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Memory of famine: The persistent impact of famine experience on food waste behavior

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ABSTRACT

The 1959–1961 Great Famine in China was one of the most devastating events in history and had long-term effects on economic behavior. This paper seeks to provide a novel explanation for heterogeneous food waste behaviors across age cohorts from the perspective of differing famine experiences. Based on 2004–2009 China Health and Nutrition Survey (CHNS) data, this paper constructs a difference-in-difference estimator to explore the long-term effects of the early-life famine experience of the household head on household food waste behavior in later life. The results indicate that the more serious famine that the household head experienced in early life was, the less wasted food and lost calories per capita there were, especially for adolescence during the famine. The mechanism analysis shows that households whose heads experienced the 1959–1961 Great Famine in early life tend to save more than those whose head did not. The findings contribute to a better understanding of the formation of preference and the variation in household food waste behaviors across age cohorts.

1. Introduction

Studies of experienced utilities reveal that consumers' choices often involve experiences they have already had (Kahneman & Thaler, 2006; Schurr, Rodensky, & Erev, 2014). One possible explanation is that life experiences of extreme events can shape preferences and can have long-term effects on individual behaviors. Individuals who experience extreme events may change their perceptions of the likelihood of a future extreme event and become more cautious in their behaviors due to risk perception bias and confirmation bias through memory (Chater & Loewenstein, 2016; Kahneman & Tversky, 1979; Kahneman & Tversky, 1988). In particular, an extreme event experienced in childhood can have a profound influence on the formation of individuals' beliefs and preferences as well as on their behavioral choices in adulthood (Becker, 1992).

Food loss and waste are increasingly becoming a global problem and exacerbate the long-standing challenges of food security. Nearly 690 million people are hungry, and 821 million people are undernourished. In sharp contrast to this, approximately one-third of the world's food is wasted, causing an economic loss of approximately one trillion dollars a year (FSIN, 2021). In addition, the COVID-19 pandemic could undermine sustainable food systems, implying that zero hunger (one of the 17 Sustainable Development Goals) may not be on track to be achieved by 2030 (UN, 2021).

Food waste at the household level is one of the largest contributors to total food loss and waste in both developed and developing

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countries. While household food waste in rich countries has leveled off, the increased food waste in low- and middle-income countries accounts for most of the growth in food waste that has occurred in the past three decades (Barrera & Hertel, 2021; Calvo-Porral, Medín, & Losada-López, 2017; Porpino, Parente, & Wansink, 2015).

The heterogeneity of food waste is highly related to consumers' age cohorts (Ellison & Lusk, 2018; Smith & Landry, 2020). Empirical evidence shows that elderly people (persons aged 60 and above) are the least likely to discard food (Quested, Marsh, Stunell, & Parry, 2013; Smith & Landry, 2020; Stancu, Haugaard, & Lahteenmaki, 2016). The question of why consumers' food waste behavior differs so much across age cohorts is of interest because it relates directly to adequate food policies. Does food waste behavior differ between the young and elderly generations? Do people in some age cohorts waste food in an "as if" irrational way? If so, what accounts for this heterogeneity in food waste behavior? A better understanding of individuals' food consumption-waste motives will contribute to identifying the heterogeneity of food waste behaviors across age cohorts. One major aim of this paper is to shed light on this issue.

Differences in food waste behavior across age cohorts may arise from early-life experiences. In the context of China, the 1959-1961 Great Famine provides a quasi-natural experimental setting in which to explain this heterogeneous food waste behavior. Early-life famine experiences may create two psychological states. One is the compensatory psychology for loss. Individuals who experienced food scarcity in early life may seek compensation in later life, leading to belly worship and the search for high-quality food, which may involve more food waste in later life (Cheng & Zhang, 2011; Gluckman, Cutfield, Hofman, & Hanson, 2005; Kesternich, Siflinger, Smith, & Winter, 2015). The other is irrational preventive psychological motivation (Chamon & Prasad, 2010; Wei & Zhang, 2011). Individuals who experienced the famine in childhood were deeply impressed by the scarcity of food, which may have induced "fear" memories of hunger (Cui, Smith, & Zhao, 2020). These "fear" memories brought about by the famine may have encouraged these famine victims to form frugal consumption habits and reduce potential food waste in later life. As the severity of the 1959-1961 Great Famine across regions is arguably orthogonal to later economic shocks (such as trends of food consumption) that may affect food waste, the 1959–1961 Great Famine provides a compelling natural experiment to identify the heterogeneity of food waste behavior by age cohorts.

This paper contributes to the literature in three ways. First, our study fills a gap by analyzing the heterogeneity of food waste due to the experience of an exogenous extreme shock. Using the 1959–1961 Great Famine as a quasi-natural experiment, this paper tests whether an extreme food scarcity experience of the household head in early life can profoundly influence food waste behavior in late life, providing a novel explanation for heterogeneous household food waste behavior. The second contribution is that our study develops a novel theoretical utility model that incorporates the concept of the psychological price of food. The theoretical innovation of this model is that consumers with famine experience may place a different psychological or subjective value on food beyond real market price. The nature of heterogeneous food waste behavior is that consumers make food purchase decisions based on the psychological price rather than the market price of the food. The third contribution is that this paper supplements the literature associated with the long-term effects of famine experience from the perspective of behavioral economics.

The rest of the paper proceeds as follows. Section 2 briefly introduces the 1959–1961 Great Famine and household food waste situation in China. Section 3 discusses the theoretical model and its psychological underpinnings. Section 4 develops an empirical framework for examining the long-term impacts of early-life famine experience on household food waste behavior in China. Section 5 introduces the data and descriptive statistics. Section 6 presents the baseline results, robustness check results, heterogeneous results and mechanism analysis results. Finally, Section 7 concludes.

2. Background

2.1. The 1959–1961 Great Famine

China experienced an unprecedented famine in 1959–1961. On the eve of the famine, agricultural production was collectivized (Meng, Qian, & Pierre, 2015). In 1958, the Great Leap Forward movement was implemented nationwide and was mainly manifested in the establishment of large-scale people's communes and a rationing system for food supplies (Lin, 1990; Lin & Yang, 2000). When the food supplied was insufficient, people in both urban and rural areas lacked the calories required for survival, and a famine eventually occurred (Johnson, 1998; Kung & Lin, 2003; Yang & Su, 1998). A prominent feature of the 1959–1961 Great Famine was the sharp rise in the mortality rate for elderly persons and young children and the drop in the fertility rate during 1959–1961 (Ashton, Kenneth, Piazza, & Zeitz, 1984; Lin & Yang, 1998). The mortality rate in rural areas was much higher than that in urban areas because the food rationing system favored urban residents at that time (Gørgens, Meng, & Vaithianathan, 2012; Lin & Yang, 2000). To date, there is still no consensus about population loss during the famine with estimates range from approximately 15 million to 45 million (Ashton et al., 1984; Banister, 1987; Meng et al., 2015; Riskin, 1990).

