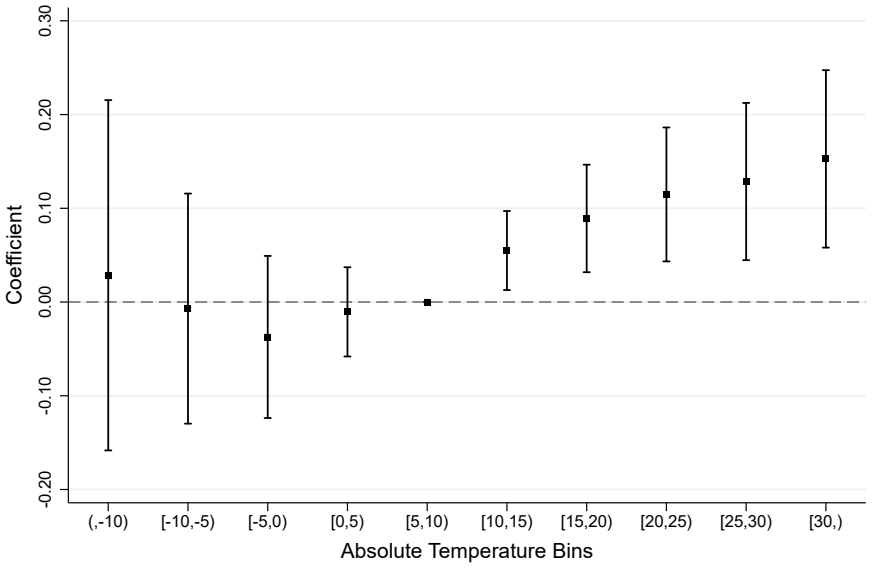
Notes. This figure presents the cumulative effect of temperature on purchase rate, estimated using city-daily level data. Panel A is plotted using abnormal temperature, while Panel B is plotted using absolute temperature.

Figure 2. Impact on purchase rate by temperature quantiles (city-daily level)

Panel A: Abnormal Temperature



Panel B: Absolute Temperature



Notes. This table presents the impact of temperature on insurance purchase rate by temperature quantiles using city-daily level data. We divide them into different quantiles based on abnormal temperature (Panel A) and absolute temperature (Panel B). 95% confidence intervals are provided for each estimate.

Internet Appendix
Not Intended for Publication

Table A1. Robustness: impact of alternative temperature indices on insurance purchase rate (city daily level)

Dependent variable: Purchase Rate					
	(1)	(2)	(3)	(4)	(5)
Abnormal temp (5-day moving window)	0.0063***				
	(0.0020)				
Abnormal temp (15-day moving window)		0.0057***			
		(0.0020)			
Abnormal temp (1971-2000)			0.0046**		
			(0.0019)		
Abnormal temp (1985-2005)				0.0043**	
				(0.0019)	
Abnormal avg temp					0.0045*
					(0.0027)
Rain	-0.0124	-0.0132	-0.0145	-0.0149	-0.0186
	(0.0206)	(0.0206)	(0.0207)	(0.0207)	(0.0209)
Win	-0.0184**	-0.0187**	-0.0192***	-0.0194***	-0.0214***
	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0075)
City-year-month FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes
N	1125037	1125037	1125037	1125037	1125037
R^2	0.443	0.443	0.443	0.443	0.443

Notes. This table reports a robustness test of temperature's impact on insurance purchase rate , based on city-daily data. The dependent variable *Purchase Rate* is the number of insurance policy sold per 1,000,000 residents. In Column 1, the independent variable is the deviation of daily maximum temperature from the historical calendar day maximum temperature centered on a 5-day window for the base period from 1961 to 1990. In Column 2, the independent variable is the deviation of daily maximum from the historical calendar day centered on a 15-day window for the base period from 1961to1990. In Column 3, the independent variable is the deviation of daily maximum temperature from the historical calendar day centered on a 10-day window for the base period from 1971 to 2000. In Column 4, the independent variable is the deviation of daily maximum temperature from the historical calendar day centered on a 10-day window for the base period from 1985 to 2005. In Column 5, the independent variable is the deviation of daily average temperature from the historical calendar day centered on a 10-day window for the base period from 1985 to 2005. All columns control for city-year-month fixed effects, day-of-week effects, holiday fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Impact of temperature on insurance contract payment period (contract level)

