

Climate Variations, Culture, and Economic Behaviors by Chinese Households

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Research Article

Keywords: Climate variation, Culture, Economic behavior, Household survey

Posted Date: February 19th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-213863/v1>

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Version of Record: A version of this preprint was published at Climatic Change on July 13th, 2021. See the published version at <https://doi.org/10.1007/s10584-021-03145-6>.

Abstract

Societies adapt to climate variation and develop unique cultures that lead to distinctive economic behaviors across different regions. To estimate the climate-economic link and test the hypothetical role of culture, this paper uses a nationwide survey at the household level in China, together with historical temperature data at the prefectural city level for empirical analysis. The results show the significant role of local climate variation on consumption, savings, and investment decisions by households. Harsh weather conditions are associated with lower consumption, lower income, and higher savings. It is also associated with a lower probability of purchasing risky financial assets. Using a sample of migrating families, we find strong evidence that culture is an important channel in the climate-economic relationship. Additional support for this view is found through the 'catching up with the Joneses' effect documented in the economics literature. Overall, this research provides an alternative perspective for understanding the long-run behavioral impact of climate change.

1. Introduction

Climate change has had profound impacts on the global economy and become one of the biggest threats to human sustainability. Increasing temperatures can raise sea levels (Domingues et al., 2008), cause more frequent and more severe natural disasters (Aldunce et al., 2015), affect agricultural production (Falco et al., 2019), and restructure the industrial sectors in an economy (Babiker, 2005). Together, these effects will lead to substantial welfare losses by individual households (Skjeflo, 2013; Ciscar et al., 2011). Policies and collective efforts to mitigate climate change are therefore critically important across the world (Edenhofer, 2015).

To make climate policies feasible and effective, it is important to explore broadly how climate factors affect human society, especially from a socioeconomic perspective. For example, Kriegler et al. (2012) elaborate the need to include this perspective in analyzing the impacts of climate change and the importance of creating an integrated system that is incentive driven. Policymakers must realize that the impacts of climate change not only apply to macroeconomics but also are fundamentally relevant to all people living on this planet. Although the impacts of climate change on aggregate socioeconomic outcomes have been extensively explored at the macro level, the climate-economic links at the micro-level remain underexamined.

In the literature, the relationship between climate and income has long been recognized since Huntington (1915). Evidence of the negative impact of global warming is abundant—for example, an increase in temperature of just 1 degree Celsius is associated with a decline in per capita income of 8.5% (Dell et al., 2009). A substantial portion of the differences in cross-country income can be explained by temperature alone. Comparing extremely hot or cold years, years in which the temperature is higher (i.e., by 1 degree Celsius) have economic growth that is 1.1% lower (Dell et al., 2012). From a global perspective, high temperatures and extreme weather can slow the global economy by 0.25% (Carleton and Hsiang, 2016), and further global warming is expected to lead to an additional 0.28% decrease.

Katz and Brown (1992) suggest that the climate variability is more important than the average temperature. The economic impacts of climate variability are especially relevant to developing countries, which are less able to cope with environmental challenges (Jury, 2002; Thurlow et al., 2012). Moreover, the agricultural sector, which is especially sensitive to changing weather conditions, is more important to these countries. China, as one of the fastest-growing developing economies, is in this category and is thus worthy of investigation.

Dell et al. (2009) suggest that an alternative method for understanding the time-series dimensions of climate variability is to examine the geographic differences in climate variability and the impacts on household economic outcomes. Several recent studies also focus on the effects of climate variability on households (Skoufias and Vinha, 2013; Skjeflo, 2013). Our study takes this approach in examining a nationwide household survey in China. Following the main idea in Dell et al. (2009), we examine the response to local climate variation among Chinese households across different regions. In addition, inspired by the idea that “climate creates cultures” (Van de Vliert, 2007), we introduce a cultural element into the climate-economic link. The logic is that society develops its own unique culture as a way of adapting to climate variation. For example, the cultural differences between Italians and the British might be due to environmental factors (Tavassoli, 2009). These differences can be explained at least partially by the attitude toward pleasure, which differs between people in countries with a colder climate and those in countries with warmer temperatures.

In fact, the study of culture and climate has been popular in interdisciplinary research for a long time (for a review, see Crate, 2011). Human dimensions of climate change are explored in cultural theory (Pendergraft, 1998), and cultural knowledge is useful in explaining people’s heterogeneous responses to climate change (Nielsen and Reenberg, 2010; Crona et al., 2013). Expanding on these concepts, Adger et al. (2012) demonstrate how culture can mediate the linkage between changes in society and the climate. Climate change can affect material and lived aspects of a society, creating an important cultural dimension in climate-related perceptions. Cultural adaptations to long-term climate change is shown to be important and valuable in understanding people’s responses to future climate change (deMenocal, 2001; Leonard et al., 2013).

In China, climate variations range from the freezing Mongolian Plateau to the mild Sichuan Basin, and this great variation in local climate leads to great variation in regional cultures. For example, the Mongolians in the north have a substantially different culture from that of people in the warmer southern regions. These cultural differences and their intrinsic links to climate variability translate into consumer behavior through homeostatic processes (Parker and Tavassoli, 2000).

To explore the climate-culture-economic link in China, we use a nationwide household survey, the China Household Finance Survey (CHFS). Combining the micro-level survey information with their local climate variations, we can effectively establish statistical links between the climate change and household economic decisions. The climate variations across regions in China are captured by the long-term historical variations in temperatures at the prefectural city level, and then we combine them with data on

individual households to determine whether and to what extent climate variability affects household economic outcomes.

