



Urban household water usage in adaptation to climate change: Evidence from China

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ABSTRACT

While it has been concluded that climate change poses a significant threat to worldwide supply of freshwater resources, it is unclear if and how demand for water would also be affected. To fill this knowledge gap, we leverage on ‘big data’ collected using smart water meters from over 40,000 Chinese urban households, spanning nine years and ten provinces to examine the relationship between daily household water usage and climate variability. At the baseline, we find that municipal water is not only a coping mechanism for heat, but its usage is accelerated during heatwave events. Heterogeneity analyses reveal that households from lower-valued properties are more likely to substitute water for electricity to counter heat. Importantly, we find evidence of adaptation behaviors where over time, households are using increasingly more water to cope with high-temperature days. In all, after feeding our results into climate projection models, it is estimated that household water usage will increase by around 7–44% in the long-term (2080–2099) under emissions scenarios of SSP245 and SSP370. Our findings are especially relevant for water-scarce countries such as China as well as developing countries where water is a cheaper and more accessible resource to cope with heat.

1. Introduction

The 2018 World Water Development report projected that due to population and income changes, there will be a 20–30% increase in water demand by 2050 (WWAP, 2018). At the same time, global water resources are likely to decrease such that around 3 billion people will live in severely water-scarce area (WWAP, 2018). Amongst the many countries that will be affected by water shortages, China is one of the largest and most vulnerable (Jiang, 2009; Liu and Yang, 2012; Liu et al., 2013). China’s current per capita water supply is already lower than world’s average as the country has around 20% of the world’s population, but only 7% of freshwater resources (Piao et al., 2010). Acute water shortages is apparent in certain parts of the country as China had implemented the largest inter-basin water transfer program in the world to deliver water from the Southern to Northern provinces (Webber, Crow-Miller, and Rogers, 2017). Further compounding this natural constraint are pollution and rising domestic demand. Lack of regulatory

oversight has led to several freshwater sources being contaminated to the extent that they cannot be used (Cheng and Hu, 2012). Moreover, rising income and lifestyle changes have drastically increased households’ water demand. Zhou et al. (2020) estimated that urban water usage increased from 0.6 kg-m³ per year in 1975–1992–2.21 kg-m³ per year in 1992–2013, far out-pacing the rate of change for other water usages.

In this study, we examine a factor that has yet to be explored, but may have a significant impact on future water resources – impact of climate change on household water usage. Numerous earlier studies attempted to predict how climate change would affect China’s supplies of freshwater resources (Cheng and Hu, 2012; Piao et al., 2010; Tao et al., 2005). They found that while climate change would have heterogeneous impacts on water supply over China, the overall effects are most likely to be negative. However, there are no corresponding studies that examine how climate change would affect household water demand in Chinese settings even though there are ample evidence suggesting that

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water usage is a function of weather variability (Adamowski et al., 2012; Breyer, Chang, and Parandvash, 2012; Guhathakurta and Gober, 2007; Maidment and Miaou, 1986; Martínez-Españeira, 2002; Praskievicz and Chang, 2009; Ruth et al., 2007; Wong, Zhang, and Chen, 2010).

One of the main impediments of conducting such research is data that can faithfully reflect daily variations in water usage and temperature, and yet span across long time periods and geography to respectively reflect climate variability and spatial heterogeneity.

Toward this end, we utilize a novel dataset where daily water usage from over 40,000 households (in ten provinces) were collected over the years 2010–2019 using smart meters, to investigate how household water demand is affected by weather and climate variability. After controlling for factors that change in each household at a yearly basis (e.g., income, household composition), and various locational and seasonal conditions, we arrive at the following conclusions. First, we find increasing marginal impacts of water usage with respect to temperature intervals. Compared to a below 5 °C day, water usage increased by around 16 l/household-day at the 5–10 °C interval to 45 l/household-day at the highest interval of above 30 °C. The daily-level dataset also enables us to investigate the accumulative impacts of heatwaves and cold-waves on water usage. We find that households use more(less) water per day for every additional day of a heatwave(cold-wave). Second, there are several pieces of evidence to suggest that households substitute between water and electricity to cope with heat. We find that households from higher-valued properties use relatively more water on lower-temperature days, and relatively less water on hotter days. Similar usage patterns ensue when we demarcate households by average residential electricity usage. Third, we find concrete evidence of long-term adaptation where households use increasingly more water to cope with high heat over time. Putting all these results together, we project that, all else being equal, China's household water usage will increase by around 7.2–43.8% in the long-term (2080–2099) under emissions scenarios of SSP245 and SSP370. This projected increase in water demand would add the water stress that China is already predicted to experience in the future.

Our study is closely related to two major strands of literature.

First, the relationship between weather and household water usage has been an area of active research. Studies in this literature found strong and consistent evidence that household water usage increases with ambient temperature, where the findings are repeated across countries (e.g., United States, Spain) (Breyer et al., 2012; Maidment and Miaou, 1986; Martínez-Españeira, 2002) and climates (e.g., arid, temperate, tropical, etc.) (Adamowski et al., 2012; Guhathakurta and Gober, 2007; Ruth et al., 2007). While the reasons provided for increased water demand on hot days are outdoor usages such as gardening and swimming pools, we also see similar relationships in urban cities such as Hong Kong, Seoul, and Singapore where vast majority of residents live in apartments (Praskievicz and Chang, 2009; Salvo, 2018; Wong et al., 2010). One possible explanation is that urban residents use more water for indoor activities such as laundry and baths on hotter days (Salvo, 2018). To a large extent, this literature was mostly focused on predicting short-term variation in aggregate water demand (i.e., residential, commercial, and industrial) to inform the operations of water-treatment facilities in single location (Ruth et al., 2007). However, because climate change is a long-term phenomenon with highly varied impacts and behavioral adaptations across locations, a richer dataset of micro-level observations over a long period of time is needed to accurately assess the relationship between water usage, and weather and climate. This is especially true for large countries such as China where landscape, climate, and socioeconomic development are highly heterogeneous.

The second strand of literature are studies that examine the impacts of climate change on household utility consumption (e.g., Auffhammer, 2014; Auffhammer and Aroonruengsawat, 2011; Auffhammer et al., 2017; Giannakopoulos et al., 2016; Gupta, 2016; Li et al., 2019; Salvo, 2018; Thornton et al., 2016; Wenz et al., 2017). This literature has

mostly focused on the impact of climate on residential energy usage, with the exception of Salvo (2018) who used data from Singapore's households to examine both water and electricity usage in response to weather changes. Studies in this literature have established that household electricity usage shares a positive relationship with temperature. Specifically, research conducted in Chinese settings found that households purchased more air-conditioners (Auffhammer, 2014) and consume more electricity when temperature spikes (Li et al., 2019). However, there are no studies conducted in China that examine the relationship between climate change and household water usage. An important distinction of this literature from the former is that it uses careful econometric models to rigorously establish the relationship between temperature changes and household utility usage. In return, their results are more suited for making climate change projections. On this note, we apply methods from climate change-household utilities consumption literature to isolate the impact of temperature on household water usage in China.