Dependent variable: Ln (Payment period)		
	(1)	(2)
Abnormal temp	-0.000256*	
	(0.000148)	
Max temp		-0.000273**
		(0.000138)
Control	Yes	Yes
City-year-month FE	Yes	Yes
Day of week FE	Yes	Yes
Holiday FE	Yes	Yes
Insurance company-year FE	Yes	Yes
N	5192227	5192227
R^2	0.292	0.292

Notes. This table presents the impact of temperature on insurance premium payment periods based on contract level data. The dependent variable is the natural logarithm of payment periods. *Max temp* is the maximum temperature on the purchase date (in thousands of yuan). Insurance contracts missing premium payment term are excluded from the regressions. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3. Urban Heat Island Effect

	(1)	(2)
Dependent variable	Abnormal temp	Max temp
Urban	0.0084***	0.3500***
	(0.0030)	(0.0342)
Constant	0.8181***	18.8443***
	(0.0020)	(0.0244)
City-date FE	Yes	Yes
N	9406064	9406064
R^2	0.977	0.992

Notes. This table tests the urban heat island effect using county- daily level data across all of China from 2008 to 2018. *Max temp* is the daily maximum temperature at county-level. *Urban* is a dummy variable that takes the value of 1 if the county is located in an urban area, and 0 otherwise. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the daily maximum temperature from 1961 to 1990. City- date fixed effects are included. Standard errors in parentheses are clustered at the county and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4. Impact of temperature on insurance purchase rate: Heterogeneity by age (city daily level)

Dependent variable: Age-Specific Purchase Rate						
	(1)	(2)	(3)	(4)	(5)	(6)
Age	<18	<18	18-50	18-50	>50	>50
Abnormal temp	0.0041**		0.0079**		0.0010**	
	(0.0017)		(0.0033)		(0.0004)	
Max temp		0.0039**		0.0078**		0.0010***
		(0.0016)		(0.0031)		(0.0004)
Control	Yes	Yes	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1125037	1125037	1125037	1125037	1125037	1125037
R^2	0.229	0.229	0.240	0.240	0.163	0.164

Notes. This table presents the impact of temperature on insurance purchase rate by age, based on city-daily data. The dependent variable *Age-Specific Purchase Rate* is the number of insurance policies for insured in a given age group per 1,000,000 total residents. The first row of the table specifies the age groups. *Max temp* is the maximum temperature on the purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the purchase day's maximum temperature from 1961 to 1990. All columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. The 30-day-lag represents the maximum temperature of the past 30 days. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5. Impact of temperature on insurance purchase rate: Heterogeneity by gender (city daily level)

Dependent variable: Gender-Specific Purchase Rate				
	(1)	(2)	(3)	(4)
Gender	Male	Male	Female	Female
Abnormal temp	0.0061**		0.0070**	
	(0.0025)		(0.0028)	
Max temp		0.0059**		0.0068***
		(0.0023)		(0.0026)
Control	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
N	1125037	1125037	1125037	1125037
R^2	0.230	0.230	0.240	0.240

Notes. This table presents the impact of temperature on insurance purchase rate by gender, based on city-daily data. The dependent variable *Gender-Specific Purchase Rate* is the number of insurance policies for insured in a given gender group per 1,000,000 total residents. The first row of the table specifies the gender. *Max temp* is the maximum temperature on the purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the purchase day's maximum temperature from 1961 to 1990. All columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A6. Impact of temperature on insurance purchase rate: Heterogeneity by risk profile (city daily level)

Dependent variable: Risk Profile -Specific Purchase Rate				
	(1)	(2)	(3)	(4)
	Standard risk	Standard risk	Substandard risk	Substandard risk
Abnormal temp	0.0131**		0.0000	
	(0.0054)		(0.0000)	
Max temp		0.0127**		-0.0000
		(0.0049)		(0.0000)
Control	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
N	1125037	1125037	1125037	1125037
R^2	0.250	0.250	0.043	0.043