Our empirical strategy also includes exploring the role of culture in the climate-economic linkage. Specifically, we use data on migrating families to test our hypothesis about cultural influences. We also extend the “catching up with the Joneses” hypothesis in the economics literature (Abel, 1990) for further confirmation. Overall, this research provides an alternative perspective for understanding the long-run impact of climate change and contributes to the existing literature from an interdisciplinary perspective. Given that cultural influences tend to be long lasting; additional implications of climate change can be derived.

The rest of this paper is structured as follows. Section 2 gives a detailed description of the empirical data used in this research, together with the empirical strategies applied in the analysis. Section 3 reports the empirical results, together with a discussion. Section 4 concludes the paper.

2. Data And Research Design

2.1. Household Survey

The household-level data are critical for our empirical analysis. They must have sufficient coverage and representativeness and, at the same time, contain relevant information to perform the empirical analysis. The CHFS survey, performed by the Survey and Research Centre for China Household Finance, is a very good source of information and is perfectly suitable for this study. The initial round of the survey was conducted in 2011 and has been repeated every two years since then. The CHFS survey provides information on consumption, savings, income, and other important financial and demographic characteristics of Chinese households across the country. The sample size of this survey has increased to cover more people in more subjects and has become a very popular source for understanding household behavior in China (Zhang, 2016).

The first round has only 8,438 samples, so it is not regionally representative. Thus, we use the second round (2013) in our research. In the 2013 round, the full-sample survey covers 29 provinces, 262 counties, 1,048 communities, and a total of 27,775 households across China. Even within a province, substantial differences exist in terms of climate variations because of the large size of provinces in the country. County is a smaller administrative level than prefecture city but was used in the CHFS sampling method. These 262 counties belong to 162 prefecture cities. Due to data availability and also the concern that the regional level should not be too small to have a meaningful cultural difference, we decide to match households and climate information at the prefecture city level, which gives us a total of 162 valid geographic regions.

2.2. Climate Data

Given the fact that a long period of climate variability is needed to shape a particular culture, we also need historical data. In addition, human activity can cause climate change (Franzke, 2014). It creates reverse causality that can affect statistical results. To avoid this issue, we use data from a reasonably long historical period in our assessment of regional climate variations.

Among all the climate factors, temperature is obviously a good measure among the various factors that determine climate change (Ji et al., 2014). We use data from the National Meteorological Information Center (NMIC) from 1981 to 2010. The original source is from 2,160 ground weather stations and then compiled to monthly frequency. We exclude temperature information from earlier years for the following two reasons (other than availability). First, the Cultural Revolution (1966-76), a major structural change in China, ended a few years before our sample begins. It was a major disruption in China in almost all respects, especially culturally; therefore, anything related to that period needs to be excluded. Second, our analysis focuses on cross-sectional variability, and a coverage period of over thirty years gives a sufficient description of a particular region's climate.

2.3. Variable Definitions and Descriptive Statistics

The key economic variables examined in this paper include disposable income, consumption, savings rate, and investment decisions on risky assets. Among them, the impacts on consumption are of key interest as they relate directly to individual decision-making. When income is fixed, the savings rate can be derived from the share of consumption. Notably, climate variations can also affect income at the same time; therefore, their impacts on savings rates might differ from the consumption-side effects.

(Insert Table 1 here)

Moreover, consumption can be divided into necessary consumption (necessities) and discretionary consumption (Hallerod et al., 1997), and they might respond to climate variation in different ways. According to the sample statistics, average annual household consumption is RMB 36,140 (about USD 5,900 using exchange rate in 2013). The highest value is as much as RMB 224,300, while the lowest is only RMB 1,930, indicating that a large variation of living standard exists in China.

On average, necessary consumption accounts for around two-thirds of total consumption in China, and income from wages is the main source of revenue. Notably, the average ratio of consumption to income is around 257%, which is due to some extremely low values of reported disposable income. The savings rate is relatively low because of some samples have a negative savings rate. These are both distributional issues and do not affect the general conclusions. Moreover, these values are generally consistent with those in several recent studies (Gao and Liang, 2019).

Many demographic factors can be extracted from the survey. As reported in Table 1, they include the household head's age, marital status, education level, health status, family size, employment status, political status, risk preference, and residential status. These factors allow us to control for the large heterogeneity of household characteristics in the regressions and to make our key results comparable to those in existing studies.

Two variables are constructed from the NMIC data. The first is *Temp_std*, the standard deviation of the monthly average temperature over thirty years (see appendix 1 for the construction of this variable). A high value in this variable for a city indicates greater variation in that city. For example, the highest variation is 15.60, and the city is Suihua, Heilongjiang Province, whereas the lowest is 2.77, corresponding to Laibin, Guangxi Province. Figure 1 shows a map of the temperature variations in all 162 sample cities. Areas with less climate variation, which are expected to be more comfortable to live in, are all located in south or southwest China. Cities in the northeast and some northwestern areas have distinctly higher levels of climate variation.

(Insert Fig. 1 here)

The second variable is *Temp_extre*, to measure the number of days with extreme weather conditions. Here, we define having temperatures of over 40 degrees Celsius or lower than minus 30 degrees as extreme weather conditions. The variable is a simple annual count of the number of days under these conditions; the annual counts are then averaged over 30 years. Given that *Temp_std* and *Temp_extre* are highly correlated (correlation = 0.372), the following analysis concentrates on the first one, but we use the second variable for additional analysis.