A large number of studies have provided evidence regarding the impacts of the 1959–1961 Great Famine on institutional reform, human capital accumulation and health as well as marriage (Almond, Edlund, Li, & Zhang, 2010; Brandt, Siow, & Vogel, 2016; Chen & Zhou, 2007; Gørgens et al., 2012; St. Clair et al., 2005; Yang & Su, 1998). Provinces that were severely affected by the famine were also those that carried out earlier agricultural de-collectivization and household responsibility system reform (Kung & Bai, 2010; Yang, 1996; Yang & Su, 1998). Persuasive evidence reveals that children who survived the nutritional deprivation of the famine faced severe deleterious long-term health effects, such as stunting, obesity, lower cognitive ability, depression and schizophrenia (Chen & Zhou, 2007; Cui et al., 2020; Gørgens et al., 2012; St. Clair et al., 2005). Besides these adverse health outcomes, famine-born cohorts tended to be at a disadvantage in the marriage and labor markets when they grew up (Almond et al., 2010; Brandt et al., 2016; Chen & Zhou, 2007; Gørgens et al., 2012). In addition, an "echo effect" has been observed in subsequent generations, such as negative effects upon entering junior high school (Almond et al., 2010; Kim, Deng, Fleisher, & Shi, 2014).

While the existing literature has highlighted the health consequences and intergenerational impacts of the 1959–1961 Great Famine, to the best of our knowledge, few studies have focused on the long-term effects on economic behaviors. The only exception is the study by Cheng and Zhang (2011), which provided evidence that households whose head experienced this famine in early life showed a higher propensity to save. This study also provides additional evidence of the long-term impacts of Great famine on household food waste behavior.

In the recent developments of the literature on the long-term impacts of extreme events, considerable effort has been made to support the experience mechanism (Cameron & Shah, 2015; Gignoux & Menéndez, 2016). For example, Callen (2015) showed that Sri Lankan wage workers who were severely affected by the Indian Ocean earthquake tsunami tend to exhibit more risk aversion behaviors than those who were not. Turning to the long-term impact of a devastating event on individual consumption behaviors, Fransen et al. (2016) showed that exposure to famine early in life may be associated with a higher prevalence of unhealthy behaviors later in life, such as smoking and alcohol addiction. Kennett-Hensel, Sneath, and Lacey (2012) revealed that the disruption caused by Hurricane Katrina led to dramatic changes in lifestyle, consumption attitudes and purchasing behavior.

2.2. Household food waste in China

Household food waste is defined as food waste that occurs in the interval between when food reaches the consumer and when it is eaten (Alexander et al., 2017). Given that households are utility-maximizing agents, a household's attempt to trade off food safety against food saving is usually made under income constraints (Ellison & Lusk, 2018).

A growing number of governments and NGOs are participating in initiatives and actions to reduce food waste worldwide. For example, the US Food Waste Challenge Program (USDA, 2013) and the UK Waste Resources Action Program (WRAP, 2017) were launched to share best practices for waste reduction and food recovery across the supply chain. In 2013, the Food and Agriculture Organization (FAO) launched a global food-saving initiative that aimed to raise awareness and provide information for households on the impact of and solutions for food loss and waste (FAO, 2016). In addition, the FAO named 29 September 2020 the first International Day of Food Loss and Waste and provided severe warnings about global food waste.

Household food waste-related issues have also received considerable attention in China given the large population. In regard to consumer involvement in food waste reduction, the "Clean Your Plate Campaign" was initiated by an NGO in 2013 and is still going strong. The campaign advocates for not wasting food when dining out and has been especially promoted in Chinese schools (China Daily, 2020; Miranda, Rosa, & Garrett, 2018). In April 2021, China passed the anti-food waste law with the aim of establishing a long-term mechanism to prevent food waste behavior (China Daily, 2021).

While household food waste has attracted lots of attention worldwide, relatively few recent works focus on food waste behavior in the household sector. Furthermore, the existing literature on household food waste behavior has primarily been descriptive in nature. This paper focuses on testing the hypothesis that early-life famine experience has significant long-term effects on household food waste behavior.

3. Theoretical framework

This paper develops a simple framework to model the impacts of famine experience on household food waste behavior based on utility theory. Assuming that the utility derived from food consumption depends only on how much the consumer takes in, the utility function can be written as

$$U_T = U[(1-\alpha)Q_T, w] \tag{1}$$

where Q_T represents the food purchased in period T and α represents the proportion of wasted food; w is the nonfood consumption. Assume the utility function satisfies $U(0) = 0$, $U'(x) > 0$ and $U''(x) < 0$, $\forall\, x$. Suppose the budget constraint faced by the consumer is

$$p_T^* Q_T + p_w w \leq m \tag{2}$$

where p_T* and p_w are market prices for food and nonfood products, respectively, faced by the consumer, which are exogenous. mm is the outlay of the consumer.

Solving Eqs. ((1), (2)),

$$U_1(1-\alpha) = \lambda p_T^* \tag{3a}$$

$$U_2 = \lambda p_w \tag{3b}$$

where $U_1 = \frac{\partial U}{\partial[(1-\alpha)Q_T]}$, and $U_2 = \frac{\partial U}{\partial w}$. (3b) shows that λ is a constant. Then, Eq. (3a) becomes

$$K \equiv \frac{U_1}{\lambda} = \frac{p_T^*}{(1-\alpha)} \tag{4}$$

where K is also a constant clearly determined by the solution for Eqs. ((1), (2)) and Eq. (4) shows a relationship between p_T* and α. In this case, there is no famine shock.

However, food is a basic human need, and hunger due to food scarcity yields additional experience value. A person with famine experience may place a different psychological or subjective value on food beyond the real price (Bénabou & Thaler, 2016; Caplin & John, 2001; Kahneman & Tversky, 1988) because food represents life security.

We define the psychological price of food as

$$\widetilde{p}_T = p_T^* + p_T^e \tag{5}$$

where $\widetilde{p}_T$ is the psychological price of food in period T. $p_T{}^e$ is the additional experience value for consumers who experienced the 1959–1961 Great Famine and is not determined by markets. Clearly, the consumer makes food purchase decisions based on the psychological price rather than the market price of the food. Then, Eq. (4) under the famine shock can be rewritten as

$$K \equiv \frac{U_1}{\lambda} = \frac{p_T^* + p_T^e}{(1-\alpha^e)} \tag{6}$$

Eq. (6) shows the relationship between the experience value $p_T{}^e$ and food waste α^e. To maintain the constant K, we have

$$\frac{\partial p_T^e}{\partial \alpha^e} < 0 \tag{7}$$

Assume the experience value $p_T{}^e$ depends only on the severity and duration of the famine the consumer experienced. Assume the consumer experienced N years of famine duration. The experience value $p_T{}^e$ can be further written as

$$p_T^e = \sum_{i=1}^{N} \psi^* EDR_{t_i}{}^* e^{-r(T-t_i)} \tag{8}$$

where EDR_{ti} represents the excess death rate of the ith year's famine the consumer experienced in period t and r is the constant discount rate. $\psi > 0$ is a parameter that captures the linear relationship between famine experience and experience value.