Notes. This table presents the impact of temperature on insurance purchase rate by risk profile. The dependent variable *Risk Profile -Specific Purchase Rate* is the number of insurance policies for insured in a given risk profile group per 1,000,000 total residents. The first row of the table specifies the risk profile. *Max temp* is the maximum temperature on the purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the purchase day's maximum temperature from 1961 to 1990. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A7. Impact of temperature on insurance purchase rate: Heterogeneity by Region (city daily level)

Dependent variable: Region -Specific Purchase Rate				
	(1)	(2)	(3)	(4)
	Urban	Urban	Suburb	Suburb
Abnormal temp	0.0080***		0.0051**	
	(0.0030)		(0.0025)	
Max temp		0.0079***		0.0048**
		(0.0028)		(0.0022)
Control	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
N	1125037	1125037	1125037	1125037
R^2	0.282	0.282	0.218	0.218

Notes. This table presents the impact of temperature on insurance purchase rate by region, based on city-daily data. The dependent variable *Region-Specific Purchase Rate* is the number of insurance policies for insured in a given region group per 1,000,000 total residents. The first row of the table specifies the region. *Max temp* is the maximum temperature of purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the purchase day's maximum temperature from 1961 to 1990. All columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A8. Impact of temperature on insurance purchase rate: Heterogeneity by city tier (city daily level)

Dependent variable: Purchase Rate				
	(1)	(2)	(3)	(4)
	Tier-1 and Tier-2 Cities	Tier-1 and Tier-2 Cities	Tier-3 to Tier-5 Cities	Tier-3 to Tier-5 Cities
Abnormal temp	0.0083***		0.0056***	
	(0.0029)		(0.0019)	
Max temp		0.0068**		0.0058***
		(0.0031)		(0.0021)
Control	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
N	196881	196881	928156	928156
R^2	0.483	0.483	0.425	0.425

Notes. This table presents the impact of temperature on insurance purchase rate by city tier, based on city-daily data. The dependent variable *Purchase Rate* is the number of insurance policy sold per 1,000,000 residents. The first row of the table specifies the city tier. Columns 1 and 2 analyze samples from first- and second-tier cities, whereas Columns 3 and 4 use third-, fourth-, and fifth-tier cities samples. *Max temp* is the maximum temperature of purchase date. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from the purchase day's maximum temperature from 1961 to 1990. All columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A9. Impact of purchase date temperature on the possibility of future claims for different types of diseases (contract level)

	(1) Tumor	(2) CVDs	(3) Other disease	(4) Other death
Panel A: Abnormal temperature				
Purchase-date abnormal temp	0.000007	0.000012	0.000014	-0.000004
	(0.000012)	(0.000012)	(0.000020)	(0.000018)
Male	0.001143***	0.000706***	0.000949***	0.000701***
	(0.000174)	(0.000119)	(0.000168)	(0.000166)
Age	0.000429***	0.000247***	0.000308***	0.000281***
	(0.000018)	(0.000008)	(0.000009)	(0.000009)
Urban	-0.001304***	-0.001003***	-0.000448**	-0.000190
	(0.000209)	(0.000150)	(0.000185)	(0.000189)
Substd	0.012590***	0.009830***	0.004555***	0.005175***
	(0.001609)	(0.001410)	(0.001654)	(0.001899)
Offline sale	0.004186***	0.002092***	0.002843***	0.001478***
	(0.000341)	(0.000299)	(0.000426)	(0.000293)
Rain	0.000194	0.000416**	0.000430	0.000055
	(0.000213)	(0.000193)	(0.000355)	(0.000382)
Wind	-0.000090	-0.000048	-0.000028	-0.000091
	(0.000065)	(0.000069)	(0.000120)	(0.000098)
Panel B: Absolute temperature				
Purchase-date max temp	-0.000005	0.000007	0.000001	0.000001
	(0.000009)	(0.000007)	(0.000004)	(0.000003)
Male	-0.001698***	0.001690***	0.000649***	0.000467***
	(0.000087)	(0.000119)	(0.000043)	(0.000028)
Age	0.000205***	0.000147***	0.000036***	0.000013***
	(0.000006)	(0.000014)	(0.000002)	(0.000001)
Urban	0.000057	-0.000867***	-0.000252***	-0.000149***
	(0.000089)	(0.000167)	(0.000045)	(0.000025)
Substd	0.007690***	0.002477***	0.000965**	0.000036
	(0.001156)	(0.000621)	(0.000431)	(0.000209)
Offline sale	0.002270***	0.000835***	0.000546***	0.000284***
	(0.000190)	(0.000163)	(0.000103)	(0.000074)
Rain	-0.000089	0.000171	-0.000039	0.000051
	(0.000154)	(0.000104)	(0.000072)	(0.000052)
Wind	-0.000102**	-0.000036	0.000031	-0.000000
	(0.000043)	(0.000039)	(0.000021)	(0.000014)
City-year-month FE	Yes	Yes	Yes	Yes
Day of week Ft	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Insurance company-year FE	Yes	Yes	Yes	Yes
N	5192260	5192260	5192260	5192260
R^2	0.016	0.019	0.014	0.013