Before discussing our methodology, we plot the link between climate variation and consumption in Fig. 2, in which climate variations in the 162 prefectural cities are divided into five quantiles and then linked to the city-average consumption level in the boxplot. Q1 refers to cities with the lowest climate variation, whereas Q5 corresponds to those with the highest climate variation. A clear downward trend is indicated by whether the mean (red diamond) or the median value (black line in the box) is used in each quantile. In other words, cities with the mildest weather (Q1) have the highest average consumption level, whereas cities with the harshest weather (Q5) have the lowest average consumption level. Although the plot does not consider other factors, it still demonstrates the existence of climate-economic linkages in China.

(Insert Fig. 2 here)

It is also worth to note that the range of consumption in the fifth quantile (Q5) is significantly smaller than others. This quantile covers households living in the harshest weather conditions. Their expectation on higher variations in the future is stronger, and hence majority of people in this condition tend to take similar precautionary savings or behave in a more consistent way.

2.4. Research Design

To ensure that the trend demonstrated in Fig. 2 makes sense, several factors have to be controlled, so we need to use a formal econometric procedure. Here, the climate-economic links are examined by regressing economic factors at the household level on the proxy for local climate variation. We expected that people who live in areas with cold/harsh weather conditions have low sensitivity to pleasure from consumption (Tavassoli, 2009), so they have a low propensity to consume. With all other factors being equal, households in areas with harsh weather conditions or regions with high temperature variations tend to consume less. Climate changes and harsh weather conditions can also cause changes in the perception

of risk (Menapace et al., 2015). As a result, households develop distinctive risk preferences in the process to adapt to the local climate. Specifically, people living in areas with harsh weather conditions must prepare for the climate uncertainty, which means they increase their savings (Willows et al., 2003). In other words, we hypothesize that savings rates tend to be higher in areas with harsh weather conditions.

Although the existing literature suggests that countries in colder regions (Dell et al., 2009, 2012) can have high growth or income, households within a country might have a very different experience. Extreme weather conditions can reduce agricultural output, damage production (Ciscar et al., 2011), and have negative impacts on household income or welfare (Skjeflo, 2013; Skoufias and Vinha, 2013). From this perspective, the following is a testable hypothesis: with all else being equal, harsh weather conditions are associated with lower income levels.

We test this hypothesis by applying the following linear regression model as a first step in examining the climate-economic relationship in households:

$$Y_{ij} = \alpha + \beta Cv_j + \Gamma X_{ij} + \varepsilon_{ij} \quad (1)$$

where Y_{ij} denotes the consumption/income/saving rates for household i in city j . Cv_j is the measurement of climate variation in city j , where X_{ij} is a vector of demographic variables, and ε_{ij} is the error term; α is the constant, Γ is a vector of coefficients and β is the key coefficient of interest. Empirically, we expect to see a negative value of β for consumption and income, but a positive value for savings.

The second step is incorporating the cultural elements into our empirical model. Note that direct measurement of culture is difficult and often has multidimensional definitions (Beugelsdijk and Maseland, 2010; Fellows and Liu, 2013)—for example, Kroeber and Kluckhohn (1952) found 164 definitions. Nevertheless, a few clues from these definitions can help in setting up a mechanism for indirectly incorporating culture into the climate-economic relationships. The first clue is that culture is formed on the basis of fundamental beliefs and assumptions (Schwartz and Bardi, 2001), and thus it is stable over a long period. In other words, the shared values rooted in a culture are unlikely to change, even when people move around. Given this, we expect that migrating families tend to retain their original cultural traditions. If the cultural hypothesis is confirmed, then the economic behavior of migrating families will be affected by climate variations in the region where they originally lived.

In our sample, approximately 8% of the households are migrating families, representing a total of 2,113 sample households (for the distribution of this sample, see Fig. 3). A small proportion of those samples had moved less than one year earlier (132) and between one and three years earlier (355), whereas the majority of the migrating families in our sample had moved between three and ten years or above ten years earlier (663 and 473, respectively). An additional 490 migrating families did not report how long ago they had migrated. This distribution in the migrating samples allow us to examine the long-term effects of culture. Nonetheless, we omit samples of those who had migrated only recently as a robustness check.

(Insert Fig. 3 here)

The second clue is that culture is formed collectively among human groups (Fellows and Liu, 2013), often large groups, and the consequential behavior in one group distinguishes it from another (Hofstede, 2001). Another related concept, which is often used in the asset pricing literature, is “catching up with the Joneses” (Abel, 1990) or habit consumption (Campbell and Cochrane, 1999). This means that an individual consumption decision can be affected by a habit level or the average level where they live. If the climate-economic link includes a cultural role, then the local average level of propensity to consume should play an important mediating role in individual household decisions. We captured this effect by introducing a city-level average share of consumption in total disposable income. This variable can be interpreted as the propensity to consume—an important decision for households. Our hypothesis is that climate variation can affect the individual propensity to consume and that this link is affected by the local average, which is a proxy for habits or culture.

3. Empirical Analysis

3.1. Baseline Regressions

In the climate-economic link, our main interest is in the impacts of climate variations on three main economic variables at the household level: consumption, income, and the savings rate. Combining city-level climate variations with the household survey data, we perform regressions based on Eq. (1), and the main empirical findings are reported in Table 2. The first three models (models 1–3) study consumption-side impacts, whereas models 4–6 report results for income and its subcategories. The last two models are about savings.

(Insert Table 2 here)

To examine consumption, we distinguish necessary consumption from discretionary consumption. The results for models 1 and 2 are statistically significant at the 1% level, and the coefficients are all negative, which indicate that higher climate variation in a city of one standard deviation is associated with a reduction in average consumption of RMB 560 and that this effect arises mainly from necessary consumption. This finding is particularly worrying, as we believe that this type of consumption ensures basic household welfare.