This study makes the following contributions to the broad literature on water resources and climate change. First, this is one of the first studies to examine households' usage of water to cope with heat. In turn, our results are applicable not just for our study setting of China, but also for the broader developing world who share similar socioeconomic characteristics. Second, we leverage on the granularity and long time span of the dataset to estimate the extent to which adaptation or behavioral changes have taken place over time. In turn, this allows us to project future water usage under various climate change scenarios, thus contributing to prominent efforts on predicting future water balances and impacts of climate change.

2. Methods and material

2.1. Panel regression

The primary empirical approach deployed in this study is panel fixed-effects regression:

$$y_{ijt} = \alpha + f(temp_{jt})\gamma + X_{jt} + \delta_{ij} \bullet year_t + \theta_t + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} is daily water usage for household i in county j at calendar date t . $f(temp_{jt})$ is a series of temperature intervals to recover non-linear relationship between daily average temperature and water usage. There are seven temperature intervals for average daily temperature and defined as less than 5 °C, 5–10 °C, 10–15 °C, 15–20 °C, 20–25 °C, 25–30 °C, and above 30 °C. These intervals are included as binary variables, and thus their associated coefficients (γ) are interpreted as increased water usage for an additional day in the specific temperature interval. From an economics perspective, due to the panel regression structure, (γ) are interpreted as the short-term or direct causal effect of temperature on water usage (Hsiang, 2016).

X_{jt} is a vector of selected daily weather controls (which may affect water usage) up to quadratic terms, including total precipitation, relative humidity, windspeed, hours of sunlight, and atmospheric pressure.

We include a highly flexible series of calendar-date fixed effects (θ_t) where say, 1st January 2010 is a different fixed effect from 1st January 2011. These time fixed-effects serve to control for any temporal or seasonal patterns related to water usage, e.g., households' water usage may vary on weekends, summer months, or public holidays.

As water usage data is collected through smart-meters linked to residential addresses, we also include dwelling-by-year fixed effects ($\delta_{ij} \bullet year_t$). Most other studies in the literature that use microlevel data of utilities consumption (e.g., Auffhammer and Aroonruengsawat, 2011; Li et al., 2019) also employ individual fixed effects to control for any time-invariant factors at the household- or dwelling-level. We further introduce yearly variation in the form of dwelling-by-year fixed effects so that we not only control for time-invariant factors, but also for

time-varying characteristics that typically change at the annual-level, such as household characteristics (income and family composition), and community characteristics (water tariffs and local economic development). This set of fixed-effects would also control for varying characteristics due to new households moving into the residential unit. Moreover, $(\delta_{ij} \bullet year_t)$ is particularly important in this study as we are examining the changing patterns of household water usage in China over the period 2010–2019. In this period, per capita GDP in China has increased by between 5.7% and 10% annually, potentially leading to a large income effect in water usage. Hence, the inclusion of dwelling-by-year fixed effects would help control for changes to water usage due to income.

After controlling for an array of time- and space-varying confounding explanations, the vector of coefficients (γ) are statistically identified by comparing the daily temperature of any city with the average temperature for the remaining sample.

Lastly, ε_{ijt} is an idiosyncratic shock to water usage clustered at the dwelling-level.

A central issue of high-frequency household utilities usage datasets is that some residential addresses may not have any occupants for particular days, are predominantly unoccupied, or may have been repurposed for commercial usages (Auffhammer and Aroonruengsawat, 2011; Li et al., 2019). To remove residences that are mostly unoccupied, we drop the entire year for the household if there is no water usage for more than 60 days (or around 1/6 of the year). Additionally, we drop the entire year for any households if their average daily water usage for the year is less than 0.2 m^3 or more than 0.8 m^3 (respectively at the 5th and 95th percentile of usage). We also exclude any observations where no water usage is recorded. There are two reasons for doing so. First, unlike household utilities such as electricity, it is much more likely observations of “no water usage” indicates that the residential unit is unoccupied on that day. Second, the main purpose of this study is to examine the intensive margin of water usage with respect to temperature. Inclusion of observations with no water usage would entail effects of both extensive and intensive margins. To ensure that the results are not driven by model selection and data cleaning, we conduct several robustness checks in a latter section to test our assumptions.

2.2. Long difference

The temperature regression coefficients in Eq. (1) represents the direct or short-term effects of temperature on household water usage. However, the long-term adaptation effect is also of interest to climate change scientists and policymakers. One way to recover both direct and long-term adaptation effects is to estimate a cross-sectional model by aggregating all household data over time. The problem with this approach is that we will not be able to include spatial or temporal controls to account for confounding factors (Hsiang, 2016). Another way to uncover the adaptation effects is by using long-difference model where the dataset is split into two time periods, and the difference between usage is regressed their explanatory counterparts (Burke and Emerick, 2016). Specifically, we estimate the following model:

$$\Delta y_{ij} = \alpha + \Delta f(temp_j) \gamma_{LD} + \Delta X_j + \Delta \varepsilon_{ij} \quad (2)$$

where Δy_{ij} refers to difference in average water usage between period 1 (2010–2014) and period 2 (2015–2018), and similarly for the other variables (the year 2019 is excluded from long-difference analysis as we do not have the full year data). The coefficients of interest here is the vector of γ_{LD} which estimates the extent changes in water usage across the two time periods is associated with changes in temperature across the same temporal spectrum. Implicit in this setup is that all household-level time-invariant factors across the two periods has been removed by the differencing. To deliver unbiased estimates of γ_{LD} , we would require $\Delta f(temp_j)$ to not be correlated with any time-varying factors. This

assumption is likely to be challenged by rising income trends in China throughout the study period. As such, we use a second way to quantify adaptation or changing behaviors by combining the short-term approach with long-difference method. We separate the dataset into two four-year periods and conduct individual panel regressions. Accordingly, we can control for changing income over time in panel fixed-effects models by using dwelling-by-year fixed effects. And so any statistical differences between the coefficients from these two models can thus be interpreted as adaptation behaviors.

2.3. Projections of water usage

To predict future water usage, we first obtain temperature projections from the IPCC-led Climate Model Intercomparison Project.² Specifically, we use projections for three distinct scenarios: SSP126, SSP245, and SSP370.

SSP 370 is a high-emissions scenario where there are no GHG mitigation policies. This scenario corresponds to a combination of representative concentration pathway (RCP) 7.0 and shared socioeconomic pathways (SSP) 3. It is projected that temperature in year 2100 will be around 4°C above pre-industrial levels (Pielke et al., 2021).

SSP 126 represents the policy scenario where governments worldwide succeed in decarbonizing their economies. Similarly, this optimistic scenario corresponds to the combination of RCP2.6 and SSP1. In here, temperature in year 2100 is projected to be around 1.7°C above pre-industrial (Pielke et al., 2021).

SSP 245 represents a middle-of-the-road scenario where decarbonization is incomplete, and future temperature is projected to be around 2.8°C above pre-industrial.

We download county-level daily temperature from 10 different climatic models, for the medium-term (2030–2049) and long-term (2080–2099), and use the average across different projection models as the future temperature (Li et al., 2019). These two time periods are chosen to represent 20 years before the two milestones of mid-century and end-century. In total, there are six distinct scenarios being projected along the dimensions of SSP (126, 245, and 370) and time period (middle- and long-term).

