Supplementary Information:
Adaptation Mitigates the Negative Effect of Temperature Shocks on Household Consumption

Intertemporal Substitution.

We use two methods to examine the role of intertemporal (day-to-day) substitution and determine how many day-lags should be included in the model. In the first method, we estimate the effects of current-day temperature extremes, past days' temperature extremes (denoted as negative on the x-axis), and future days' temperature extremes (denoted as positive on the x-axis) on current-day spending per card (in ¥). We focus on two types of temperature extremes: temperatures above 90°F and below 30°F, respectively. The reference bin is temperatures between 30°F and 90°F. Overall, the coefficient estimates at the daily frequency (plotted in Supplementary Fig. 1) are noisy due to the high autocorrelation of daily temperatures, justifying our approach of using the average temperature in a 10-day window in our baseline analysis.

Nevertheless, two patterns emerge. First, both current-day heat and cold shocks decrease contemporaneous consumption (indicated by the coefficient estimates on day 0). The temperature effects from 2-7 days ago (indicated by coefficient estimates on day -2 to -7) are noisy and exhibit swings. The effect of temperature shocks from a week ago appear to be relatively more stable, with a small and insignificant effect on current-day consumption. These patterns suggest that the scope of intertemporal substitution and lagged effects of temperature shocks are likely to be limited to 10 days for most consumption activities, motivating the time window in our baseline analysis. Second, current consumption does not seem to be significantly affected by future temperature shocks (indicated by coefficient estimates on day 1-3), supporting the causality of the estimates.

In the second method, we keep the 17 temperature bins in each time window as in Eq. (1) and test the significance of the consumption impacts of the average temperature bins from three 5-day windows: past day t-4 to t, past day t-9 to t-5, and past day t-14 to t-10. The results are presented in Panel (a) of Supplementary Fig. 2. Both average-temperature bins from past day t-4 to t and past day t-9 to t-5 have negative impacts on consumption, but the impacts from past day t-14 to t-10 are close to zero. This supports our choice of using average-temperature during the immediate 10-day window. As a falsification test, we add in Eq. (1) average-temperature bins based on the immediate future 5 days. The results, shown in Panel (b) of Supplementary Fig. 2, reveal two findings. First, after controlling future temperature bins, the temperature impacts from the last 10 days are similar to those in the baseline regression. Second, the impacts from the future 5-day window are close to zero, supporting that our estimated effects are not spurious.

The Role of Income.

Income affects consumption response to temperature changes through two competing channels: composition and adaptation. On one hand, rising income changes the composition of consumption: the share of necessity spending drops while that of discretionary spending increases. Because discretionary spending could be more responsive to temperature shocks, the negative consumption impact of temperature gets larger as income increases. On the other hand, a higher income facilitates a better ability to adapt, and adaption (for example, air conditioners or increasing car usages instead of walking) could mitigate the negative impact of temperature extremes on consumption.

Supplementary Fig. 3 shows the temperature's impact on consumption by high- and low-income regions (75th and 25th percentile, respectively), while holding climate at the median. On hot days, the negative impacts are larger in high-income regions than in low-income regions, suggesting that the reduction of discretionary spending (that is, the composition channel) plays a dominant role relative to the adaptation channel. On cold days, the impacts are similar across high and low income regions, suggesting that the two channels may cancel each other out. These interesting and nuanced findings highlight the interaction of competing forces and the challenge in understanding the impact of climate changes on the economy.

Note that our future projections do not fully capture the effect of income on consumption for three reasons. First, the main effect of income is absorbed by the fixed effects in our empirical analysis and hence is not identified. The part of the income effect that our empirical model can identify is captured by the coefficient on the interaction between GDP per capita and temperature: the coefficient characterizes how income growth affects the slope of the consumption-temperature relationship. Second, income is hold fixed in the corresponding future in both parts of the Eq. (3) (Eq. (4)), and hence partially shut down the channel of income growth. Specifically, based on Eq. (2), we differentiate between Eq. (3) with Eq. (5) below to elucidate the role of income:

$$\Delta\hat{y}_{c,\tau}^{Adapt} = f(TP_{c,\tau}, CM_{c,\tau}, GDP_{c,2018}; \hat{\theta}) - f(TP_{c,2018}, CM_{c,2018}, GDP_{c,2018}; \hat{\theta}), \quad [5]$$

where the subscript of GDP is 2018. Eq. (5) fixes income in 2018 in both parts of the expressions such that consumption change is due to climate change alone. Eq. (3) fixes income in 2100 in both parts of the expressions and thus measures consumption changes from climate change and the (partial) effect of income growth.