The coefficients for the other control variables are generally consistent with our basic intuition. High-income families, larger families, married couples, families whose household head has a higher level of education, healthy families, and families with party members tend to consume more. Consumption is negatively related to the age and the number of employed members in a household. Rural families have significantly lower levels of consumption. City-level control variables also have significant impacts, and they are also intuitively consistent with general beliefs. Households in more developed cities, as measured by the gross domestic product (GDP) per capita, consume more, but the industrial share has a negative impact on household consumption.

Not surprisingly, higher climate variation is associated with lower income. In particular, a temperature variation in a city that is one standard deviation higher can lead to an average reduction in disposable income of RMB 1,200 for households in that city. The main effect comes from wage income, whereas income from other sources increases with climate variation. Presumably, harsh weather conditions reduce working hours and productivity. Other control variables also show a relationship with income. Families with members who are employed, married, more highly educated, healthy, and party members all had a statistically significant and positive relationship with income. Some samples that are affected by these variables differed in wage income and other types of income. For example, party members have relatively higher wage incomes but no significant differences in terms of other types of income. Having a local *hukou*, or household registration of legal residence in a particular area, can increase wage income but is associated with a lower level of other types of income. Once again, city-level control variables are significant and intuitively consistent.

Reducing consumption naturally leads to the belief that saving rates increase, but in this situation, the climate effect on income is also negative. Therefore, boosting the savings rate is not a simple consequence of decreasing consumption. We used both ordinary least squares (OLS) regression and the Tobit model (as the savings rate is truncated) to check for robustness, and we confirm a statistically significant relationship between climate variations and savings rates. The effect, however, is economically small. An increase in temperature variation of one standard deviation increased savings rates by only 0.553% (relative to the sample average of 11.51%). Nonetheless, the significant results support our initial hypothesis that people living in areas with harsh weather conditions have a greater need to save for the future because it is unpredictable. Over longer periods, this need will become ingrained as a habit. Of course, we need to interpret this result with caution, as the savings rate variable is calculated based on the difference between consumption and disposable income.

We also use *Temp_extre* as a key variable for measuring climate, and the results are generally consistent with the main findings above (see Table 3). A few differences, including a significant decrease in discretionary consumption and economically stronger impacts on savings rates, further support our main conclusions from Table 2. We also perform a set of additional analysis to control for other factors that were not covered in the baseline regressions. For example, including household compositions, additional city-level characteristics, quadratic forms of income and wealth etc. There are marginal numerical

differences but have no significant impacts on our main conclusions, these results are reported in the Appendix.

(Insert Table 3 here)

3.2. Cultural Effects: Migrating Families

As mentioned above, we use two approaches to incorporate cultural elements into the climate-economic links. The first is the use of migrating families. Cultural effects are persistent and do not change quickly (Lambert et al., 2020); in other words, migrating families tend to retain their original culture even after they move to another place. We explore this idea by looking at some possible ways in which this might occur. Given that consumption is the key decision-making variable, we concentrate on the impacts on consumption here. The results are reported in Table 4, which includes five models.

(Insert Table 4 here)

The first four models use samples from migrating families, whereas model 5 is the sample without migrating families. The effects of recently migrated families are avoided by allowing models (2) and (4) to replicate models (1) and (3) by excluding families that had moved to a new city within the previous year. As the results show, the effects are generally consistent. First, the coefficients for the climate variation from the migrating families' city of origin (*CV_Past*) are significant and negative (-0.61/-0.60), whereas the coefficients for the climate variation from the city where they currently live (*CV_Present*) are not. Second, the effects from non-migrating families are statistically significant (-0.057). These results are generally consistent with our hypotheses and confirm the initial assumption that the climate-economic link includes a cultural role.

It is worth to note that migrating households may have different characteristics from those native families (see appendix 7 for detailed information), and thus raising sample selection problem. To resolve this problem and possible biasedness, we adopt a simple propensity score matching (PSM) approach to redo Table 4 (see appendix Table 7.4). Although the estimated coefficients changed slightly, they are generally consistent with the initial results and provide supporting evidence to the main story.

3.3. Cultural Effects: Catching up with the Joneses

The second approach for modeling cultural effects is to use the local average consumption share to represent local culture. This strategy is also in line with the literature on habit formation or "catching up with the Joneses." In other words, individual consumption decisions are often affected by their neighbors' choices. Culture also refers to the behavior of a reasonably large population group (Fellows and Liu, 2013); therefore, using the city-level average to represent local consumption culture is an option. If the climate-economic link has a cultural element, then the share of city-level average consumption should be a significant mediating variable. Table 5 shows the empirical results for the consumption share, as well as the share for necessary consumption, of disposable income.

(Insert Table 5 here)

The results in Table 5 provide strong support for our hypothesis. First, a one-standard-deviation in city climate variation can reduce the average consumption share in a city by 3.64%. Second, a statistically significant mediating role is found in models (1) to (3) and in models (4) to (6). Regardless of the total consumption shares or the share of necessary consumption, we can comfortably confirm a statistically significant role of the city-level average. In other words, a “catching up with the Joneses” effect exists in China, which further confirms the impact of cultural elements.

4. Conclusions

This paper explores the link between climate variation and household economic decisions using a sample of over 20,000 households in China, together with long-term data on temperature variation at the level of 162 prefectural cities. Our findings contribute to recent debates on the socioeconomic consequences of climate change using detailed micro-level data. In particular, we incorporate cultural elements into this climate-economic link by examining migrating families and the “catching up with the Joneses” hypothesis. By revealing the cultural effects, our research offers new insights into the mechanisms through which climate change could bring about long-term behavioral change and, in turn, have significant economic impacts.