Next, in order to compute changes to water usage, we need to predict how daily weather will change in the future relative to current conditions. We followed Li et al. (2019) by first computing the average number of days in a year that fall within each temperature interval for the time period of 2010–2018 (“current conditions”). Second, we repeat this exercise for the middle-term under SSP126. Third, we then take the difference in each temperature interval between current conditions and the middle-term. These three steps yield the change in number of days belonging to each temperature interval for each year in the middle-term time-period.

This exercise is then repeated for the five remaining combinations of SSP scenarios and time-periods (See Fig. S1 for the change in number of days in each temperature intervals under the six scenarios).

Lastly, changes to household water usage are obtained by multiplying the change in each temperature interval by its corresponding coefficient.

2.4. Datasets

The dataset used in this analysis is compiled from two sources. First, household water usage is an unbalanced nine-year (from 1st January 2010–20th May 2019.) panel of daily water usage from 41,649 urban households located in ten provinces in China (see Fig. 1 for represented provinces). These ten provinces are mostly located in the heavily populated and economically active Southeastern part of China, and the

² We thank an anonymous referee for providing helpful suggestions in projecting future water usage.

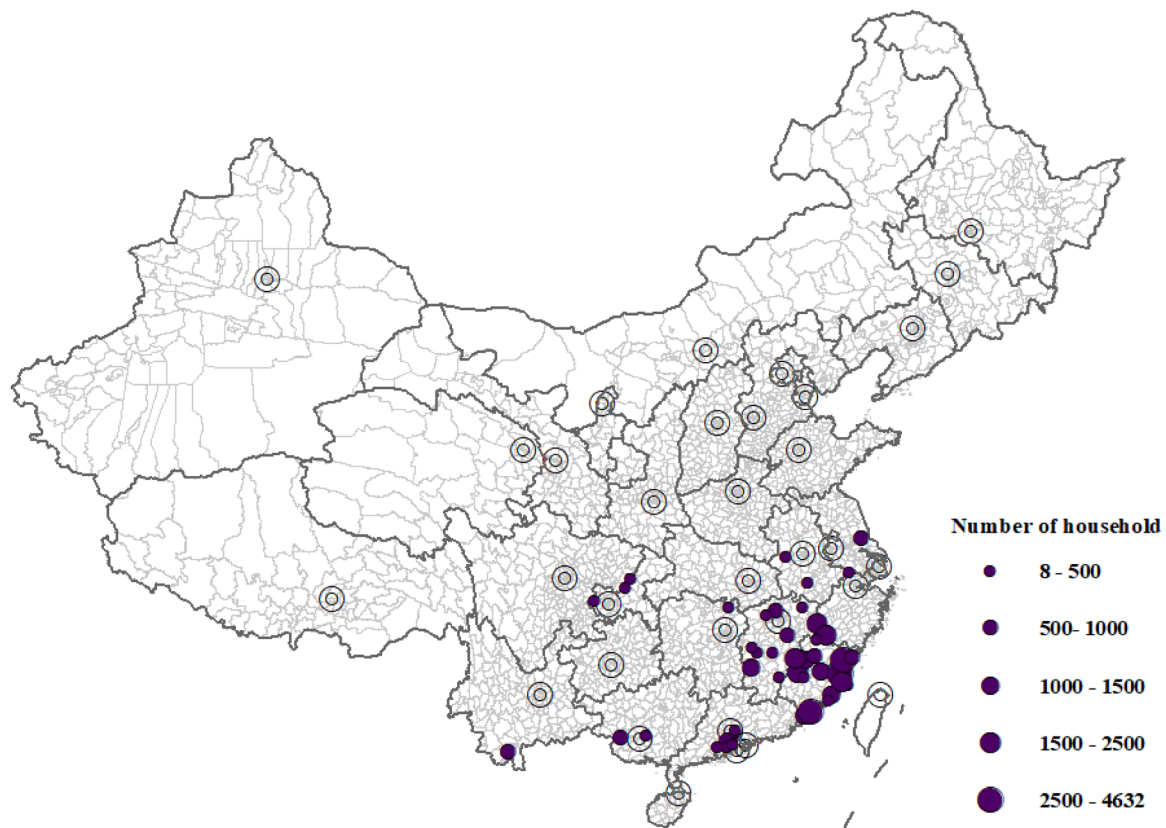


Fig. 1. Location of households in dataset, *Notes:* The represented provinces are Anhui, Chongqing, Fujian, Guangdong, Guangxi, Hunan, Jiangsu, Jiangxi, Zhejiang, Yunnan.

households are all located in apartment buildings (as opposed to stand-alone houses). The dataset is obtained from a major company that specializes in installation of ‘smart’ water meters (Zhiheng Technology, <http://www.gszh.cn/>). The company do not transact directly with the households as installation of smart meters are often made on behalf of local governments or water utilities companies. Specifically, installation of ‘smart’ water meters in China mostly occurs through two channels. First, some provinces such as Fujian regulate that new residential constructions need to be installed with ‘smart’ utility meters. Second, there are many neighborhood renewal projects around China where installation of ‘smart’ meters is prioritized as part of the program. According to the company, it is estimated that around 20% of all Chinese households have installed ‘smart’ water meters (in comparison 80% have installed ‘smart’ electricity meters). Once installed, the meters transmit daily water usage data to the installation company using a combination of radio waves and cellular networks. Each daily observation as provided to us contains the dwelling’s water meter ID, water usage, and location specified up to the neighborhood-level (neighborhoods are the urban administrative equivalent of villages in rural areas). As these meters are installed for the purpose of billing household water usage, it is likely water usage is measured with high degree of accuracy. However, to the extent that household water usage data has non-systematic measurement errors, these errors would cause attenuation bias in the regression analyses (i.e., estimated coefficients will tend toward zero) (Wooldridge, 2015).

The second source of data is daily weather Information is obtained from the 337 ground weather stations owned by China Meteorological Data Service Center. We use inverse distance weighting to attribute weather for each county in the dataset (Currie and Neidell, 2005; Deschenes and Greenstone, 2007; Schlenker and Walker, 2015).

The summary statistics are presented in Table 1. On average, households use around 0.45 m³ or 450 l of water each day. Days with

Table 1
Summary statistics.

Variable	Mean	SD	Min	Max
Daily water usage (m ³)	0.45	0.29	0.002	5
Temperature interval (<5 °C)	0.02	0.15	0	1
Temperature interval (5–10 °C)	0.10	0.30	0	1
Temperature interval (10–15 °C)	0.17	0.38	0	1
Temperature interval (15–20 °C)	0.19	0.39	0	1
Temperature interval (20–25 °C)	0.22	0.41	0	1
Temperature interval (25–30 °C)	0.28	0.45	0	1
Temperature interval (>30 °C)	0.02	0.14	0	1
Heatwaves (days)	0.06	0.58	0	27
Cold-waves (days)	0.08	0.76	0	38
Relative humidity (%)	78.60	10.55	25.28	99.97
Daily precipitation (mm)	4.64	10.73	0.00	316.41
Daily hours of sunlight	4.46	3.80	0.00	13.08
Sea pressure (Pa)	990.83	23.52	791.74	1040.19
Wind speed (m/second)	2.00	1.03	0.02	11.60

Note: Number of observations = 28,122,387. Daily water usage is observed at the household level. The remaining weather-related variables are observed at the county-level. Heatwaves count the number of days of a heatwave event, which in turn refers to an event where average temperature is at least 30 °C for three consecutive days. Cold-waves are defined in similar manner, except for days where average temperature is below 5 °C. Days without heatwave or cold-wave are given a value of 0.

average temperature between 25 and 30 °C are most common as they account for 28% of all observations. This is because our data are predominantly from the warmer Southern provinces. However, we still observe a wide range of temperature as proportion of days with average temperature between 5 and 10 °C is non-trivial at 10% of all observations.