The first-order condition of $p_T{}^e$ with respect to EDR_{t_i} is

$$\frac{\partial p_T^e}{\partial EDR_{t_i}} = \psi e^{-r(T-t_i)} \tag{9}$$

Clearly, $p_T{}^e$ and EDR_{ti} are positively correlated.

Combining Eqs. ((7), (9)), we establish the following proposition.

Proposition. The more severe the famine consumers experience in early life, the less food waste they will have.[1]

4. Empirical strategy

The key to studying the long-term effects of famine experience on individual economic behaviors is the identification strategy. The 1959–1961 Great Famine is an ideal quasi-natural experiment to individuals that created exogenous variations in exposure to famine (Chen & Zhou, 2007). This paper uses a cohort difference-in difference (DID) identification strategy that builds on variations across birthplaces and cohorts. Following Duflo (2001), we estimate the effects of famine experiences on each cohort using the following equation (the 1970–77 age cohort serves as the baseline group):

$$lnY_{ijct} = \gamma_0 + \sum_{c=1}^{11} \gamma_c \left(EDR_j \times cohort_{ic}\right) + \alpha_j + \beta_c + \delta_t + \varnothing Trend + \varepsilon_{ijc} \tag{10}$$

[1] We also use budget constraint lines under different conditions and indifference curves to characterize the equilibrium of food waste and famine in Fig. A1. Note that the famine experience systematically changes the consumption structure of the consumer. The budget constraint under the case of no food waste and no famine experience is given by w_0f_0, which is the baseline of the analysis. If a certain percentage of food is wasted, the consumer must purchase more food to maintain the amount of food taken in, as if food prices have increased. Thus, the budget constraint considering food waste with no famine experience is w_0f_1. According to the above theoretical model, a consumer who experienced a famine has an additional experience value $p_T{}^e$ for food, and the budget constraint will move around the indifference curve and become much flatter as w_0f_2 due to an "as if" substitute between food and nonfood consumption. Finally, the real budget line crosses points w_0 and E, where the indifference curve is a tangent of w_0f_2. The distance between f_1 and f_3 is the effect of famine experience on food waste reduction. In other words, the distance f_1f_3 is compensation for the famine experience, which leads to a higher psychological price for food than the real price.

Table 1
Death rates (1‰) and excess death rates (1‰) in the sampled provinces.

Provinces	Death rates				Excess death rates		
	1956–1958	1959	1960	1961	1959	1960	1961
Liaoning	8.27	11.80	11.50	17.50	3.53	3.23	9.23
Heilongjiang	9.90	12.76	10.52	11.13	2.86	0.62	1.23
Jiangsu	10.90	14.60	18.40	13.40	3.70	7.50	2.50
Shandong	12.33	18.20	23.60	18.40	5.87	11.27	6.07
Henan	12.83	14.10	39.60	10.20	1.27	26.77	−2.63
Hubei	10.01	14.49	21.21	9.08	4.48	11.20	−0.93
Hunan	11.19	12.99	29.42	17.48	1.80	18.23	6.29
Guangxi	12.18	17.49	29.46	19.50	5.31	17.28	7.32
Guizhou	13.57	20.30	52.30	23.30	6.73	38.73	9.73
Nation	11.39	14.59	25.43	14.24	3.20	14.04	2.85

Source: China Compendium of Statistics 1949–2008 (National Bureau of Statistics of China, 2010).
Note: Excess death rates are calculated as the difference between death rates in the famine year and the average of the death rates in 1956–1958.

where lnY_{ijct} represents the logarithm of household food waste or calorie loss per capita in survey year t for household i whose head was born in province j and age cohort c. EDR_j is the excess death rate for birthplace j in 1960, the worst year of the famine.[2] This is the proxy variable for famine severity in province j where the household head was born. The birth year and the birthplace jointly determine whether the household head was exposed to the famine shock and the severity of that shock. $cohort_{ic}$ is a dummy variable indicating whether the head of household i was born in a certain cohort c ($c = 1, \ldots, 11$). For the sake of analysis, sampled households are divided into age cohorts every four years.[3] Note that the interaction term of the EDR_j and the 1970–77 cohort is dropped. α_j is the birthplace fixed effect, which absorbs all time-invariant differences across provinces. β_c is a cohort fixed effect, which controls for all changes across cohorts that affect all provinces similarly. δ_t is the survey year fixed effect. For example, if regions with radical institutions are more prone to famine and these institutions do not change over a short period of time, then differences in institutional radicalism can be controlled by birthplace fixed effects (Kung & Chen, 2011; Meng & Qian, 2009).

Because our identification relies on a cohort DID strategy, a potential concern is confounding factors. Fig. A2 points to a clear positive relationship between birth year of sampled household heads and the corresponding household food waste per capita in the survey year. Therefore, we additionally control the time trend *Trend* in Eq. (10) to alleviate potential age effects.

The main parameters of interest are γ_c ($c = 1, \ldots, 11$), which are the coefficients of the interaction terms between EDR_j and $cohort_{ic}$. These coefficients capture the differential effect of famine experience on household food waste and calorie loss per capita later in life. In particular, we hypothesize that the effect of famine experience in early life on the household's food waste and calorie loss later occurs mainly for adolescent cohorts (who were 13–25 years old when the famine occurred) considering their corresponding deeper famine memory.[4] ε_{ijc} is the error term, which is clustered at the provincial level. Following Cameron, Colin, and Douglas (2008), we address the small sample bias in the clustered standard errors by calculating p values derived from wild bootstraps.

5. Data and descriptive statistics

5.1. Data source and samples

This paper mainly uses the dataset from the China Health and Nutrition Survey (CHNS), which is longitudinal and includes ten waves covering 1989–2015 to date. The survey took place over a 7-day period using a multistage, random cluster process to draw samples that varied substantially in geography, economic development, public resources, and health indicators. The CHNS mainly focused on the effects of socioeconomic changes on health and nutritional status in China and collected information on food waste only in the 2004, 2006, and 2009 waves. The modules recording food waste were consistent among the three waves, which facilitated our identification strategy. During the 2004–2009 waves, the CHNS collected data in 9 provinces: Guangxi, Guizhou, Henan, Hubei, Hunan, Jiangsu, Liaoning, Shandong, and Heilongjiang.

As the severity of the 1959–1961 Great Famine across the regions was predetermined before the survey years and arguably orthogonal to individual and family characteristics by age cohorts, which may affect food waste, the 1959–1961 Great Famine allows

[2] Following Chen and Zhou (2007), the excess death rate is used to proxy famine severity and allows variation in famine severity across provinces. The excess death rate is defined as the difference between the death rate in the famine year and the average death rate for three years before the 1959–1961 Great Famine. The data on death rates during the famine period 1956–61 are calculated according to the China Compendium of Statistics 1949–2008 (NBS, 2010), which is reported in Table 1.