Notes. The dependent variable in Column 1 equals to 1 if the insurance contract has been claimed due to tumor, and 0 otherwise. The dependent variable in Column 2 equals to 1 if the insurance contract has been claimed due to cardiovascular diseases (CVDs), and 0 otherwise. The dependent variable in Column 3 equals to 1 if the insurance contract has been claimed due to diseases other than tumor and cardiovascular and cerebrovascular disease, including disabled, nervous system, respiratory system, digestive system, etc., and 0 otherwise. The dependent variable in Column 4 equals to 1 if the insurance contract has been claimed due to non-disease-related deaths, including suicide, accident, etc., and 0 otherwise. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A10. Impact of temperature on insurance coverage periods (contract level)

	(1)	(2)
Dependent variable	Ln(Insurance coverage period)	Ln(Expiry age)
Panel A: Abnormal temperature		
Abnormal temp	0.000266	0.000204
	(0.000265)	(0.000185)
Control	Yes	Yes
	Yes	
Panel B: Absolute temperature		
Max temp	0.000157	0.000117
	(0.000287)	(0.000201)
Control	Yes	Yes
City-year-month FE	Yes	Yes
Day of week FE	Yes	Yes
Holiday FE	Yes	Yes
Insurance company-year FE	Yes	Yes
N	5191023	5191023
R^2	0.310	0.329

Notes. This table presents the impact of temperature on insurance coverage period based on contract level data. In column 1, the dependent variable is the natural logarithm of insurance coverage period. In column 2, the dependent variable is the natural logarithm of the insured age when the insurance expires. *Max temp* is the maximum temperature on the purchase date (in thousands of yuan). *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effect. Standard errors in parentheses are clustered on city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A11. Impact of purchase date temperature on claim refusal (contract level)

	(1)	(2)
	Refusal	Refusal
Purchase-date abnormal temp	0.000018	
	(0.000522)	
Purchase-date max temp		0.000009
		(0.000466)
Male	0.007659*	0.007659*
	(0.004511)	(0.004510)
Age	-0.001552***	-0.001552***
	(0.000193)	(0.000193)
Urban	-0.003568	-0.003569
	(0.005255)	(0.005251)
Sub-standard risk	0.004384	0.004382
	(0.021728)	(0.021730)
Offline sale	-0.009558	-0.009554
	(0.022036)	(0.022021)
Rain	0.000854	0.000841
	(0.012357)	(0.012339)
Wind	0.000817	0.000816
	(0.002405)	(0.002404)
City-year-month FE	Yes	Yes
Day of week FE	Yes	Yes
Holiday FE	Yes	Yes
Insurance company-year FE	Yes	Yes
N	34990	34990
R^2	0.327	0.327