Our empirical analyses support the hypothesis that a harsh climate in a region can reduce household income and necessary consumption, while raising the household savings rate. An increase of one standard deviation in climate variation can reduce income by RMB 1,200, reduce consumption by RMB 560 and increase savings rates. These results are robust to an alternative climate measurement.

Using migrating families and a city’s average propensity to consume indirectly confirm the role of culture in the climate-economic linkage. Specifically, migrating families, even long after they have settled in their new city, retain their sensitivity to climate variations in their original location. Moreover, the cultural effects are stronger for harsh weather conditions than for milder ones. The average propensity to consume at the city level plays a significant mediating role in the climate-economic link for individual households. We offer further elaboration of the concept of “catching up with the Joneses” by providing additional support for cultural elements.

This research offers policy implications from a bottom-up perspective. First, we present similar arguments to support actively addressing climate change at a global scale, conditioned on the fact that global warming leads to greater climate variation and more extreme weather conditions. Second, the results show that households suffer significant welfare losses due to climate variation. These variations can therefore cause further income inequality and, more importantly, a reluctance to consume, which can have a negative economic impact on the macro-economy. Policy supports are needed for regions with harsh weather conditions. Lastly, the long-term effects of cultural elements indicate that the behavioral consequences of climate variation can have long-lasting effects and thus are difficult to change. Efforts to cope with climate change and to adapt to climate change therefore have both long and persistent effects.

A few limitations of the current studies worth to be clarified: first, the sampling issues should be taking with cautious. Although we have tried our best to make sure the econometric analyses are robust, the research is constraint by data availability. For example, we need to know more about migrating families to avoid the impacts of non-observable characteristics. Second, the survey is not particularly designed for such study, and thus affect our ability to make any precise analysis. In the future, when a long time dimensional data is available, technically more advanced methods can be applied to the same set of questions. Third, using the rich information of this micro-survey, further analyses can be done in the future to provide more explanations to some results here, for example, making a more accurate matching between household and climate conditions, which of course, subject to data availability.

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Tables

Table 1. Descriptive statistics

Variable	Definition	Mean	Std. Dev.	Minimum	Maximum
Dependent variables					
Consum	Consumption expenditure (10K RMB)	3.614	3.688	0.193	22.43
N_consum	Necessary consumption (10K RMB)	2.204	1.816	0.127	10.28
U_consum	Discretionary consumption (10K RMB)	1.384	2.372	0.006	15.59
Income	Disposable income (10K RMB)	4.827	5.898	0.040	37.80
Income_W	Income from wage (10K RMB)	2.928	4.378	0	24.00
Income_O	Income from other sources (10K RMB)	0.485	1.821	-0.600	14.87
Saving	Saving rate (%)	11.51	61.838	-179.46	92.226
Risky	Risky financial assets to total financial assets ratio(%)	4.848	16.765	0	91.071
CS_hh	Household consumption share over income (%)	257.45	730.989	8.259	5854.247
Climate variables					
Temp_std	Climate variation in cities	9.199	2.444	2.766	15.60
Temp_extre	Extreme climate in cities	0.317	1.433	0	22.00
Control variables					
F_size	Family size	3.026	1.388	1	7
Age	Age of the household head	51.50	14.82	22	84
Employ	Number of members in employment	1.777	1.228	0	5
Marital	Dummy variable (married=1)	0.843	0.364	0	1
Education	Dummy variable (high school or above=1)	0.372	0.483	0	1
Health	Dummy variable (healthy=1)	0.796	0.403	0	1
Party	Dummy variable (party member=1)	0.154	0.361	0	1
Gender	Dummy variable (Female=1)	0.466	0.499	0	1
Rural	Dummy variable (Rural=1)	0.318	0.466	0	1
Hukou	Dummy variable (local Hukou=1)	0.908	0.289	0	1
Risk	Dummy variable (Prefer risk=1)	0.266	0.442	0	1
City level variables					
Structure	Industrial structure (share of secondary industries, %)	47.38	10.41	20.60	81.40
CS_city	City average consumption share over income (%)	257.45	110.124	97.222	955.216
GDP_city	City level per capita GDP (in log term)	10.39	0.624	8.556	11.49

Note: Statistical values are calculated after winsoring at 1% and 99% level (to remove outliers). Other incomes (Income_O) include business income, agricultural income and income from assets. Savings rate is calculated by (Income-Consum)/Income.