Third, the potential role that the income plays in consumption response to temperature is ambiguous. We find that the negative effect of climate change on consumption is amplified as income increases. This finding itself does not speak to the benefit or cost of income growth. This differs from Carleton et al. (2020) which examines mortality as the outcome variable. Income intuitively could mitigate the negative mortality impact of temperature through adaptation or changes in the baseline mortality rate.

Next, we report the changes of consumption (in %) in the future relative to the 2018 level on an annual basis from both Eq. (3) and Eq. (5). The results are reported in Supplementary Fig. 4. Green lines and red lines show the results under the RCP4.5 and RCP8.5 scenarios, respectively. Solid lines and dashed lines present no adaptation and adaptation of climate change, respectively. Two findings emerge. First, our key conclusion remains that adaptation mitigates the negative effect of temperature on consumption. Second, the negative effect of climate change on consumption is amplified as income increases. Our conjecture is that rising income increases discretionary spending and discretionary spending is more responsive to temperature shocks.

Given the effect of income is partial and the potential role that the income plays in consumption response to temperature is ambiguous, the negative effects in panel (a) do not mean that climate change counteracts the entire benefits of income growth. Instead, the differences between panel (a) and (b) characterize how income growth could affect the slope of the consumption-temperature relationship. In fact, it is very likely that income growth from 2018 to 2100 would increase the overall consumption were we able to identify and incorporate the full impact of income growth on consumption.

Robustness to Payment Methods.

Electronic payment methods (notably WeChat and Alipay, either through mobile phones or internet) have increased significantly overtime. We acknowledge the caveat that some of the observed relationship between temperature and spending could be driven by substitution between UnionPay and other payment methods. In addition, we provide evidence to support that the substitution effects, if exist, should be small.

Panel (a) in Supplementary Fig. 5 documents the share of spending by payment types in China from Kapron and Meertens (2017). While electronic payment methods increases overtime, they primarily come at the cost of cash payment – people use electronic payments instead of cash for their consumption. In contrast, the share of spending that is accounted by bank cards has been quite stable over our sample period.

Our bank card database reports the amount of cash people withdraw from the UnionPay system. In light of the declining importance of cash and the substitution between cash payment and electronic payments, we examine the robustness of our results by removing the cash category from our analysis. If this does not affect our main finding, then it provides evidence that our results are unlikely to be affected by the substitution between payments methods.

Panel (b) reports the estimates from the non-cash spending. Take the results from the bin of <10 F and the bin of >85 F as examples. On cold days, the spending decreases by 3.18% (-2.87/91.92) and, on hot days, the spending decreases by 5.84% (-5.28/91.92). These estimates are very similar to those based on the total spending (including both cash and non-cash), -3.2% and -5.9% in Figure 1. This suggests that our key finding is unlikely to be driven by the substitution between payments methods.

Seasonality.

To control for omitted variable bias, our baseline model includes city fixed effects (FEs), day-of-the-sample FEs, city by year-quarter FEs, city by holiday FEs as well as other weather and pollution controls. However, seasonality may still be a concern. For example, we find a invert U-shape between temperature and clothes. If people generally buy winter clothing in the fall and summer clothing in the spring, this would give rise to a spending pattern where spending is highest when temperatures are moderate. This interpretation is possible but unlikely to be the case in our context.

First, while the baseline model uses city-by-quarter fixed effects (FEs), the robustness checks adopt finer time fixed effects to control for seasonality. Panel (a) in Supplementary Fig. 6 uses the city-by-month FEs and the estimates are stable. Second, we explore the effect of temperature on spending in the fur store. Panel (b) shows that the spending significantly increases on cold days but decreases on hot days: no inverted U-shape is found for fur stores. This suggests that our results are unlikely to be driven by the off-season purchasing behavior (i.e., buying winter clothing in the fall and summer clothing in the spring). The evidence should alleviate the concern on the seasonality. Third, the residuals in panel (c) of Extended Fig. 5 do not exhibit any seasonable patterns, suggesting that the baseline model performs well in capturing seasonality.

Additionally, we would like to clarify the following caveat. While intertemporal substitution and lagged effects of temperature shocks are likely to be limited to 10 days for the overall spending, it does not mean that the substitution for each category is within 10 days. Therefore, for goods that are durable beyond 10 days, the analysis of sub-categories may not fully capture the effects. We note to readers that the findings on the sub-categories should be interpreted with caution.

Alternative Modeling Choice.

Our baseline model uses the level of temperature as the variables of interest. However, given the observed different consumption effects of temperature by climatic regions, one alternative way is to model the temperature deviations from local mean temperature. Below we first discuss the current practice in the literature. Then we present the conceptual differences and the empirical tests to support the choice of temperature-level model in our context.