[3] The age cohorts are as follows: $cohort_{ic}$ ($c = 1, \ldots, 11$) represents the head of household i born before 1930, 1931–34, 1935–38, 1939–42, 1943–46, 1947–50, 1951–54, 1955–58, 1959–61, 1962–65, and 1966–69, respectively. We also use alternative cohort widths in the robust check analysis to enhance the robustness of our main results.

[4] Adolescence is a transitional period for children to change to their adult roles. During this period, the external environment can have profound influences on the formation of people's preferences and beliefs and on their behavioral choices in adulthood, as Becker (1992) argues.

Table 2
Descriptive statistics for the variables.

Variable	Variable definition	Mean	S.D.
Dependent variable			
FWP	Quantity of household food waste per capita over 3 days (g)	122.410	177.540
CLP	Household calorie loss per capita over 3 days (kcal)	116.950	230.550
Characteristics of the household head			
Age	Age of the household head (years)	54.090	12.280
Gender	Gender of the household head (1 = male; 0 = female)	0.882	0.323
Education	Years of education (years)	8.409	3.776
Hukou	Registration (1 = urban; 0 = rural)	0.426	0.495
Work status	Whether he/she is working (1 = yes; 0 = no)	0.658	0.474
Work intensity	1 = light; 2 = moderate; 3 = heavy	1.965	0.949
DKI	Dietary knowledge index	5.585	3.665
Household characteristics			
Log(income)	Natural logarithm of family income per capita inflated to 2015 (yuan)	8.668	1.466
Family size	Number of household members subject to OECD standard	2.424	0.831
Proportion(≤14)	Proportion of household members aged 14 and under	11.020	17.849
Proportion(≥60)	Proportion of household members aged 60 and above	24.921	38.842
Community characteristics			
UDI	Urbanization development index	64.740	20.200
Vegetable price	Price of vegetables at the community level (yuan/jin)	1.291	0.565
Cereal price	Price of cereals at the community level (yuan/jin)	4.145	0.872
Chicken price	Price of chicken at the community level (yuan/jin)	17.690	5.846
Pork price	Price of pork at the community level (yuan/jin)	21.260	4.156
Observations		9560	

Source: Authors' calculation using the CHNS data (2004–2009).
Note: The variable family size is computed according to the OCED standard: the household head in the household has a weight of 1, each additional adult aged 14 and over has a weight of 0.5, and each child aged under 14 has a weight of 0.3 (OECD, 2021). 1 jin =0.5kg. Standard deviations are reported in parentheses. Differences are t-test results of means. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

us to separate the sample into treatment and comparison groups. A subsample born before 1962 is categorized as the treatment group, and the comparison group is derived from subsamples born in 1962 and after. After dropping the samples with missing information, the final samples used in this paper include 9651 households from the 2004, 2006 and 2009 waves whose heads were born between 1922 and 1977.

5.2. *Descriptive statistics*

Numerous studies have validated the reliability of the quality of food waste modules in the CHNS (He et al., 2018; Min, Wang, & Yu, 2021). To ensure the quality of the data, the CHNS enumerators recorded food consumption during a period of three randomly selected consecutive days from Monday to Sunday; thus, the measurements were spread over the whole week. Furthermore, for each food item consumed at home, the CHNS also recorded how much of it was wasted in grams. This enabled us to generate one of the dependent variables: household food waste per capita (g/3 days).

In addition, we employed the food code of wasted food along with nutritional content information on various foods provided by the China Food Consumption Table (Min et al., 2021; Tian & Yu, 2015; Yang, Wang, & Pan, 2002) to calculate wasted food in caloric units (kcal/3 days) as the other dependent variable in this study.[5] The calorie loss measurement of diverse wasted foods appears to be a good indicator that is important for understanding nutrition improvement (WHO, 2019).

Table 2 reports the definition and descriptive statistics for the two dependent variables. On average, the household food waste per capita over 3 days was approximately 122 g, corresponding to a household calorie loss of 117 kcal per capita over 3 days. The control variables include the individual characteristics of the household heads (age, age squared, gender, education, *hukou*, work status, work intensity and dietary knowledge index), household characteristics (logarithm of family income per capita, family size and family age structure variables) and community characteristics (the price of cereals, vegetables, pork, and chicken and urbanization development index) (Min et al., 2021; Ren, Li, & Wang, 2019).

To illustrate the role of famine experience, we divide survey provinces evenly into high- and low-EDR provinces.[6] Table 3 presents

[5] The nutritional content of food includes calories, protein, fat, carbohydrates, and other nutritional elements. Calories are widely recognized as a primary nutrition metric because they reflect the energy from food used to support physical functions.

[6] We divide the high- and low-EDR provinces according to the EDR of 1960 in Table 1. The high-EDR provinces include Heilongjiang, Liaoning, Jiangsu, Hubei and Shandong, while the low-EDR provinces include Guangxi, Hunan, Henan and Guizhou.

Table 3
Comparisons for the variables between high- and low-EDR provinces.

	Full sample			Born in 1922–61			Born in 1962–77		
	High EDR province	Low EDR province	Difference	High EDR province	Low EDR province	Difference	High EDR province	Low EDR province	Difference
	(1)	(2)	(1)–(2)	(3)	(4)	(3)–(4)	(5)	(6)	(5)–(6)
Household food waste per capita	111.956 (167.226)	131.460 (185.540)	−19.505***	104.975 (161.436)	125.128 (175.407)	−20.153***	135.003 (183.265)	147.299 (207.962)	−12.297
Household calorie loss per capita	117.599 (242.504)	117.114 (221.277)	0.485	112.281 (242.204)	111.729 (215.114)	0.552	135.157 (242.788)	130.583 (235.523)	4.574
Age	55.193 (12.431)	53.163 (12.086)	2.030***	60.076 (9.606)	58.709 (9.449)	1.367***	39.071 (4.625)	39.29 (4.328)	−0.219
Gender	0.857 (0.350)	0.902 (0.297)	−0.045***	0.841 (0.366)	0.886 (0.318)	−0.045***	0.911 (0.284)	0.942 (0.233)	−0.031***
Education	7.838 (3.759)	8.884 (3.720)	−1.046***	7.207 (3.810)	8.339 (3.913)	−1.132***	9.922 (2.681)	10.245 (2.751)	−0.323***
Hukou	0.363 (0.481)	0.476 (0.499)	−0.113***	0.368 (0.482)	0.499 (0.500)	−0.131***	0.345 (0.476)	0.419 (0.494)	−0.074***
Work status	0.642 (0.479)	0.680 (0.467)	−0.037***	0.566 (0.496)	0.574 (0.495)	−0.008	0.895 (0.307)	0.944 (0.230)	−0.049***
Work intensity	2.006 (0.942)	1.942 (0.954)	0.064***	1.958 (0.960)	1.883 (0.971)	0.075***	2.165 (0.863)	2.089 (0.894)	0.076**
DKI	5.095 (3.570)	5.982 (3.694)	−0.886***	4.94 (3.592)	5.892 (3.691)	−0.952***	5.608 (3.446)	6.206 (3.692)	−0.598***
Log(income)	8.398 (1.568)	8.895 (1.314)	−0.497***	8.32 (1.512)	8.843 (1.298)	−0.552***	8.656 (1.716)	9.027 (1.343)	−0.370***
Family size	2.643 (0.908)	2.253 (0.717)	0.391***	2.76 (0.973)	2.313 (0.800)	0.447***	2.258 (0.480)	2.102 (0.409)	0.156***
Proportion(≤14)	13.450 (20.370)	9.092 (15.300)	4.363***	10.611 (19.608)	5.876 (12.761)	4.735***	22.845 (20.009)	17.135 (17.942)	5.710***
Proportion(≥60)	24.790 (37.710)	25.024 (39.720)	−2.233	31.572 (40.427)	33.999 (43.464)	−2.427***	2.404 (8.226)	2.575 (9.673)	−0.171
UDI	63.408 (20.431)	65.693 (19.967)	−2.285***	63.109 (20.543)	66.858 (19.908)	−3.749	64.393 (20.038)	62.778 (19.822)	1.614*
Vegetable price	1.363 (0.557)	1.234 (0.564)	0.130***	1.359 (0.557)	1.235 (0.558)	0.124***	1.378 (0.556)	1.232 (0.579)	0.146
Cereal price	4.458 (0.826)	3.899 (0.830)	0.560***	4.468 (0.833)	3.876 (0.805)	0.593***	4.426 (0.803)	3.957 (0.886)	0.469***
Chicken price	20.340 (6.020)	15.590 (4.747)	4.750***	20.565 (6.059)	15.611 (4.624)	4.954***	19.612 (5.832)	15.548 (5.043)	4.064***
Pork price	21.875 (4.073)	20.795 (4.170)	1.080***	21.915 (4.110)	20.897 (4.179)	1.018***	21.745 (3.947)	20.54 (4.136)	1.204***
Observations	4224	5336		3242	3812		982	1524	

Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard deviations are reported in parentheses. Differences are t-test results of means. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

mean differences in household food waste and calorie loss per capita between high- and low-EDR provinces. Although there appears to be no significant difference in household calorie loss per capita between high- and low-EDR provinces, the average household food waste per capita of high-EDR provinces is significantly smaller than that of low-EDR provinces, ignoring the age cohort effects for the full sample. More interestingly, while the difference of average household food waste per capita between high- and low- EDR provinces is insignificant for the comparison group (born in 1962–77), the average household food waste per capita of high-EDR provinces is significantly smaller than that of low-EDR provinces for the treatment group (born in 1922–61). The pattern across EDR and treatment status provides useful inspiration for using cohort DID to further explore heterogeneous effects for different age cohorts in the following empirical analysis.

6. Results

6.1. Baseline results

Table 4 presents the results estimating the long-term effect of famine experience on household food waste and calorie loss per capita using the cohort DID estimation strategy of Eq. (10). Note that the dummy variables for birth cohorts and birthplaces are controlled in the regressions in Table 4, but their coefficients are not reported due to space limitations. We mainly report coefficients of the interaction terms between famine severity, EDR_j, and age cohort dummies, $cohort_{ic}$. We additionally address the small sample bias in

Table 4
Effects of famine experience on food waste and calorie loss per capita.

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(CLP)	IHS_CLP
	(1)	(2)	(3)	(4)
EDR_cohort2230	−0.021***	−0.023***	−0.014*	−0.017**
	(0.007)	(0.008)	(0.008)	(0.008)
	[0.003]	[0.003]	[0.062]	[0.043]
EDR_cohort3134	−0.018	−0.020	−0.018*	−0.021*
	(0.011)	(0.012)	(0.011)	(0.012)
	[0.110]	[0.103]	[0.089]	[0.077]
EDR_cohort3538	−0.017***	−0.019***	−0.018**	−0.020***
	(0.006)	(0.007)	(0.007)	(0.008)
	[0.008]	[0.006]	[0.012]	[0.009]
EDR_cohort3942	0.008	0.008	0.009	0.010
	(0.007)	(0.008)	(0.007)	(0.007)
	[0.291]	[0.301]	[0.149]	[0.155]
EDR_cohort4346	−0.024***	−0.028***	−0.019***	−0.023***
	(0.006)	(0.006)	(0.006)	(0.007)
	[0.000]	[0.000]	[0.001]	[0.001]
EDR_cohort4750	0.010	0.011	0.004	0.005
	(0.008)	(0.009)	(0.009)	(0.010)
	[0.233]	[0.250]	[0.608]	[0.593]
EDR_cohort5154	0.005	0.005	0.003	0.003
	(0.009)	(0.010)	(0.009)	(0.010)
	[0.605]	[0.628]	[0.745]	[0.760]
EDR_cohort5558	0.016**	0.018**	0.013*	0.015**
	(0.008)	(0.009)	(0.007)	(0.008)
	[0.041]	[0.040]	[0.054]	[0.049]
EDR_cohort5961	0.018*	0.020*	0.020*	0.022*
	(0.011)	(0.012)	(0.011)	(0.012)
	[0.091]	[0.092]	[0.071]	[0.072]
EDR_cohort6265	0.006	0.007	0.007	0.008
	(0.018)	(0.020)	(0.014)	(0.016)
	[0.740]	[0.732]	[0.598]	[0.606]
EDR_cohort6669	0.003	0.003	0.008**	0.008**
	(0.004)	(0.004)	(0.003)	(0.003)
	[0.384]	[0.437]	[0.012]	[0.018]
Control Variables	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	9615	9615	9617	9617
R^2	0.0802	0.0794	0.0816	0.0810

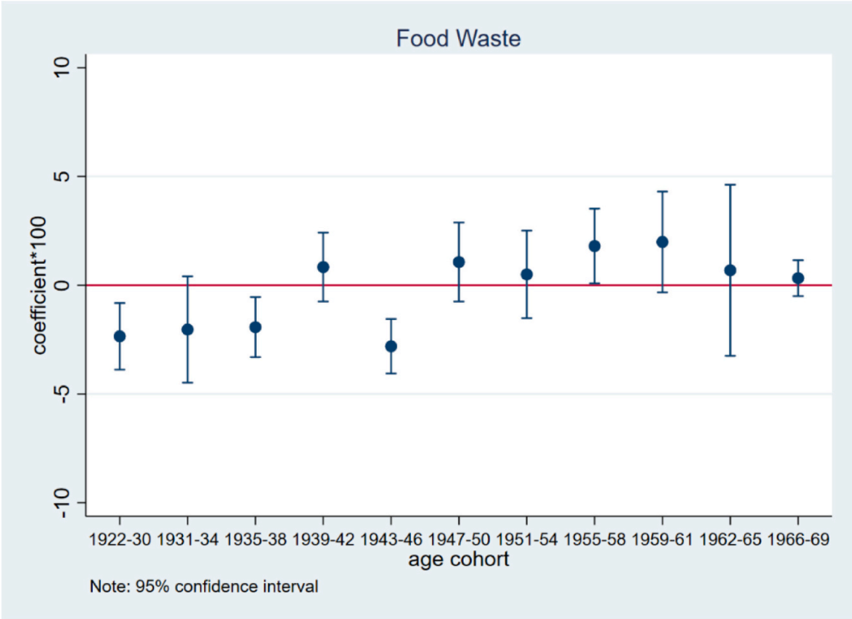
Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

the clustered standard errors by calculating p values derived from wild bootstraps (Cameron, Colin, & Douglas, 2008).