Table 2. Baseline regression results

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	Consum	N_consum	U_consum	Income	Wage income	Other income	Saving	Risky
Temp_std	-0.056*** (0.007)	-0.048*** (0.003)	-0.008 (0.005)	-0.120*** (0.013)	-0.091*** (0.009)	0.030*** (0.005)	0.553*** (0.160)	-0.235*** (0.040)
Income	0.254*** (0.007)	0.121*** (0.003)	0.127*** (0.005)				3.980*** (0.076)	0.477*** (0.030)
F_size	0.311*** (0.017)	0.221*** (0.008)	0.076*** (0.012)	0.035 (0.028)	-0.247*** (0.020)	0.040*** (0.011)	-5.308*** (0.329)	-0.182*** (0.070)
Age	-0.039*** (0.001)	-0.017*** (0.001)	-0.022*** (0.001)	-0.014*** (0.003)	-0.039*** (0.002)	-0.010*** (0.001)	0.778*** (0.030)	0.020*** (0.008)
Employ	-0.084*** (0.020)	-0.083*** (0.009)	0.003 (0.014)	1.056*** (0.032)	1.405*** (0.023)	0.105*** (0.011)	8.307*** (0.391)	-0.514*** (0.085)
Marital	0.316*** (0.053)	0.213*** (0.025)	0.125*** (0.037)	0.719*** (0.094)	0.288*** (0.064)	0.064* (0.033)	-1.637 (1.127)	1.844*** (0.285)
Education	0.586*** (0.048)	0.386*** (0.023)	0.196*** (0.034)	2.341*** (0.083)	1.807*** (0.056)	0.098** (0.033)	-1.074 (0.890)	4.729*** (0.281)
Health	0.176*** (0.041)	0.116*** (0.019)	0.050* (0.030)	0.455*** (0.067)	0.151*** (0.047)	0.139*** (0.024)	0.535 (1.024)	0.512** (0.216)
Party	0.224*** (0.060)	0.132*** (0.027)	0.086** (0.043)	1.328*** (0.110)	1.068*** (0.082)	-0.046 (0.035)	2.118** (0.999)	1.517*** (0.390)
Gender	0.073* (0.039)	0.021 (0.018)	0.061** (0.028)	-0.039 (0.069)	0.229*** (0.048)	-0.186*** (0.025)	-1.138 (0.787)	0.933*** (0.218)
Rural	-0.522*** (0.045)	-0.526*** (0.020)	-0.001 (0.033)	-1.787*** (0.067)	-1.388*** (0.049)	0.233*** (0.030)	-1.813* (1.090)	-1.484*** (0.167)
Hukou	0.129 (0.079)	0.021 (0.038)	0.127** (0.056)	0.127 (0.157)	0.287*** (0.107)	-0.122* (0.070)	-3.928*** (1.380)	2.974*** (0.393)
GDP_city	0.717*** (0.037)	0.502*** (0.017)	0.226*** (0.026)	2.330*** (0.061)	1.347*** (0.043)	0.143*** (0.021)	-3.011*** (0.725)	2.868*** (0.185)
Structure	-0.018*** (0.002)	-0.012*** (0.001)	-0.006*** (0.001)	-0.061*** (0.003)	-0.033*** (0.003)	-0.002 (0.001)	0.113*** (0.037)	-0.095*** (0.011)
Constant	-3.130*** (0.387)	-2.534*** (0.176)	-0.685** (0.279)	-18.199*** (0.625)	-9.552*** (0.445)	-1.036*** (0.246)	-22.918*** (8.066)	-26.790*** (1.935)
N	25736	25736	25736	25736	25736	22099	22357	23525
R ²	0.359	0.453	0.174	0.233	0.297	0.031	0.178	0.116
F	633.511	1086.365	206.837	442.208	581.508	55.425	303.187	137.320

*Note: Consum refers to consumption expenditure; N_consum refers to necessary consumption; U_consum refers to discretionary consumption; Income refers to Disposable income; Income_W refers to income from wage; Income_O refers income from other sources. Saving refers saving rate; Risky refers to risky financial assets total financial assets. Temp_std refers to climate variation in cities; F_size refers to family size; GDP_city refers to city level per capital GDP in log term; Structure is city level industrial structure (share of secondary industries). Robust standard errors are in brackets. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively. Clustered standard errors are also checked and the results are consistent.*

Table 3. Using extreme days as a measure of climate

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variables	Consum	N_consum	U_consum	Income	Wage income	Other income	Saving	Risky
Temp_extre	-0.047** (0.008)	-0.035*** (0.004)	-0.012** (0.006)	-0.073*** (0.015)	-0.072*** (0.011)	0.042*** (0.007)	0.836*** (0.294)	-0.174*** (0.039)
Income	0.255*** (0.007)	0.122*** (0.003)	0.127*** (0.005)				3.968*** (0.076)	0.481*** (0.031)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Constant	-3.203*** (0.392)	-2.618*** (0.178)	-0.676** (0.283)	-18.510*** (0.634)	-9.720*** (0.451)	-1.063*** (0.247)	-23.881*** (8.144)	-27.187*** (1.941)
N	25736	25736	25736	25736	25736	22099	22357	23525
R ²	0.358	0.450	0.174	0.231	0.295	0.031	0.177	0.115
F	632.635	1078.105	206.871	440.880	580.661	55.030	303.997	137.053

Note: *Consum* refers to consumption expenditure; *N_consum* refers to necessary consumption; *U_consum* refers to discretionary consumption; *Income* refers to Disposable income; *Income_W* refers to income from wage; *Income_O* refers income from other sources. *Saving* refers saving rate; *Risky* refers to risky financial assets total financial assets. *Temp_extre* refers to extreme climate in cities. “Controls” refer to the control variables used in the baseline regressions (Table 2). Robust standard errors are in brackets. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.

Table 4. Results on migrating families

Models	(1) Consum	(2) Consum	(3) Consum	(4) Consum	(5) Consum
CV_Past	-0.061** (0.030)	-0.060** (0.030)			
CV_Present			-0.051 (0.034)	-0.049 (0.036)	-0.057*** (0.007)
Income	0.278*** (0.018)	0.275*** (0.018)	0.279*** (0.017)	0.277*** (0.018)	0.249*** (0.007)
Controls	Y	Y	Y	Y	Y
Constant	-3.587* (1.875)	-3.793* (1.935)	-3.348* (1.855)	-3.506* (1.909)	-3.118*** (0.445)
N	2061	1930	2113	1981	23623
r ²	0.324	0.323	0.327	0.327	0.357
F	45.610	44.283	47.393	46.330	562.121

Note: *dependent variables* are consumption expenditure (*Consum*) in all models. *CV_Past* refers climate variation in the region before migrating, whereas *CV_Present* refers to climate variation in the current residential area. “Controls” refer to the control variables used in the baseline regressions (Table 2). Models (2) and (4) are basically the same as models (1) and (3), but exclude migrating families moved within a one-year period. *Model (5)* include all non-migrating families (natives). Robust standard errors are in brackets. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively. *Wald tests* show no statistical differences between the coefficients estimated for *CV_Past* in model (1)/(2) and (5).