Carleton and Hsiang (2016) present a thorough review on the social and economic impacts of temperature and climate. While the literature in this area has studied a host of outcomes (including mortality, labor supply, productivity, crime etc.), the common empirical specification uses the temperature level as the variable of interest. Similarly, recent papers including Auffhammer (2018), Carleton et al. (2020) and Heutel et al. (2020) also uses the measure of temperature levels. While some papers directly model the (standard) deviation of temperature (e.g. Bento et al. 2020; Hidalgo et al. 2010), their contexts of application is not human behavior but rather agricultural yields or ozone concentration.

Conceptually, it is not clear whether people response to the level of temperature or the deviation from the long-term mean. It is possible that people respond to both types of changes. The temperature-level model that we use is quite flexible in utilizing information from both the temperature level and deviations. First, by including the city fixed effects, the key identifying variation in our Eq. (1) is the temperature deviation from the sample average (though not the deviation from the historical average). Second, our Eq. (2) allows the marginal impacts of temperature changes to vary with historical average temperature, hence incorporating the channel that people may respond to the historical average temperature.

Empirically, to test which model fits the data better, we simultaneously include dummies indicating temperature levels and dummies indicating temperature deviation into the same equation. The results are reported in Supplementary Fig. 7 and two findings emerge. First, the marginal impacts (panel(a)) from the dummies of temperature level are largely stable, comparing with the baseline model with only dummies for temperature levels (Fig. 1). Second, after controlling for the impacts of temperature levels, the coefficient estimates on many dummies for temperature deviation become insignificant (panel(b)), particularly on cold days. These findings suggest that people are more likely to response to the level of temperature, which is in line with the model setup of the majority of the existing literature. In the extended model (Eq. (2)), we allow the slop in Supplementary Fig. 7 to vary by climate zones, which further incorporate the margin of temperature deviation (from the historical average).

Supplementary Information: Tables and Figures

Supplementary Table 1. Percentage of spending by category: NBS vs. UnionPay

Category	NBS category	NBS Ratio	UnionPay	UnionPay Ratio
1	Food	0.31	EU 1, 2, 11 and 15	0.15
2	Clothing	0.08	EU 3	0.02
3	Residence	0.22	EU 4 and 14	0.17
4	Household Facilities and Articles	0.06	EU 5	0.01
5	Transport and Communications	0.13	EU 7 and 8	0.13
6	Education, Culture and Recreation	0.11	EU 9, 10 and 12	0.36
7	Health	0.07	EU 6	0.03
8	Others	0.02	EU 13	0.14

Notes: The table tabulates the percentage of retail sales by category as reported by NBS and the percentage of spending by category among UnionPay transactions. Some of the discrepancies arise from differences in the category definition. For example, food and clothing related transactions are sometimes classified in other categories under UnionPay, which groups transactions based on the merchants' core business. Cash and other payment methods (e.g. mobile payment) also contribute to the discrepancies across categories.

Supplementary Table 2. Summary Statistics

	Mean	Std. Dev.	Min.	Max.	N
Value of Transactions per Card, Daily, *yuan*(¥)					
Total Consumption	120.14	51.02	50.00	309.99	594,706
Food	18.29	16.80	5.29	82.45	594,706
Clothes	2.41	2.24	0.33	12.21	594,706
Entertainment	6.84	4.60	0.73	25.06	594,706
Transportation	4.31	4.18	0.18	28.47	594,706
Department Store	13.99	13.05	1.93	64.55	594,706
Cash	29.11	14.75	7.99	253.44	594,706
Health	3.17	1.92	0.19	11.49	594,706
Online	0.02	0.03	0.00	4.18	385,610
Weather					
Mean Temperature, °F	58.95	19.46	-36.56	98.55	594,706
Precipitation, *mm*	2.95	6.54	0	180.332	594,706
Relative Humidity, *%*	69.35	17.16	5.05	100.00	594,706
Snow Depth, *mm*	0.83	6.50	0	249.97	594,706
Others					
Air Pollution Index	81.16	47.71	8.59	500	594,706
GDP per capita, ¥	33737	22611	7193	175125	594,706

Notes: The unit of observation is city by day. Consumption data are from the UnionPay network for the 283 largest cities in China from 2013 to 2018. Weather data are from the European Center for Medium-Range Weather Forecasts (ECMWF). Air pollution data are from China's Ministry of Ecology and Environment. The category of online purchases is not precisely identified and has a large number of missing values.