Column 1 of Table 4 reports the OLS results from estimating Eq. (10) using the logarithmic form of household food waste per capita as the dependent variable. We find that adolescent and adult exposure to the famine has a strong relationship with the late-life reduction of household food waste per capita. In particular, households whose heads were born in 1943–46 waste 2.43% less food per capita with every one-unit increase in EDR, contributing the largest part to the famine experience effect.[7] The salient effect of the 1943–46 cohort is consistent with psychological evidence on psychological vulnerability during adolescence, suggesting that extreme shocks such as hunger in adolescence are especially harmful to mental health (Andersen & Teicher, 2008; Cui, Smith, & Zhao, 2020).

However, infancy and early childhood exposure appears to have insignificant effects on household food waste in later life. Moreover, the 1955–58 and 1959–61 cohorts seem to be significantly positively affected by the famine experience. This may be explained by infantile amnesia due to the underdevelopment of the infant brain, which would preclude memory consolidation (Alberini & Travaglia, 2017; Blair & Raver, 2016). Thus, early episodic memories during infancy and early childhood may be

[7] There is also a growing literature examining long-term consequences of childhood hunger associated with large-scale wars (Kesternich et al., 2014, 2015). The significant negative effect of 1922–30 cohort and 1935–38 cohort may also be influenced by the Sino-Japanese war (1937–45) and civil war (1946–49), when 1922–30 cohort and 1935–38 cohort were mainly in their adolescence. Existing evidence has shown that agricultural productivity will be dropped due to large-scale war destruction of farm buildings and machinery, as well as death and displacement of workers. Breakdowns of trade and transport infrastructure was another reason for famine during wars.



A. Impacts of famine experiences on household food waste per capita

B. Impacts of famine experiences on household calorie loss per capita

Fig. 1. Impacts of famine experiences on household food waste and calorie loss per capita.
Note: The points in the figure represent the estimated effects of famine experiences on household food waste and calorie loss per capita, controlling for the full sets of cohort fixed effects, birthplace fixed effects, survey year fixed effects and time trend. The error bars represent the 95% confidence intervals.
(Source: Authors' calculation using the CHNS data (2004–2009).)

inaccessible or dispensable to adult behaviors. Another possible reason is that when experiencing the shock of food shortage, parents ration limited food among their children. The distribution of food resources among children is therefore prioritized to infants and young children, while older children (such as the 1943–46 cohort) are likely to suffer more because they can help support the family during lean times. This finding shows a striking consistency with hunger episode evidence from Cui et al. (2020), who found that the gender-specific effect on the cognitive consequences of hunger episodes is mainly by hunger at age 13–17, while there is no significant

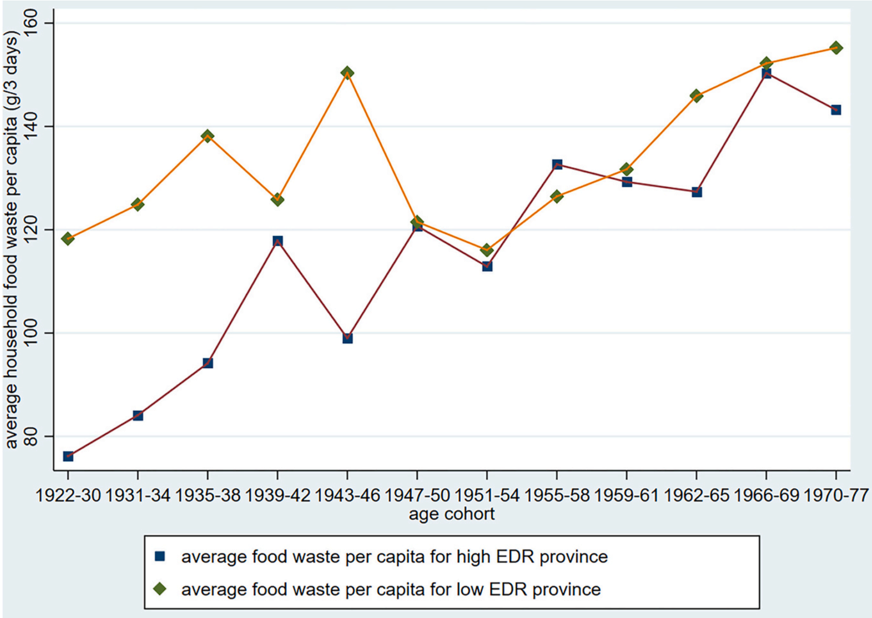


Fig. 2. Parallel trend test.
(Source: Authors' calculation using the CHNS data (2004–2009).)

impact on this gender difference from hunger for children under the age of 5.

Given that the dependent variable is censored due to zero values, we use the inverse hyperbolic sine (IHS) function of household food waste per capita as the dependent variable in column 2 of Table 4. The results of the Tobit model specification are also conducted as robustness checks and reported in Appendix Table A1.[8] Again, the effects of the famine experience across different age cohorts are similar to the results in column 1. The famine experience significantly reduces later-life food waste for households whose heads were born before 1946, and the adverse effects remain largest for the 1943–46 cohort. We additionally explain this in Fig. 1A by showing the estimated coefficients of column 2. There is a prominent pattern in which adolescent famine experience exerts long-term effects on household food waste behavior. Moreover, we complement our analysis by substituting birth-year fixed effects for cohort fixed effects. The results are shown in Appendix Table A2 and are consistent with the main results in Table 4.

Turning to the household calorie loss per capita, the results in columns 3–4 also show a striking consistency with the results in columns 1–2.[9] For households whose heads were born in 1943–46, every one-unit increase in EDR significantly reduces household food waste per capita by 1.95%–2.27% in later life. We also display the estimated coefficients of column 4 in Fig. 1B and observe a clear turning point for people born in 1943–46. This implies that other things being equal, households whose heads experienced more severe hunger during adolescence or adulthood lost fewer calories per capita in later life. These prominent results provide strong evidence for the proposition in Section 3 and confirm that adolescent and adult exposure to famine has a strong relationship with the later-life reduction of household food waste per capita.[10] Furthermore, this finding provides new evidence of the relatively low probability of wasting food among elderly people (Smith & Landry, 2020; Stancu et al., 2016).

6.2. Parallel trend test

The key assumption of the DID estimation strategy is the parallel trend assumption before treatment. This requires that in the absence of the 1959–1961 Great Famine, there should be no significant difference in the amount of household food waste per capita across age cohorts, which implies that there are no omitted variables that affect both EDR and the amount of household food waste per capita. While the counterfactual is not observed, we provide some evidence to support the parallel trend assumption. Fig. 2 reveals two

[8] The IHS function is similar to logarithmic transformation but is well defined for values of zero. Thus, we use both the logarithmic form and the IHS function of food waste and calorie loss in all regressions.