We plot annual temperature and precipitation to detect if there are significant changes to the climate over the 9-year study period (Fig. 2).

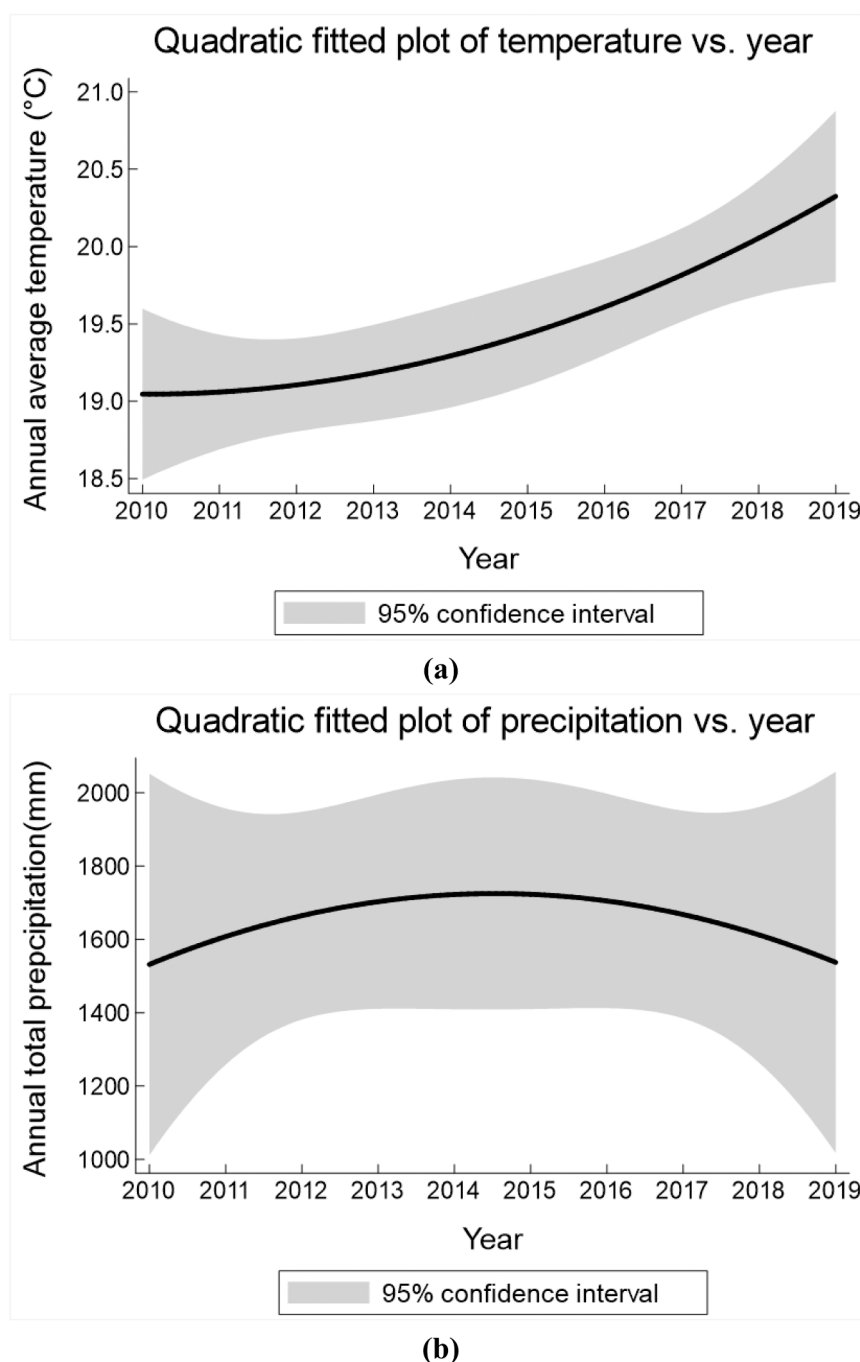


Fig. 2. Quadratic fitted plots of weather variables against year (panel (a) for temperature and panel(b) for precipitation).

We can see that while annual temperature shows a large increase of around 1 °C over the study period (panel A), there is no overall increasing or decreasing trend for precipitation (panel B). Similarly, when regressed over years and county-fixed effects, the coefficients for temperature and precipitation models are respectively 0.14 °C/year (p-value=0) and 0.61 mm/year (p-value=0.9). In this regard, even though our study period of nine years is relatively short compared to the conventional time period for defining climate, our data have displayed substantial changes to the main covariate of interest – temperature.

3. Results

3.1. Daily household water usage

We first regress daily household water usage on daily average temperature to discern the basic relationship between water usage and temperature. The marginal impact or direct effect of average temperature on water usage is positive and statistically significant at around 3.3 l for every °C change to daily temperature. However, evidence from earlier studies of temperature and household electricity usage suggest that it is likely water usage shares a non-linear relationship with temperature (Li et al., 2019). As such, we recategorize daily temperature from a single continuous variable into seven binary variables in temperature intervals of 5 °C, starting from below 5 °C and ending with

above 30 °C. As each day is certain to fall into one of the seven mutually exclusive temperature intervals, it is necessary to omit one category of temperature interval to avoid perfect collinearity. In this regard, the lowest temperature interval of less than 5 °C is omitted, and all resulting coefficients should be interpreted with respect to this interval. The results for this regression analysis are depicted in Fig. 3 where we see that daily household water usage shares a non-linear relationship with daily average temperature. Daily water usage increases by around 16 l when average temperature is between 5 and 10 °C. The next five intervals respectively record an increasing trend of 30 l, 39 l, 42 l, 44 l, and 45 l. The first inference from these results is that households use more water on hot days relative to cooler days. This finding is also consistent with other studies that examined household water usage in urban areas (Praskievicz and Chang, 2009; Salvo, 2018; Wong et al., 2010). Next, unlike the U-shaped relationship observed in household electricity usage, water usage continually increases with temperature. The most plausible explanation is that electricity is used for both heating and cooling purposes while water is predominantly used to cope with heat.

Second, we exploit the daily-level observations to examine the effects of heatwaves and cold-waves on water usage. Specifically, we want to investigate if there are cumulative effects of prolonged extreme weather. We do so by defining a heatwave event as at least three consecutive days of average temperature exceeding 30 °C. The first day of a heatwave event will take a value of one, second day will take a value of two, and as follows. Similarly, cold-waves are defined as at least three consecutive days of below 5 °C. Regardless of temperature, days without heatwaves or cold-waves are assigned a value of zero. The results in Table S1, Column 2 show that households use increasingly more water as a heatwave prolongs. The coefficient for heatwave is around 0.9 l, and can be interpreted as follows: compared to days without prolonged extreme weather, a household use 0.9 l more water on the first day of a heatwave, 1.8 l on the second day, and so on. In comparison, the effects of cold-wave is a decrease in usage of 2.7 l for every additional day. As climate change is likely to increase heatwaves and decrease cold-waves occurrences in many places, our results show that there will be additional household water demand arising from these events.