Notes. This regression is based on contract data from the claim records sample. The dependent variable *refusal* is a dummy variable that equals to 1 if the claim request is refused, and 0 otherwise. All columns control for city-year-month fixed effects, day-of-week fixed effects, holiday fixed effect and insurance company-year fixed effects. Standard errors are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

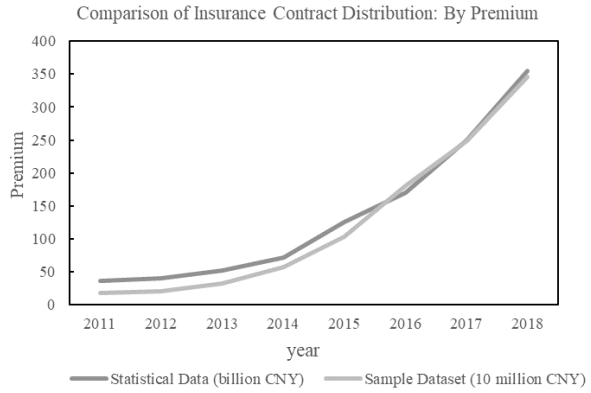
Table A12. Impact of temperature on insurance contract characteristics (contract level)

Dependent variable:	*Ln (sum insured)*		*Ln(premium)*	
	(1)	(2)	(3)	(4)
Abnormal temp	-0.000890**		-0.000432	
	(0.000416)		(0.000371)	
Max temp		-0.000418		-0.000388
		(0.000490)		(0.000457)
Control	Yes	Yes	Yes	Yes
City-year-month FE	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes
Insurance Company-year FE	Yes	Yes	Yes	Yes
N	5192260	5192260	5192260	5192260
R^2	0.428	0.428	0.516	0.516

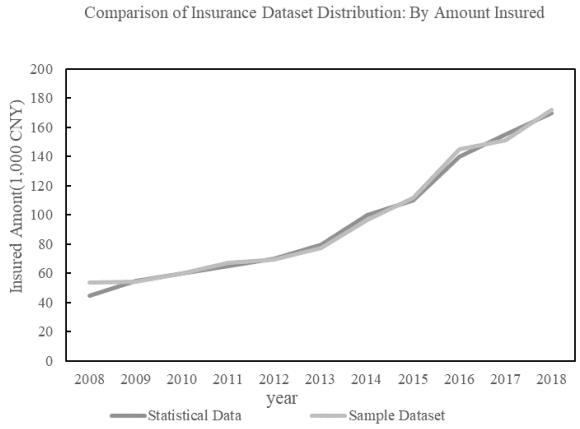
Notes. This table presents the impact of temperature on sum insured and premium using contract level data. In column 1 and 2, the dependent variable is the natural logarithm of the insured amount. In column 3 and 4, the dependent variable is the natural logarithm of the premium. *Abnormal temp* is measured by subtracting the average maximum temperature of the corresponding date and the five days before and after it from 1961 to 1990 from the purchase day's maximum temperature. *Max temp* is the maximum temperature on the purchase date. Control variables include insurance characteristics, such as the insured's age, risk profile, urban/rural residence, offline sales channels, as well as weather condition including rain and wind speeds. All the columns control for city-year-month fixed effects, day-of-week fixed effects and holiday fixed effects. In panel A, 30-day-lag represents the abnormal temperature of the past 30 days, whereas in Panel B, it represents the maximum temperature of the past 30 days. Standard errors in parentheses are clustered at the city and date level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure A1. Comparison of Insurance Dataset Distribution:

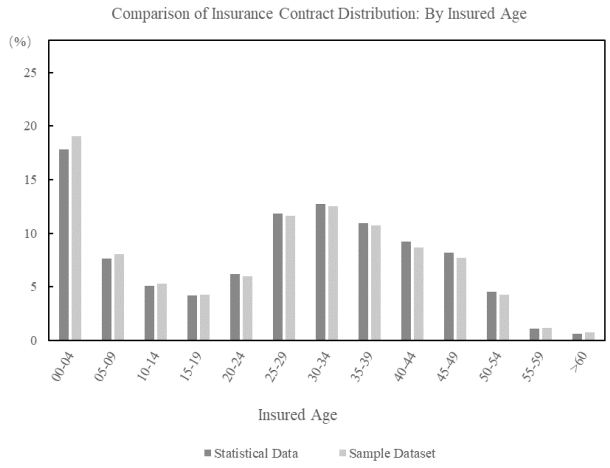
Panel A: Premium



Panel B: Coverage Amount



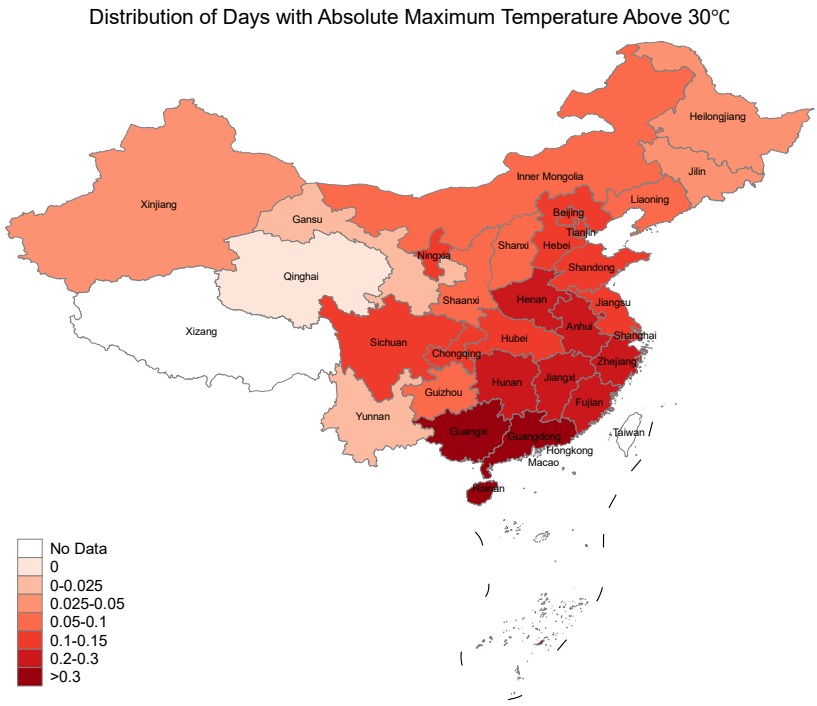
Panel C: Insured demographics



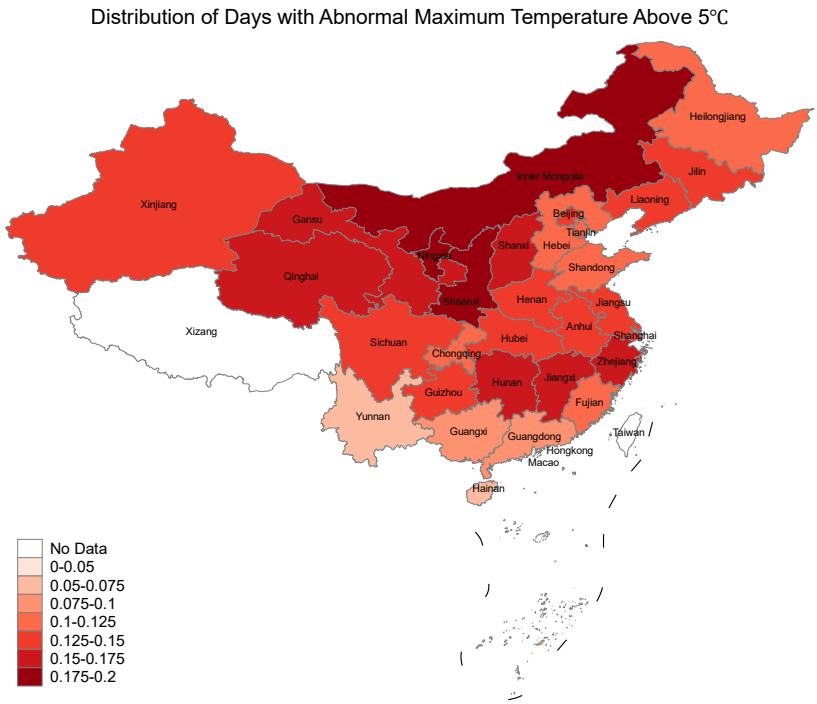
Notes. In these figures, we compare our sample dataset with the statistical database from the China Banking and Insurance Regulatory Commission. The light grey charts represent our sample dataset, while the dark grey charts represent the statistical data.