Supplementary Table 3. Consumption Responses to Temperature Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Conley S.E.			
Temperature bins	Coef.	P-Value	S.E.	95% CI	300 km		500 km	
					Uniform	Bartlett	Uniform	Bartlett
<10	-3.867	0.002	1.266	(-6.359 -1.375)	1.678	1.662	1.685	1.670
[10, 15)	-4.861	0.001	1.408	(-7.633 -2.089)	1.558	1.545	1.563	1.551
[15, 20)	-3.648	0.002	1.162	(-5.934 -1.361)	1.438	1.427	1.443	1.433
[20, 25)	-3.345	0.004	1.162	(-5.632 -1.058)	1.459	1.453	1.454	1.455
[25, 30)	-3.010	0.001	0.911	(-4.803 -1.216)	1.552	1.546	1.551	1.548
[30, 35)	-2.253	0.015	0.924	(-4.071 -0.434)	0.988	0.982	0.992	0.985
[35, 40)	-1.500	0.003	0.501	(-2.485 -0.515)	0.537	0.528	0.539	0.532
[45, 50)	-0.967	0.105	0.595	(-2.139 0.204)	0.579	0.572	0.583	0.576
[50, 55)	-1.914	0.025	0.849	(-3.585 -0.242)	0.889	0.882	0.891	0.886
[55, 60)	-3.014	0.001	0.875	(-4.737 -1.291)	0.919	0.913	0.922	0.916
[60, 65)	-3.723	0.003	1.261	(-6.206 -1.241)	1.264	1.259	1.267	1.262
[65, 70)	-5.058	0.001	1.543	(-8.095 -2.021)	1.566	1.560	1.568	1.563
[70, 75)	-5.538	0.000	1.523	(-8.537 -2.539)	1.562	1.554	1.565	1.558
[75, 80)	-4.974	0.000	1.386	(-7.701 -2.247)	1.478	1.467	1.482	1.473
[80, 85)	-5.206	0.000	1.298	(-7.761 -2.652)	1.379	1.365	1.384	1.372
>=85	-7.039	0.000	1.439	(-9.871 -4.207)	1.501	1.485	1.506	1.493
Observations	594,706	-	-	-	-	-	-	-
R-squared	0.90	-	-	-	-	-	-	-

Notes: The table reports the 10-day effect on daily spending per card (in ¥) due to a temperature change from the reference bin (40-45°F) to a corresponding temperature bin according to Eq. (1). The dependent variable is daily spending per card with a sample mean of ¥120, and the unit of observation is city by day. The regression includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Column (2)-(4) report p-values, cluster standard errors, and 95% confidence intervals based on with clusters defined at the city level. Columns (5)-(8) report Conley standard errors to account for spatial correlation among cities within the 300 km and 500 km radii, respectively. The uniform kernel weights all observations within the chosen radius equally and sets the weight for all observations farther as zero. The Bartlett kernel gives linear decaying weights for observations inside the radius and zero weight for observations outside the radius.

Supplementary Table 4. Consumption Responses Accounting for Adaptation

VARIABLES	(1) Coef.	(2) P-Value	(3) S.E.	(4) 95% CI
TP	0.002	0.997	(0.651)	(-1.273 1.277)
$TP \cdot CM_c$	0.019	0.005	(0.006)	(0.007 0.031)
$TP \cdot GDP_c$	-0.059	0.357	(0.063)	(-0.182 0.064)
$TP \cdot \mathbb{1}(TP \in [40, 60))$	0.777	0.595	(1.459)	(-2.082 3.636)
$TP \cdot \mathbb{1}(TP \in [40, 60)) \cdot CM_c$	-0.013	0.069	(0.007)	(-0.027 0.001)
$TP \cdot \mathbb{1}(TP \in [40, 60)) \cdot GDP_c$	-0.052	0.663	(0.119)	(-0.285 0.181)
$TP \cdot \mathbb{1}(TP \geqslant 60)$	-0.077	0.821	(0.339)	(-0.741 0.587)
$TP \cdot \mathbb{1}(TP \geqslant 60) \cdot CM_c$	0.006	0.086	(0.004)	(-0.002 0.013)
$TP \cdot \mathbb{1}(TP \geqslant 60) \cdot GDP_c$	-0.029	0.459	(0.039)	(-0.105 0.047)
Observations	594,706	-	-	-
R-squared	0.91	-	-	-

Notes: The table reports estimation results from the semiparametric specification of Eq. (2). The dependent variable is daily spending per card with a sample mean of ¥120 and the unit of observation is city by day. Standard errors are clustered at the city level. CM_c denotes the climate condition of city c (the 30-year average temperature from 1981 to 2010). GDP_c denotes GDP per capita in 2010 in logarithmic scale. The regression includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity.