3.2. Robustness checks

In this section, we conduct several robustness checks to determine if our baseline results are driven by model selection and assumptions.

First, while some studies have found air pollution to affect water usage (e.g., Salvo, 2018), we did not include air quality in the main specification as there is no consistent metric of measurement for air quality in China for the same data period. The Chinese government relied on Air Pollution Index (API) up until 2013, and switched over to Air Quality Index (AQI) thereafter. Instead, we used part of the dataset where air quality measurement is consistent and found that the coefficients for temperature intervals are statistically similar with or without the inclusion of air quality (Table S2, Columns 2 and 3).

Second, we test the robustness of the data cleaning process in three ways. The dataset is currently trimmed at the 5th and 95th percentile of average daily water usage. We widen the cut-off to the 1st and 99th percentile, and the results are largely similar to the baseline's (Table S2, Column 4). Following Li et al. (2019), we narrow the dataset to exclude household-year with more than 30 days of no water usage. The results are larger than the baseline's. This is expected as we have further restricted the dataset to only include household with more consistent water usage (Table S2, Column 5). To investigate the intensive margin of water usage with respect to temperature, we excluded observations of no water usage. However, one may be concerned that “days with zero usage” are systematically correlated with temperature, e.g., households take vacations during periods of hot weather. As a robustness check, we now include these observations in the estimation by controlling for them using an indicator variable for “no water usage”. The coefficients for temperature intervals all retain their statistical significance and are larger than the baseline results (Table S2, Column 6). In all, it is likely that our data cleaning process have the effect of tending our results toward the lower end of the relationship between household water usage and temperature.

Third, we replace household-by-year fixed effects with household fixed effects (the overall year fixed effects are subsumed by existing calendar date fixed effects) to examine if the former are indeed absorbing the impact of changing household income. The rationale is that both temperature and income in China are on increasing trends during the study period, and since both factors are positively correlated

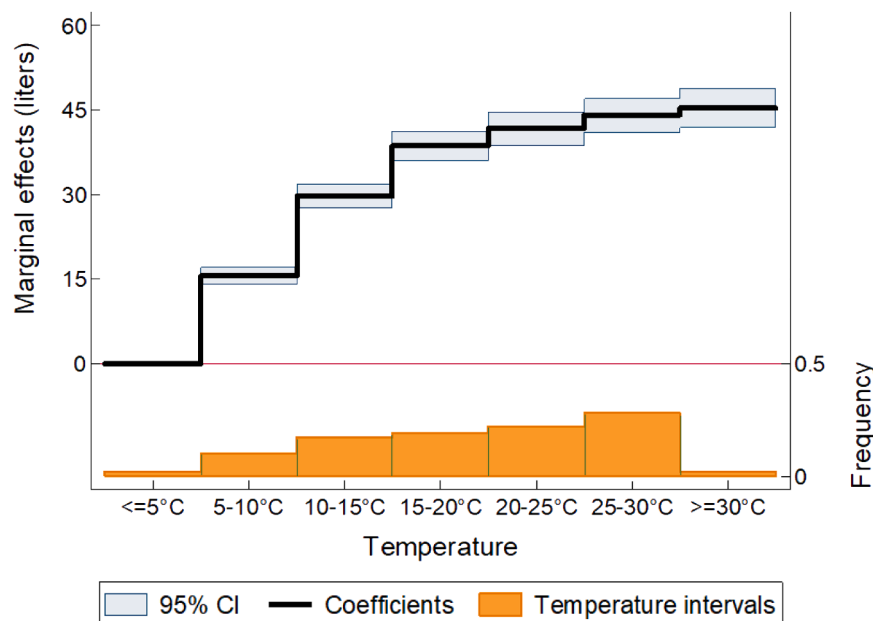


Fig. 3. Baseline results of temperature intervals with respect to household water usage, Notes: This figure shows the estimated coefficients and their 95% confidence bars of each temperature interval on water usage. The omitted temperature interval is < 5 °C, and so that the estimated coefficients of other temperature intervals are interpreted in relation to this omitted reference group (Full results in Table S1).

with household water usage, temperature may also pick up the effects of income if the latter is not adequately controlled. Toward this end, we see that the temperature coefficients estimated using only household fixed effects are around 7%–16% larger than the baseline estimates which included household-by-year (Table S2, Column 7). This disparity in results suggest that the time-varying fixed effects have indeed played an important role in our study as the impacts of temperature on water usage would have been overestimated without their inclusion.

Lastly, the standard error clusters are changed to the date and household-by-year groups respectively. The statistical significance is unchanged for all temperature coefficients (Table S2, Columns 8 and 9).

3.3. Heterogeneity analyses

Findings from climate change-household utilities literature reveal that there is substantial variation in how background environmental and socioeconomic conditions affect household demand for electricity. In this regard, we exploit the wide spatial heterogeneity of our dataset to detect heterogeneous effects along dimensions of temperature, precipitation, property value, and electricity usage.

First, we investigate how background environmental conditions may be correlated with one's behaviors (Auffhammer and Aroonruengsawat, 2011). Households residing in drier climates may exercise more prudence in water consumption compared to households in rainier regions or that households residing in hotter climates may have adapted to higher temperatures. In this regard, we separate locations into 'dry' and 'wet' regions where the former refers to locations with below-median historical precipitation (about 1623 mm annually) and vice versa. Water usage for 'wet' regions is relatively lower compared to 'dry' region at the 5–10 °C interval. However, water usage increases at a much faster rate for the remaining temperature intervals for the former (Fig. 4). A growing disparity shows up as households in 'wet' regions use increasingly more water to cope with high heat as temperature increases.

Similarly, we investigate if households living in 'cooler' vs. 'warmer' areas also display different usage behaviors. We record two findings (Fig. 4). A between-comparison shows households from locations with above-median average temperature (about 19 °C) use less water for almost all temperature intervals compared to their counterparts in below-median average temperature. A within-comparison shows

households residing in 'warmer' regions use roughly the same amount of water to cope with heat on the hottest day compared to the second hottest interval (29I). Such water usage behaviors are contrary to our findings thus far. Both these observations suggest that households from warmer climates have alternate ways of coping with heat, other than using water. One possibility is the usage of air-conditioners where Auffhammer and Aroonruengsawat (2011) found that Californian households from warmer parts of the state consume more electricity on 'hot' days due to presumably wider adoption of air-conditioners.

Second, we examine if water usage patterns are also correlated with economic well-being. When examining both electricity and water usage of Singapore's households, Salvo (2018) found that substitution effects dominate income effects for households in higher-valued residences as they use less(more) water(electricity) compared to those residing in properties of lower value to cope with the tropical heat. When solely examining electricity usage, Li et al. (2019) found evidence of income effect in Shanghai where higher-income households use more electricity to cope with the same level of heat. As we do not have actual measurement of household income, we obtained from various Chinese statistical yearbooks city-level housing value (one administrative level beneath province) as a proxy for economic status. We observe an interesting trend where initially, households residing in higher-valued properties (around US\$1055/m²) use relatively more water for temperatures between 5 and 20 °C (Fig. 5). However, the coefficients for temperature from 20 °C onward is instead larger for households residing in lower-valued properties. This difference is most pronounced at the hottest interval of above 30 °C where households in lower-valued properties use 30% more water to cope with heat. These results are consistent with other studies in the literature who found that wealthier households use more electricity than water to cope with high heat.