Figure A2. Distribution of Absolute and Abnormal Temperature

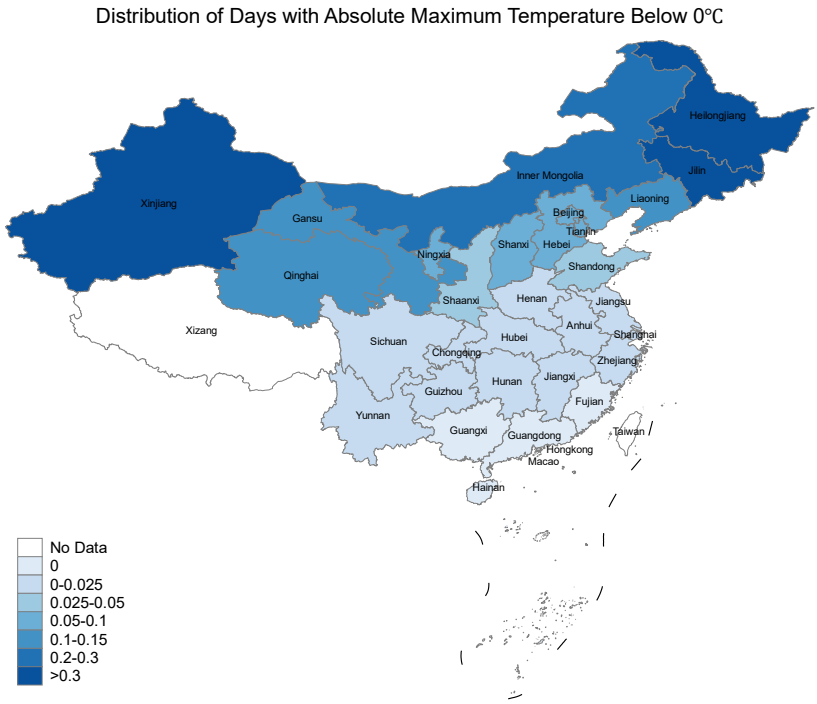
Panel A: Days with absolute maximum temperature over 30-degree Celsius.



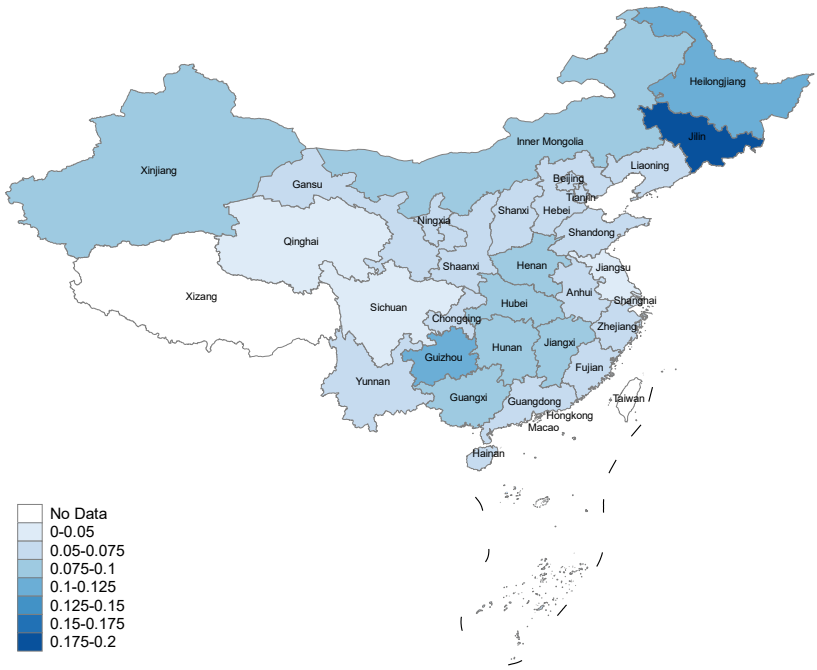
Panel B: Days with abnormal maximum temperature Above 5-degree Celsius.