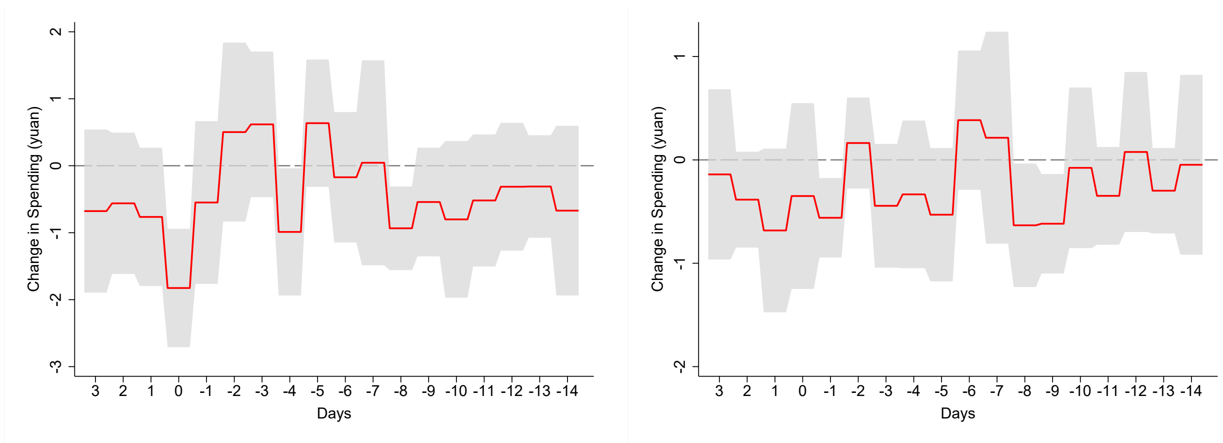
Supplementary Table 5. Consumption Responses Accounting for Adaptation with a Richer Model

VARIABLES	(1) Coef.	(2) P-Value	(3) S.E.	(4) 95% CI
TP	-0.432	0.486	(0.618)	(-1.649 0.786)
$TP \cdot CM_c$	0.017	0.006	(0.006)	(0.005 0.029)
$TP \cdot GDP_c$	-0.010	0.860	(0.059)	(-0.127 0.106)
$TP \cdot \mathbb{1}(TP \geqslant 40)$	4.022	0.002	(1.280)	(1.502 6.541)
$TP \cdot \mathbb{1}(TP \geqslant 40) \cdot CM_c$	-0.014	0.132	(0.009)	(-0.031 0.004)
$TP \cdot \mathbb{1}(TP \geqslant 40) \cdot GDP_c$	-0.347	0.004	(0.119)	(-0.581 -0.114)
$TP \cdot \mathbb{1}(TP \geqslant 50)$	-1.995	0.002	(0.653)	(-3.280 -0.709)
$TP \cdot \mathbb{1}(TP \geqslant 50) \cdot CM_c$	-0.002	0.689	(0.006)	(-0.014 0.009)
$TP \cdot \mathbb{1}(TP \geqslant 50) \cdot GDP_c$	0.198	0.001	(0.061)	(0.077 0.319)
$TP \cdot \mathbb{1}(TP \geqslant 60)$	-0.075	0.846	(0.387)	(-0.838 0.687)
$TP \cdot \mathbb{1}(TP \geqslant 60) \cdot CM_c$	0.006	0.058	(0.003)	(-0.000 0.013)
$TP \cdot \mathbb{1}(TP \geqslant 60) \cdot GDP_c$	-0.031	0.491	(0.044)	(-0.118 0.057)
$TP \cdot \mathbb{1}(TP \geqslant 70)$	-0.339	0.573	(0.600)	(-1.520 0.843)
$TP \cdot \mathbb{1}(TP \geqslant 70) \cdot CM_c$	0.003	0.378	(0.003)	(-0.003 0.008)
$TP \cdot \mathbb{1}(TP \geqslant 70) \cdot GDP_c$	0.018	0.691	(0.045)	(-0.071 0.107)
$TP \cdot \mathbb{1}(TP \geqslant 80)$	-0.411	0.154	(0.287)	(-0.976 0.155)
$TP \cdot \mathbb{1}(TP \geqslant 80) \cdot CM_c$	0.003	0.155	(0.002)	(-0.001 0.007)
$TP \cdot \mathbb{1}(TP \geqslant 80) \cdot GDP_c$	0.020	0.298	(0.019)	(-0.017 0.057)
Observations	594,706	-	-	-
R-squared	0.90	-	-	-

Notes: This table reports estimation results from a more flexible version of Eq. (2), where $f(TP_{c,t}, CM_c, GDP_c)$ is specified as follows:

$$f(TP_{c,t}, CM_c, GDP_c) = \alpha_0 TP_{c,t} + \sum_{k=4}^{8} \alpha_k \mathbb{1}(TP_{c,t} \geqslant 10 * k) \cdot TP_{c,t} + \left[\beta_0 TP_{c,t} + \sum_{k=4}^{8} \beta_k \mathbb{1}(TP_{c,t} \geqslant 10 * k) \cdot TP_{c,t}\right] \cdot CM_c + \left[\gamma_0 TP_{c,t} + \sum_{k=4}^{8} \gamma_k \mathbb{1}(TP_{c,t} \geqslant 10 * k) \cdot TP_{c,t}\right] \cdot GDP_c,$$