Results so far suggest that Chinese urban households residing in warmer regions, and from higher-valued properties may be using electricity as a substitute to cope with heat. In this sub-section, we test this hypothesis by partitioning the dataset by electricity usage. As we do not have information on electricity usage for individual households, we obtain "per capita residential electricity usage" at the city level from various Chinese statistical yearbooks to segregate our dataset into above- and below-median level of usage (around 787 kWh). The results (Fig. 5) support our hypothesis as (i) households that use more electricity tend to use more water on lower-temperature days, and relatively

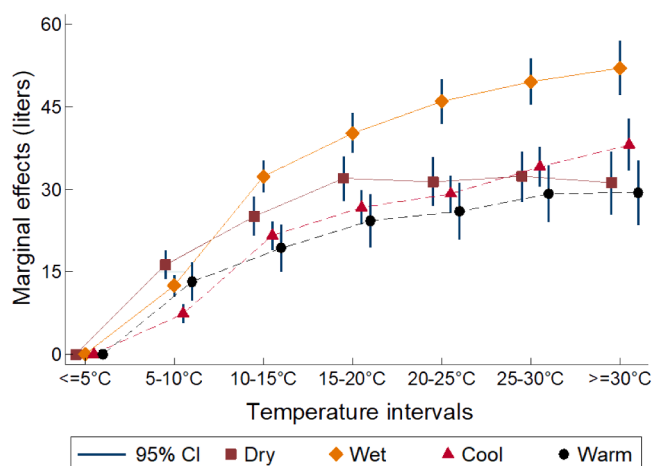


Fig. 4. Heterogeneity results of temperature intervals with respect to household water usage (by underlying climatic conditions), Notes: This figure shows the estimated coefficients and their 95% confidence bars of each temperature interval on water usage. The omitted temperature interval is $< 5^{\circ}\text{C}$, and so that the estimated coefficients of other temperature intervals are interpreted in relation to this omitted reference group (full results in Table S3). For easier comparisons, the two solid lines represent "Dry" and "Wet" cities whereas the two dotted lines represent "Cool" and "Warm".

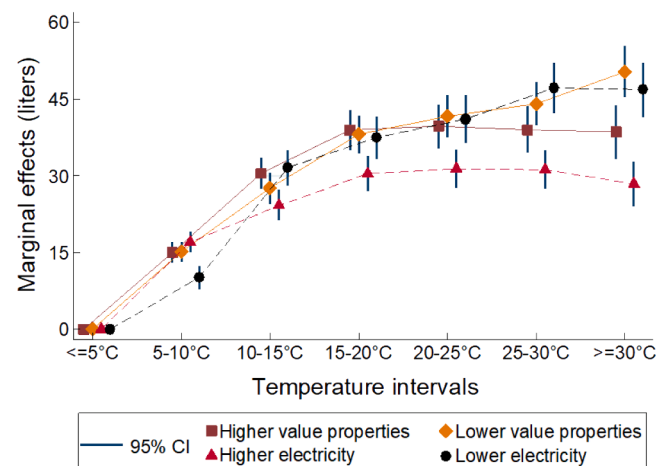


Fig. 5. Heterogeneity results of temperature intervals with respect to household water usage (by underlying socioeconomic conditions), Notes: This figure shows the estimated coefficients and their 95% confidence bars of each temperature interval on water usage. The omitted temperature interval is $< 5^{\circ}\text{C}$, and so that the estimated coefficients of other temperature intervals are interpreted in relation to this omitted reference group (full results in Table S3). For easier comparisons, the two solid lines separates cities by property values whereas the two dotted lines separate cities by household electricity usage.

less water to cope with heat, and (ii) there is a large increase in water usage on days $> 30^{\circ}\text{C}$ for the below-median electricity usage group, whereas there is a slight decrease for the above-median group.

3.4. Adaptation behaviors over time

The earlier analyses recovered what are known as the direct effects of temperature on water usage. Other than direct effects, it is highly informative for climate change policies to quantify adaptation or belief effects as households may alter their coping behaviors based on past temperature variation. Toward this end, we utilize three different empirical techniques to present a complete picture of how Chinese households adapt to temperature variation.

First, we incrementally aggregate the dataset from daily-level to weekly-, biweekly-, and monthly-level. The key covariates in the aggregated datasets are now temperature bins, which count the numbers of days belonging to the specific interval. From a statistical viewpoint, the coefficients derived from this model can be directly compared to the baseline's as they both measure the marginal impact of an additional day in the temperature interval. However, from a behavioral perspective, the coefficients recovered from the aggregated datasets incorporate adaptation behaviors on top of direct effects compared to the daily-level. As such, we expect the coefficients estimated from the aggregated datasets to be larger than their daily's counterparts as the earlier results on heatwaves suggest that there may be adaptive effects in households' coping behavior. Table 2, Columns 2 and 3 respectively presents the results when the data is aggregated to a weekly- and biweekly-level. In comparison to the daily-level analyses, coefficients for water usage are either flat or decreasing on lower-temperature days. However, we observe a 24% increase in water usage at the hottest temperature interval. Results for the monthly-aggregated data (Column 4) shows similar trends for the lower-temperature days. However, there is a clear departure for the three hottest intervals as the coefficients are around 24%–190% larger than their daily-level counterparts. Altogether, these results suggest that the amount of water required to cope with high-heat days may be under-estimated when using daily-level data.

Second, we implement a long-difference (LD) analysis which allows us to recover longer-term adaptation behaviors (Burke and Emerick, 2016; Dell, Jones, and Olken, 2014; Hsiang, 2016). This analysis is conducted by splitting the dataset into two 4-year periods, and then regress the average differences between these two periods (see Methods section for detailed description of estimation procedure). The results in Table 2 reveal statistically insignificant coefficients for the intervals of $< 5\text{--}20^{\circ}\text{C}$. In contrast, the coefficients are statistically significant and

increasing in magnitude for the two intervals between 25°C to above 30°C . One common way of interpreting the LD coefficients is to compare them to their daily-level panel counterparts. The metric $\left(\frac{\beta_{LD}}{\beta_{Daily}}\right)$ measures the extent to which adaptation has taken place. A value of < 1 indicates positive adaptation where less water is used to cope with same level of heat, and vice versa. The “adaptation index” is zero for temperature between 5 and 20°C . When applied to our results, this means that households have adapted toward using lesser water on days of lower temperatures. Similar to the earlier analyses, the results are clearest for high-temperature days as: (i) the LD coefficients display an increasing trend starting from the $20\text{--}25^{\circ}\text{C}$ interval, (ii) are larger than the daily-level coefficients, and (iii) are all statistically significant. In all, $\left(\frac{\beta_{LD}}{\beta_{Daily}}\right)$ is computed at around $2.6\text{--}2.9$ for the intervals of 20°C to above 30°C , meaning that between 2010 and 2019, households have adapted to use three times more water to cope with an additional day in these temperature intervals. However, the LD approach may not adequately capture the full adaptation effect as it can only iron out time-invariant household factors. As mentioned earlier, factors such as income is unlikely to have remained constant throughout the study period. More importantly, we would be concerned of confounding explanations if income and temperature vary at similar pulses.