[9] When the dependent variable is calorie loss per capita, the estimated coefficient of individuals born in 1966–69 is significantly positive, but its magnitude is very small. We suggest that the less robust estimates for this age cohort are due to the relatively low number of this age cohort.

[10] We are grateful for helpful comments from the editor and anonymous referees. To address the concern about nonrandom cohort division, we have conducted the robustness check of the results by dividing age cohorts into every 5 and 3 years, respectively. When dividing by 5 years, the coefficients of 1922–26 cohort, 1927–31 cohort, 1932–36 cohort, 1942–46 cohort are significantly negative. When dividing by 3 years, the coefficients of 1929–31 cohort, 1932–34 cohort, 1935–37 cohort, 1941–43 cohort and 1944–46 cohort are significantly negative. The results are very consistent with our main results by dividing cohorts every 4 years and upon request.

Table 5
Placebo test.

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(FWP)	IHS_FWP
	(1)	(2)	(3)	(4)
EDR_birth62	0.014	0.015	0.015	0.016
	(0.024)	(0.027)	(0.017)	(0.020)
	[0.555]	[0.576]	[0.372]	[0.417]
EDR_birth63	−0.010	−0.010	−0.006	−0.007
	(0.027)	(0.030)	(0.022)	(0.025)
	[0.712]	[0.733]	[0.781]	[0.794]
EDR_birth64	−0.003	−0.003	0.005	0.006
	(0.014)	(0.016)	(0.013)	(0.015)
	[0.835]	[0.873]	[0.678]	[0.684]
EDR_birth65	0.016*	0.018*	0.012	0.014
	(0.009)	(0.011)	(0.009)	(0.010)
	[0.093]	[0.096]	[0.158]	[0.141]
EDR_birth66	0.003	0.002	0.003	0.003
	(0.007)	(0.008)	(0.009)	(0.009)
	[0.708]	[0.763]	[0.721]	[0.742]
EDR_birth67	−0.007	−0.009	0.001	−0.000
	(0.019)	(0.021)	(0.021)	(0.022)
	[0.717]	[0.669]	[0.946]	[0.989]
EDR_birth68	0.009	0.010	0.012	0.014
	(0.010)	(0.011)	(0.012)	(0.014)
	[0.341]	[0.372]	[0.308]	[0.302]
EDR_birth69	0.010	0.011	0.020	0.022
	(0.015)	(0.016)	(0.014)	(0.016)
	[0.525]	[0.505]	[0.154]	[0.155]
Control Variables	Yes	Yes	Yes	Yes
Birth year fixed effects	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	2518	2518	2523	2523
R^2	0.1154	0.1154	0.1199	0.1199

Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

important patterns that support the use of DID. First, the average household food waste per capita is nearly identical between high- and low-EDR provinces during and after the famine period. Second, the trends in household food waste per capita between high- and low-EDR provinces are nearly parallel after the famine. In contrast, the average household food waste per capita in high-EDR provinces is much lower than that in low-EDR provinces before the famine and shows great divergence, particularly the 1943–46 cohort, which is consistent with the basic results in Table 4 and Fig. 1.

The interpretation of Fig. 2 is supported by placebo test results using post-treated subsamples (Chen, Fan, Gu, & Zhou, 2020; Chen & Zhou, 2007). Specifically, we use subsamples born between 1962 and 1977 (i.e., after the 1959–1961 Great Famine) to test the parallel trend. If the effect of the famine on food waste and calorie loss estimated in Table 4 is caused by omitted variables, these omitted variables will continue to play a role after the famine. If the parallel trend assumption can be satisfied, the coefficients estimated from the post-famine subsample should be statistically insignificant or have opposite signs.

We use the age cohort born in 1962–69 as the treatment group and the cohort born in 1970–1977 as the comparison group to examine whether the famine affected the household food waste and calorie loss per capita of those born in 1962–69 who were not actually exposed to the famine. Neither test in Table 5 shows negative signs of statistical significance for these age cohorts regardless of which dependent variable is employed. This suggests that the famine severity in each province is less likely to be related to omitted variables that can also affect household food waste behavior, indicating that the underlying parallel trend assumption of DID is satisfied.

6.3. *Robustness check*

6.3.1. *Migration analysis*

The existing literature has emphasized that population migration is a serious challenge to identifying the long-term effects of the famine (Chen & Zhou, 2007; Kim et al., 2014; Meng et al., 2015). If there are large amounts of migrants across regions during or after the 1959–1961 Great Famine, there can be no accurate correlation between food waste behavior in later life and the severity of the famine in early life, introducing measurement error that may bias the estimation toward zero (Meng & Qian, 2009). To solve this potential bias, this paper specifically uses the EDR of the birthplace of the household head rather than the current residential province,

Table 6
Robustness check using non-migration subsamples.

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(CLP)	IHS_CLP
	(1)	(2)	(3)	(4)
EDR_cohort2230	−0.023**	−0.026**	−0.016	−0.019*
	(0.009)	(0.010)	(0.010)	(0.011)
	[0.013]	[0.012]	[0.114]	[0.089]
EDR_cohort3134	−0.019*	−0.021*	−0.019*	−0.022*
	(0.011)	(0.013)	(0.011)	(0.012)
	[0.098]	[0.091]	[0.076]	[0.065]
EDR_cohort3538	−0.014**	−0.017**	−0.015***	−0.017***
	(0.006)	(0.007)	(0.005)	(0.006)
	[0.020]	[0.016]	[0.004]	[0.003]
EDR_cohort3942	0.010	0.011	0.012*	0.013*
	(0.007)	(0.008)	(0.006)	(0.007)
	[0.150]	[0.162]	[0.054]	[0.060]
EDR_cohort4346	−0.028***	−0.032***	−0.022***	−0.026***
	(0.007)	(0.008)	(0.007)	(0.007)
	[0.000]	[0.000]	[0.001]	[0.001]
EDR_cohort4750	0.009	0.009	0.004	0.005
	(0.008)	(0.009)	(0.009)	(0.010)
	[0.282]	[0.300]	[0.646]	[0.633]
EDR_cohort5154	0.004	0.004	0.003	0.003
	(0.009)	(0.010)	(0.009)	(0.010)
	[0.645]	[0.667]	[0.748]	[0.766]
EDR_cohort5558	0.016**	0.018**	0.013**	0.015**
	(0.007)	(0.008)	(0.006)	(0.007)
	[0.030]	[0.029]	[0.039]	[0.035]
EDR_cohort5961	0.017	0.018	0.019*	0.021
	(0.011)	(0.012)	(0.011)	(0.013)
	[0.130]	[0.132]	[0.100]	[0.102]
EDR_cohort6265	0.006	0.007	0.007	0.008
	(0.017)	(0.020)	(0.013)	(0.015)
	[0.729]	[0.723]	[0.566]	[0.578]
EDR_cohort6669	0.004	0.004	0.009***	0.009***
	(0.004)	(0.004)	(0.003)	(0.004)
	[0.310]	[0.366]	[0.005]	[0.009]
Control Variables	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	9366	9366	9366	9366
R^2	0.0853	0.0844	0.0858	0.0852