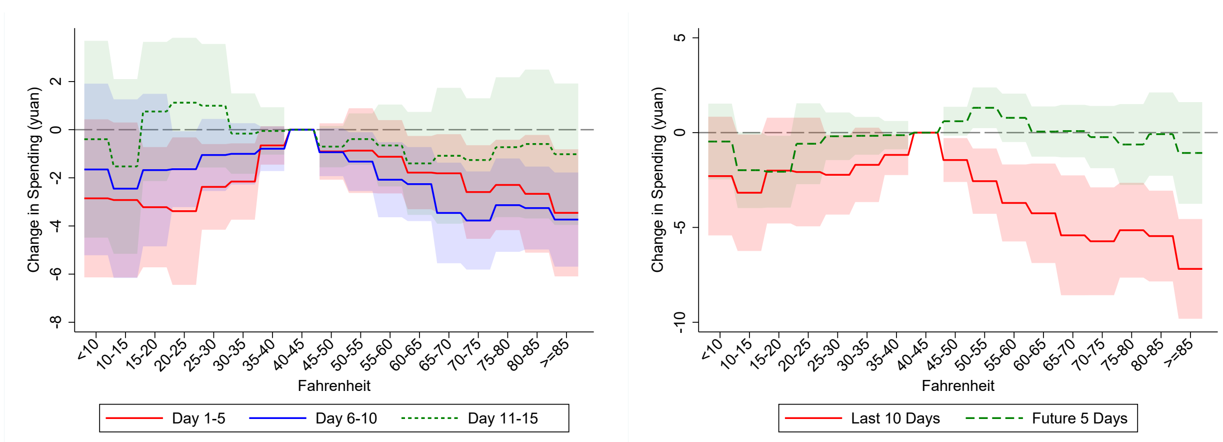
where CM_c denotes the climate condition of city c as measured by the 30-year average temperature from 1981 to 2010. GDP_c measures GDP per capita in 2010 in logarithmic scale. The dependent variable is daily spending per card and the unit of observation is city by day. The regression includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Shaded areas show the 95% confidence intervals. Standard errors are clustered at the city level.



(a) Above 90°F **(b)** Below 30°F

Supplementary Fig. 1. Impact of Temperature Shocks on Consumption

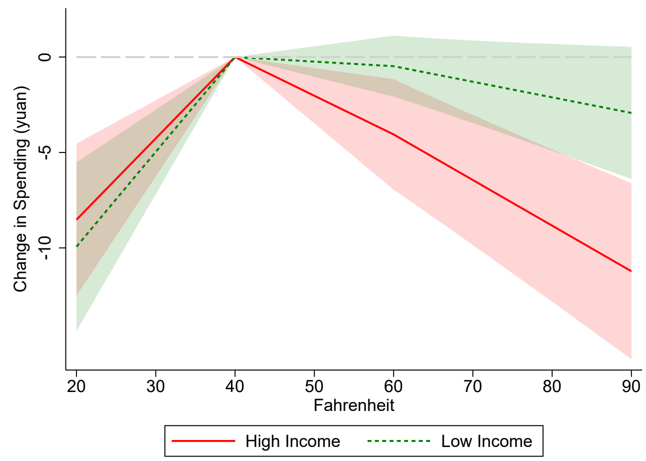
Notes: The figure reports the estimated effects of current-day temperature shocks (indicated by 0 on the x-axis), past temperature shocks (indicated by negative numbers on the x-axis) and future temperature shocks (indicated by positive numbers on the x-axis) on current-day spending per card (in ¥), using a distributed lag model with lagged daily temperature as key regressors. We focus on two types of temperature shocks: temperatures above 90°F and below 30°F. The coefficient estimates on day t ($-14 \leqslant t \leqslant 3$) are relative to temperatures between 30°F and 90°F on that day. The regression model includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Standard errors are clustered at the city level. The number of observations is 594,706.



(a) Three Past 5-Day Average-Temperature Bins **(b)** Future 5-Day Average-Temperature Bins