Table 5. Mediating effects of city average consumption share

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variables	CS_hh	CS_city	CS_hh	NCS_hh	NCS_city	NCS_hh
Temp_std	-9.113*** (1.858)	-3.964*** (0.262)	-5.841*** (1.878)	-6.947*** (1.210)	-3.375*** (0.178)	-4.188*** (1.237)
CS_city			0.825*** (0.066)			
NCS_city						0.817*** (0.067)
Controls	Y	Y	Y	Y	Y	Y
Constant	1157.364*** (102.549)	1036.129*** (16.618)	302.062*** (103.812)	762.874*** (66.393)	665.723*** (11.440)	218.797*** (65.673)
N	25736	25736	25736	25736	25736	25736
r2	0.069	0.208	0.081	0.070	0.205	0.082
F	93.294	423.877	89.915	94.344	432.800	90.849

*Note: dependent variables are shares of consumption over disposable income (CS), and necessary consumption share over disposable income (NCS). They are at household level (hh) or city level (city). “Controls” refer to the control variables used in the baseline regressions (Table 2). Robust standard errors are in brackets. *, ** and *** denote significance levels at 10%, 5% and 1%, respectively.*

Figures

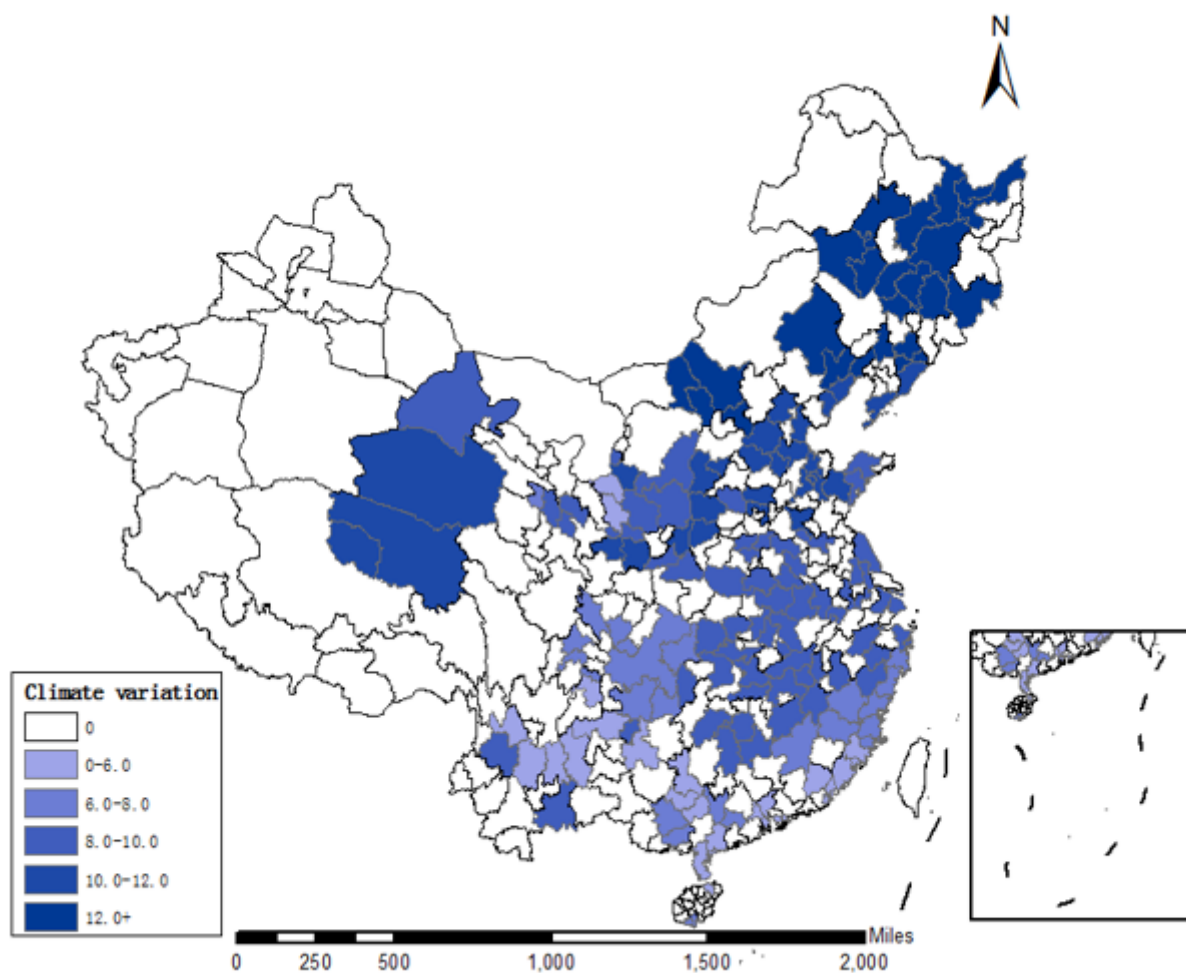


Figure 1

Map of temperature variations across sample cities. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