Panel C: Days with absolute maximum temperature below 0-degree Celsius.



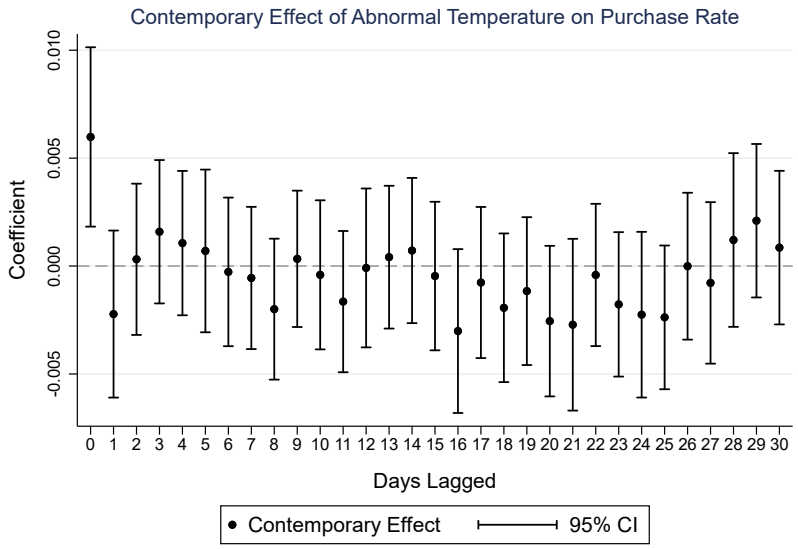
Panel D: Days with abnormal maximum temperature below -5-degree Celsius.



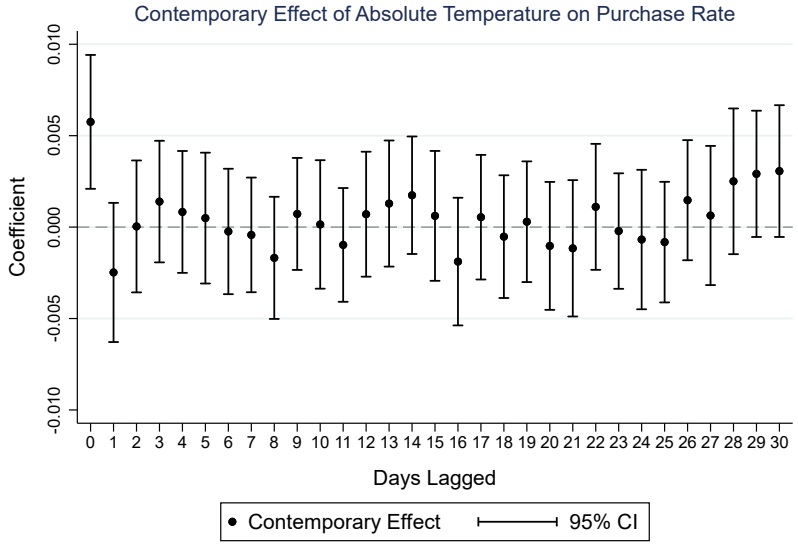
Notes. These maps present the distribution of absolute and abnormal temperature in China. The 4 maps describe the share of days with specific maximum temperature or abnormal maximum temperature in our sample of cities. The value for each province represents the average value of the sample cities that belong to that province.

Figure A3. Distribution of temperature

Panel A: Abnormal Temperature



Panel B: Absolute Temperature



Notes. These graphs present the contemporary effect of temperature on purchase rate using city-daily level data. Panel A is based on abnormal temperature, while Panel B is based on absolute temperature.