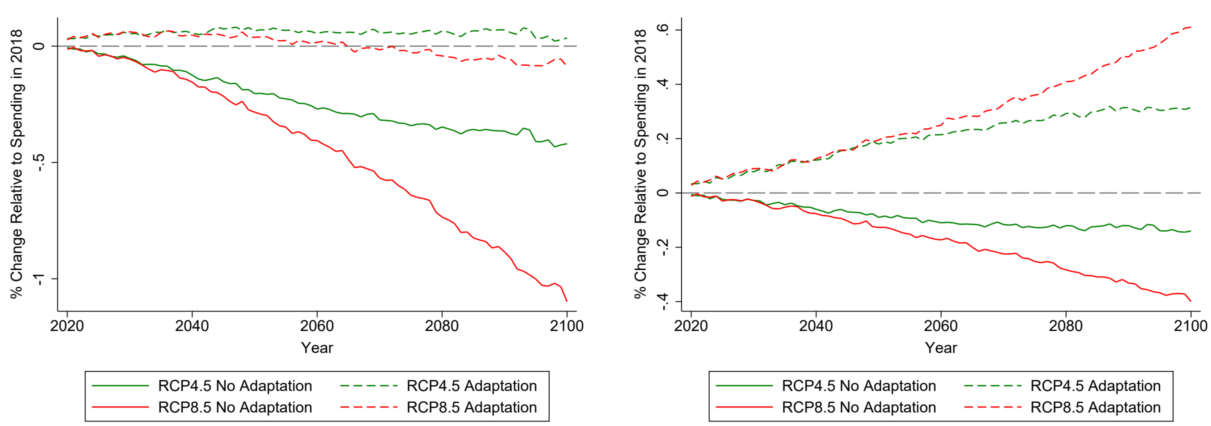
Supplementary Fig. 2. Impact of 5-Day Average-Temperature Bins on Consumption

Notes: Panel (a) estimates the consumption impacts of 51 average-temperature bins corresponding to the three 5-day windows: past day t-4 to t, t-9 to t-5, and t-14 to t-10. Panel (b) estimates the consumption impacts of the average-temperature bins from the future 5 days. The regression model includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Standard errors are clustered at the city level. The number of observations is 594,706.



Supplementary Fig. 3. Consumption-temperature Relationship by GDP per Capita (Eq.(2))

Notes: The figure reports the 10-day cumulative effect on daily spending per card (in ¥) due to a temperature change from the reference temperature (40°F) to the corresponding temperature by high- and low-income regions (75th and 25th percentile), respectively, holding climate at the median. The estimates are based on the semi-parametric specification of Eq. (2). The regression includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Standard errors are clustered at the city level. The number of observations is 594,706.

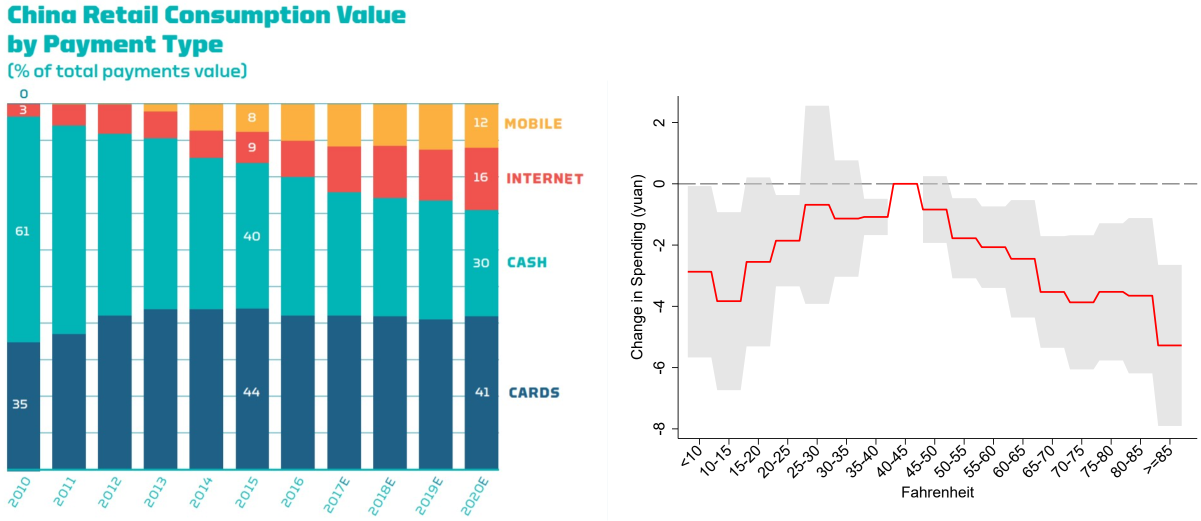


(a) With Income Effect Partially

(b) Without Income Effect

Supplementary Fig. 4. Consumption Effect of Temperature and Climate Change by Year