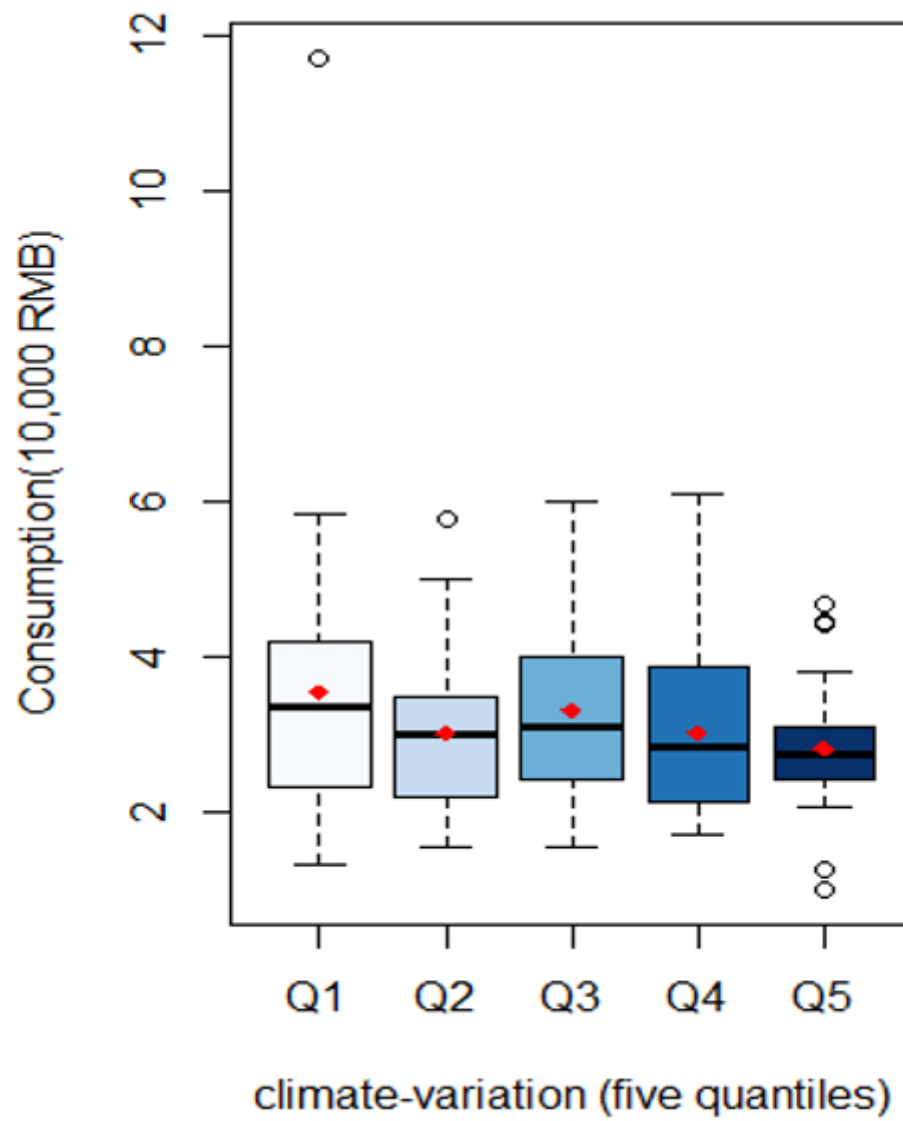


Figure 2

Boxplot of climate variation against city average consumption.

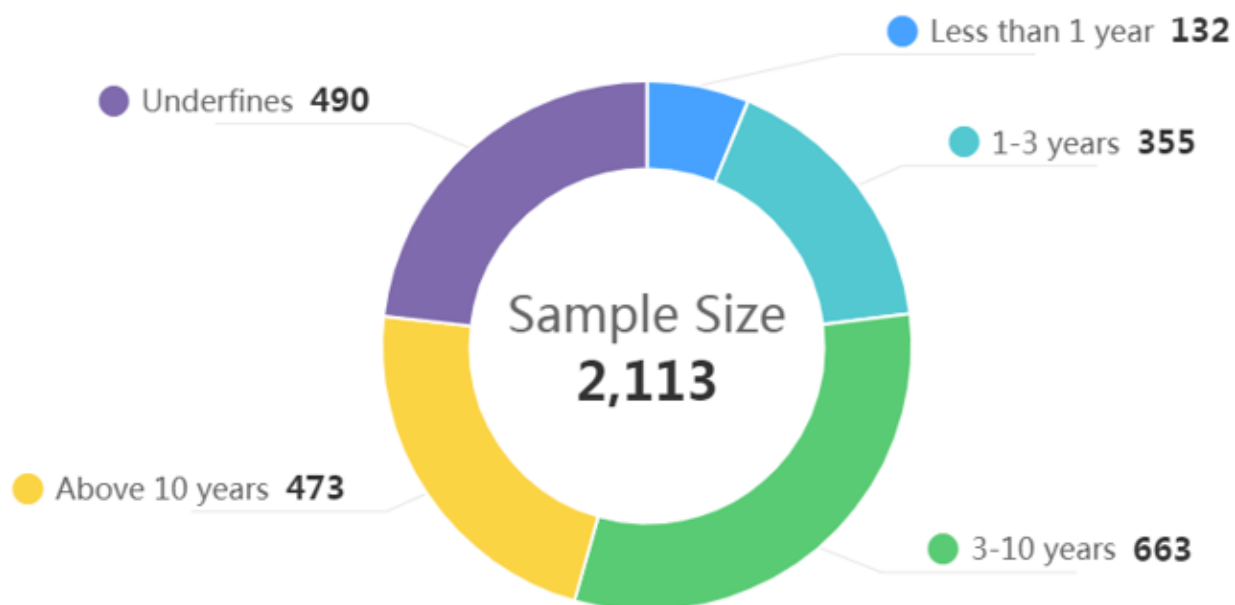


Figure 3

Sample distributions of migrating families

Supplementary Files

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