In this regard, a second way of quantifying adaptation or changing behaviors is to separate the dataset into two four-year periods and conduct individual panel regressions. The panel fixed-effects models identify the direct effects for their respective time periods, and any statistical differences between the coefficients from these two models can thus be interpreted as adaptation behaviors. Consistent with the LD model, this set of results show that the marginal impact of temperature on water usage has increased over the latter five-year period (Table 2). Specifically, we observe a comparatively smaller increase of around $31\%\text{--}55\%$ at the lower end of temperature intervals ($5\text{--}20^{\circ}\text{C}$), and a much larger increase of around $73\%\text{--}101\%$ at higher temperature intervals (20°C to above 30°C). In all, these three analyses consistently show that, after controlling for both time-varying and time-invariant factors, Chinese households are using increasingly more water over time to cope with high heat.

3.5. Water consumption projections

One of the central objectives of this study is to project the impact of climate changes on future household water usage. To do so, we use county-level daily temperature projections obtained from ten different climatic models for the period of 2030–2049 (medium-term), and

Table 2
Results from regression analyses at different temporal scales.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Daily	Weekly	Bi-weekly	Monthly	Long-difference	2014 and before	After 2014
Tem. interval ($5\text{--}10^{\circ}\text{C}$)	0.0155 *** (0.0007)	0.0154 *** (0.0006)	0.0196 *** (0.0009)	0.0220 *** (0.0014)	0.0428 (0.0348)	0.0131 *** (0.0009)	0.0174 *** (0.0010)
Tem. interval ($10\text{--}15^{\circ}\text{C}$)	0.0297 *** (0.0011)	0.0154 *** (0.0006)	0.0246 *** (0.0008)	0.0355 *** (0.0012)	0.0142 (0.0345)	0.0250 *** (0.0013)	0.0329 *** (0.0013)
Tem. interval ($15\text{--}20^{\circ}\text{C}$)	0.0387 *** (0.0013)	0.0233 *** (0.0007)	0.0296 *** (0.0009)	0.0343 *** (0.0014)	0.0682 (0.0428)	0.0291 *** (0.0016)	0.0450 *** (0.0015)
Tem. interval ($20\text{--}25^{\circ}\text{C}$)	0.0418 *** (0.0015)	0.0275 *** (0.0008)	0.0337 *** (0.0010)	0.0517 *** (0.0016)	0.0706 ** (0.0295)	0.0289 *** (0.0018)	0.0507 *** (0.0017)
Tem. interval ($25\text{--}30^{\circ}\text{C}$)	0.0441 *** (0.0015)	0.0355 *** (0.0009)	0.0451 *** (0.0011)	0.0652 *** (0.0019)	0.0923 *** (0.0321)	0.0278 *** (0.0019)	0.0559 *** (0.0017)
Tem. interval ($>30^{\circ}\text{C}$)	0.0454 *** (0.0018)	0.0451 *** (0.0011)	0.0565 *** (0.0015)	0.0801 *** (0.0024)	0.1315 *** (0.0477)	0.0315 *** (0.0022)	0.0546 *** (0.0021)
HH-Year Fixed effects (FEs)	Y	Y	Y	Y	N	Y	Y
Month-of-year FEs	N	Y	Y	Y	N	N	N
Calendar Date FEs	Y	N	N	N	N	Y	Y
Observations	28,122,387	7532,535	3746,336	1925,286	38,646	14,650,725	12,134,335
Adj R-square	0.3039	0.6255	0.6570	0.6887	0.0188	0.3090	0.3053

Notes: Dependent variable is daily water usage. The following weather variables and their quadratic terms are also included: relative humidity, precipitation, sunlight duration, sea pressure, wind speed. Standard error clustered by household-id in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2080–2099 (long-term). Additionally, we evaluate water usage under three different greenhouse gas emissions scenarios of SSP126, SSP245, and SSP370 (commonly referred to as the ‘best-case’, ‘middle-of-the-road’, and ‘worst-case’ emissions scenarios respectively). There are two caveats to these projections. First, our estimate of future water usage is accurate to the extent of uncertainties inherent to climate projection models. Second, these projections are based on current economic and technological conditions, and should be interpreted as estimated under *ceteris paribus* conditions, where future temperature and its distributions are the only changing factors, and all other factors remain constant.

Panel A of Fig. 6 shows the projected change in water usage for the mid-century projection period of 2030–2049.

First, it is unsurprising that across three emissions scenarios, the change in water usage is smallest for SSP126 as temperature change is projected to be small in this scenario and time period (see Fig. S1). Across the three sets of coefficients – daily, monthly, long-difference – water usage is projected to change from –0.28–2.3%. However, we observe an upward trajectory in future water usage for the two other emissions scenarios of SSP245 and SSP370. Due to slower pace of decarbonization, these two emissions scenarios will incur larger temperature changes in the future, especially with increase in number of hot days. As such, water usage is projected to increase by around 3.1–7.7% for SSP245, and by around 3.7–10.4% for SSP370.

Second, water usage for the end-century period of 2080–2099 (Panel B of Fig. 6) is forecasted to increase by the largest amount in the SSP370 scenario, followed by SSP245, and SSP126. Specifically, due to accumulated GHG emissions leading to continued rise in temperature, water usage is projected to increase by around 7.8–16.9% even for SSP126 scenario. On the same note, if we fail to reduce GHG emissions sufficiently, it is projected that water usage of Chinese households will increase by an average of 18% (range of 7.2–43.8%) for the two other emissions scenarios.

4. Conclusions and discussions

4.1. Summary of study and findings

The 2018 World Water Development report projects that global

water balance will worsen significantly by 2050 (WWAP, 2018). Additionally, the recent 2020 report highlights the role of climate change in affecting water supply, demand, and quality (UNESCO, 2020). These issues are especially relevant to China where their water resources were already under tremendous stress in the past decades. This problem is likely to exacerbate in future as numerous studies have examined how climate change would affect water supplies in China. However, due to lack of suitable data, there are no corresponding studies on how climate change could affect demand for water in China, or anywhere in the world. We contribute to filling this knowledge gap by leveraging on ‘big data’ collected using smart water meters to examine the impacts of climate change on urban households’ water demand – the fastest growing source of water usage in China (Zhou et al., 2020). Toward this end, we use a daily-level dataset of more than 40,000 households to deliver the first detailed analysis of household water usage with respect to temperature changes.

We find that first, unlike electricity consumption, household water demand increases monotonically with temperature. This is most likely because while households use more electricity during periods of extreme cold or heat, water is mostly used as a coping mechanism for higher temperature.

Second, by exploiting the daily-level observations, we show that heatwaves and cold-waves have accumulative effects as households use increasingly more(less) water for every additional day of heatwave (cold-wave).

Third, we find heterogeneity in water usage patterns along the lines of background environmental conditions and economic status. Our results suggest that water and electricity are likely to be substitutes in coping with heat in China as (i) households residing in warmer climates use less water to cope with heat, presumably due to wider adoption of air-conditioners (Auffhammer, 2014); (ii) compared to their lower-valued properties counterparts, households residing in higher-valued properties use more water at lower temperature intervals (income effect), and less water at the higher temperature interval (substitution effect), and (iii) households in cities with higher electricity usage use less water to cope with heat.