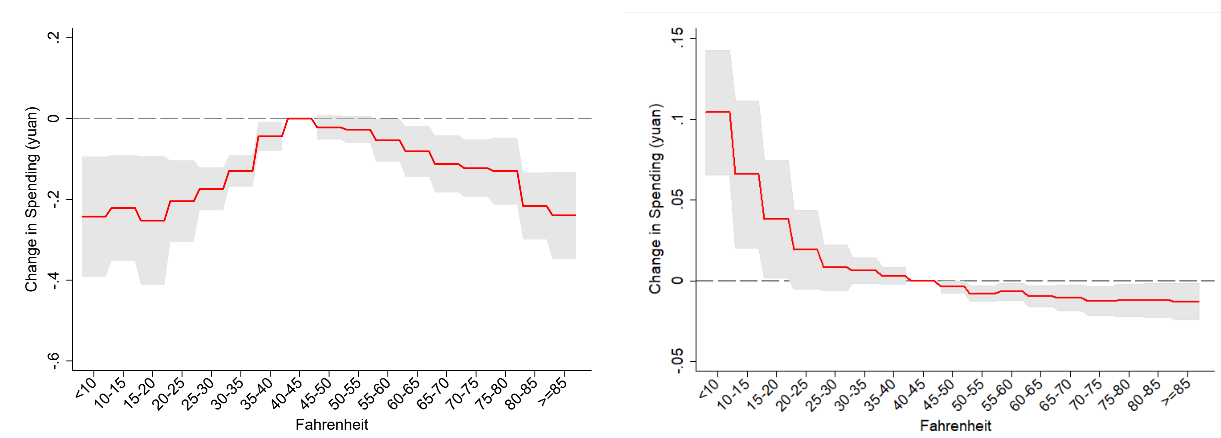
Notes: Panel (a) and panel (b) reports the changes of consumption (in %) in the future relative to the 2018 level on an annual basis based on Eq. (3) and Eq. (5), respectively. Green lines and red lines show the results under the RCP4.5 and RCP8.5 scenarios, respectively. Solid lines and dashed lines present no adaptation and adaptation of climate change, respectively.



(a) Consumption by Payment Type **(b)** Temperature Impact on Non-cash Spending

Supplementary Fig. 5. Robustness to Payment Methods

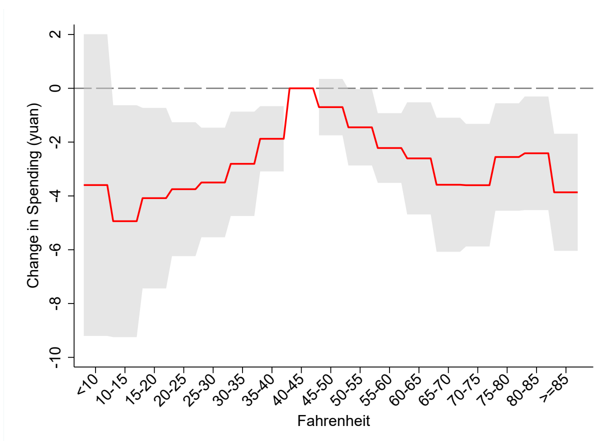
Notes: Panel (a) is from Kapron and Meertens (2017) documenting the % of spending by payment types. Panel (b) reports the 10-day cumulative effect on non-cash spending per card (in ¥) due to the temperature change from the reference bin of 40-45°F to the corresponding temperature bin. The regression model includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Shaded areas show the 95% confidence intervals. Standard errors are clustered at the city level. The number of observations is 594,706.



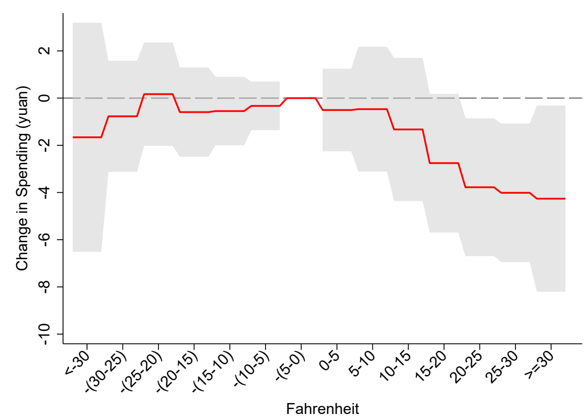
(a) Clothes **(b)** Fur Store

Supplementary Fig. 6. Robustness to Seasonality

Notes: Panel (a) reports 10-day cumulative effect on clothes. The regression model replaces the city by year-quarter FEs in the baseline model with city by year-month FEs. Panel (b) reports 10-day cumulative effect on fur spending. The regression model is the same with the baseline model. Shaded areas show the 95% confidence intervals. Standard errors are clustered at the city level. The number of observations is 594,706.



(a) Temperature Level



(b) Temperature Deviation

Supplementary Fig. 7. Joint Modeling of the Impacts of Temperature Levels and Deviations

Notes: Panel (a) and (b) report 10-day cumulative effects on spending by simultaneously including dummies indicating temperature levels and dummies indicating temperature deviation. The regression model includes day-of-the-sample fixed effects, city by year-quarter fixed effects, city by holiday fixed effects, and a set of control variables including air pollution, precipitation and relative humidity. Shaded areas show the 95% confidence intervals. Standard errors are clustered at the city level. The number of observations is 594,706.