Lastly, using three distinct regression models (i.e., aggregation to different temporal levels, long-difference, by two time periods) we find consistent evidence of long-term adaptation behaviors where over time,

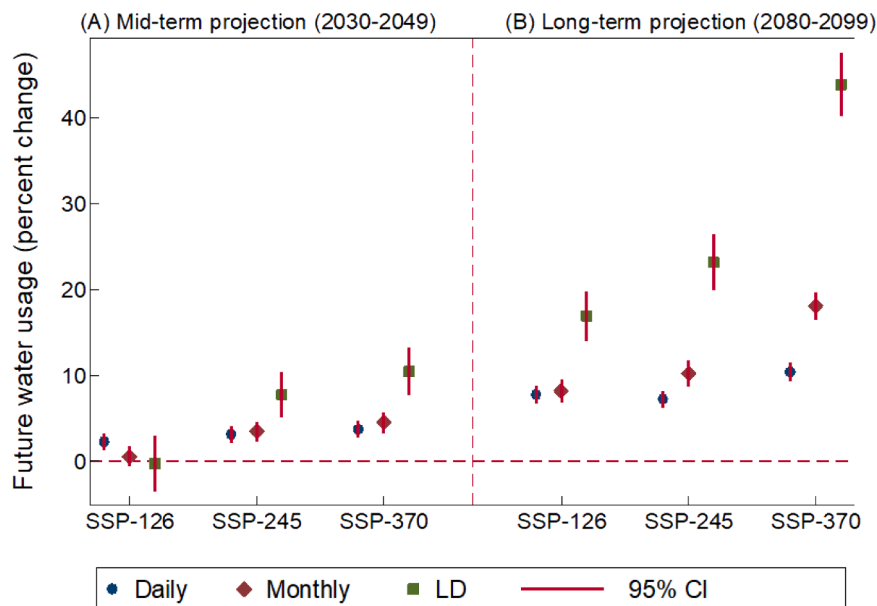


Fig. 6. Projected impacts of future warming on water usage, *Notes:* This figure depicts the predicted percentage changes in water usage based on mid-term and long-term prediction. The round, diamond, and square represent the projections based on daily estimates, monthly estimates, and long-difference estimates, respectively, while the vertical-line represent their 95% confidence intervals.

urban Chinese households are using more water to cope with high heat. In all, after feeding our results into different emissions scenarios (SSP126, SSP245, and SSP370), it is forecasted that if we fail to sufficiently reduce GHG emissions, Chinese urban household water usage will increase by around 3.1–10.4% in the medium-term (2030–2049), and by around 7.2–43.8% in the long-term (2080–2099). Coupled with the projected reduction in freshwater supplies, increased water usage would add a lot more stress to China's freshwater balance.

4.2. Discussions

Our findings have the following policy and research implications.

First, China is already facing severe water shortage as their per-capita water resources (2072 m³) is only around 35% of world's average. Moreover, it is projected that the freshwater supplies in China will be further compromised due to climate change and environmental pollution (Cheng and Hu, 2012; Piao et al., 2010; Tao et al., 2005). Our results show that there is a further negative feedback channel on the demand side as climate change induces greater households' water usage. To partially alleviate water shortages, China currently has the largest domestic water transfer program in the world – the South-North Water Transfer Project (SNWTP) (Webber et al., 2017). This costly and ambitious project, when fully completed, will transport more than 40 billion m³ of water annually from Southern to Northern provinces, and has already attracted controversies for its financial and environmental implications (Berkoff, 2003; Webber et al., 2017; Zhang, 2009). Our findings show that the goals of the SNWTP may be compromised in the future as temperature rises and water usage increases. Our results are especially applicable in this instance as the study area mostly consists of water-providing Southern provinces. This means that even though SNWTP was originally conceived as a long-term solution to alleviate water shortages in the North, it is unlikely that this solution will be sustainable especially if climate changes at a fast pace. Taken together, Chinese policymakers need to step up regulations to protect existing freshwater sources, and possibly use more aggressive price instruments (such as water tariffs) to slow down increase in household demand. On the latter point, despite inherent shortfall in water supply, Chinese residents currently have one of the lowest water tariffs in the world at around US\$0.34/m³ (world's average is US\$1.35/m³).³ As such, there is scope for Chinese policymakers to experiment with strategies such as higher tariffs (especially in well-off cities where income is closer to that of developed countries), behavioral nudges interventions, and information campaign to further regulate residential water usage.

Second, due to constraints in both water and energy supplies, and close dependence in their production, there are growing calls from scholars and practitioners to better integrate these two utility systems, that is, the water-energy nexus (Hamiche, Stambouli, and Flazi, 2016). At current, China's electricity and water sectors are largely distinct from each other. However, we show that the relationship between households' water demand and temperature is headed in different directions depending on their underlying electricity usage. A limitation of this finding is that we do not have household-level electricity usage. Combining both water and electricity demand at the household level is a promising and useful area of future research as it would illuminate the extent to which they are related, and help inform Chinese policymakers on integrating water and energy infrastructure, and their pricing.

Third, while conventional logic suggests that water usage would increase with temperature for residential units with grass lawns or swimming pools, we provide strong evidence that even residential apartment units would be affected. These findings are highly relevant in current context as urbanization is advancing at a rapid pace, especially in lower- and middle-income countries (Cohen, 2006; Hannah, 2018).

This means that water demand will increase concurrently with local temperature for over three billion population residing in cities (UN, 2019).

Fourth and related, similar to Salvo (2018), we find that households residing in lower-valued properties use more water to cope with heat, suggesting that water is a widely-used coping mechanism for heat for lower-income population. This implies that the policymakers may need to pay more attention to the distributional effect of climate change on water demand, and provide support to the most vulnerable households. Moreover, when generalized to lower-income countries where electricity supply are generally unreliable and air-conditioners mostly regarded as luxury goods, our findings predict that water demand will increase rapidly in cities across the developing world as global temperature rises, thus exacerbating projected water scarcity (Boretti and Rosa, 2019; De Wit and Stankiewicz, 2006; Hijioka et al., 2014; Niang et al., 2014; WWP, 2018). Due to lack of evidence, current research on climate change impacts have not taken into account of increased water demand (Cisneros et al., 2014; WWP, 2018). Our findings show that water usage will increase with rising temperature by a non-trivial amount for large swarth of population. This additional stress on water demand needs to be considered in future reports on water balances projections and impacts of climate change.

CRediT authorship contribution statement

Ping Qin: Conceptualization, Data curation, Methodology, Writing – original draft preparation. **Shuai Chen:** Methodology, Formal analysis, Writing – original draft preparation, Writing – review & editing. **Jie-Sheng Tan-Soo:** Methodology, Software, Formal analysis, Writing – original draft preparation, Writing – review & editing. **Xiao-Bing Zhang:** Methodology, Writing – original draft preparation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.envsci.2022.07.019.

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³ IBNet Tariffs DB. Source: <https://tariffs.ib-net.org/sites>. Last accessed: Dec 10, 2021.

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