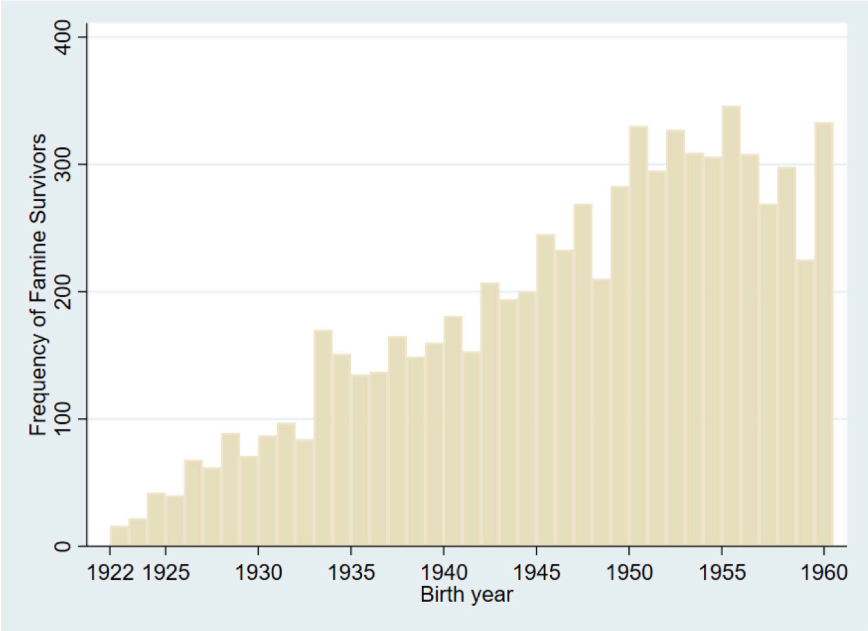
Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

which is expected to minimize the impact of selective cross-province migration in the abovementioned estimations. In addition, Table A3 reveals that 97.4% of the household heads in our sample were born and resided in the same province at the time of the survey year, which means that migration across provinces is a minor problem, in line with the findings of Zhao (2001).

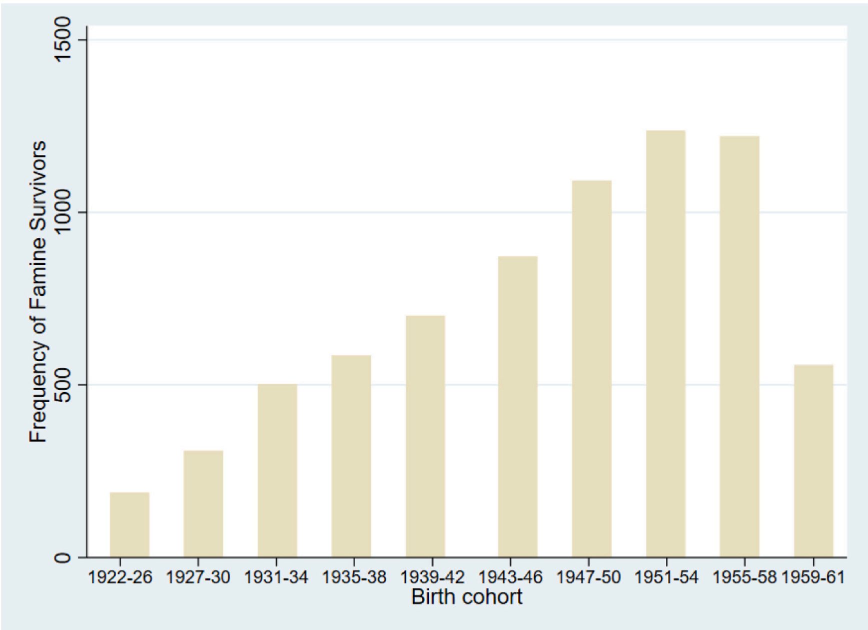
Before the 1990s, there were severe restrictions on migration because of the household registration system in China. The household registration system in 1958 decreed that all migration was subject to approval by the local government (Chen et al., 2020). Rural residents faced even more restrictions on migration across localities during the most restrictive periods of China's centrally planned economy (Chen & Zhou, 2007; Meng et al., 2015).

In spite of this, we further conduct robustness checks related to migration problems in two ways. First, if migration households differ systematically from non-migration households, the effect of early-life famine experience on household food waste behavior in late life will be biased. To address this concern, we conduct an attrition analysis to test whether the migration status of sampled households varies by age cohorts. A clear feature in Fig. A3 is that there are no significant differences in migration status across all age cohorts, suggesting that migration households are similar to non-migration households in age structure.

Second, we focus on non-migration subsamples to check the robustness of our main results. Again, the results of Table 6 are consistent with our findings in Table 4. The estimated coefficient for those born in 1943–46 is slightly larger than its counterparts in Table 4, while that for those born in 1935–38 decreases slightly. Interestingly, the pattern in which famine experience in adolescence exerts long-term effects on household food waste behavior seems more prominent when restricted to non-migration samples.



A. The distribution of famine survivors by birth years

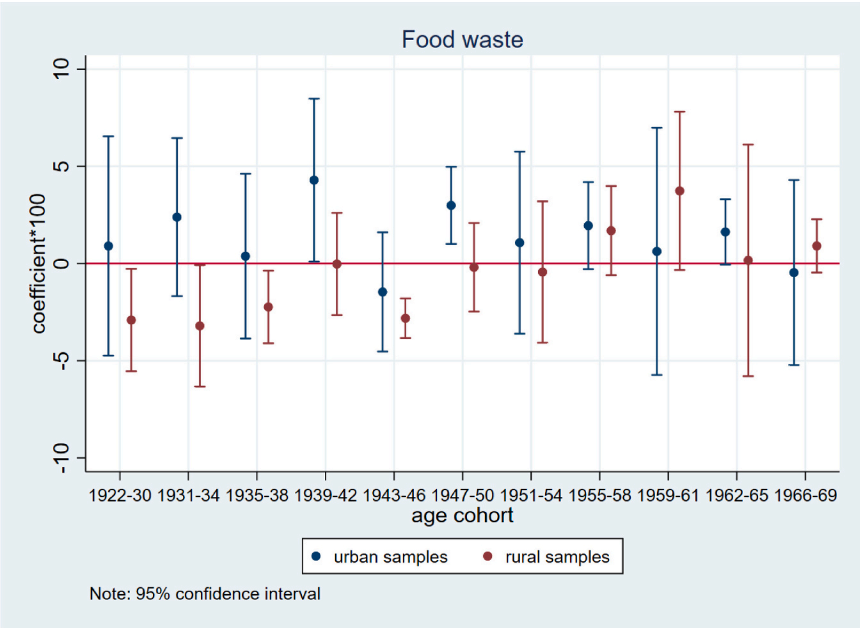


B. The distribution of famine survivors by birth cohorts

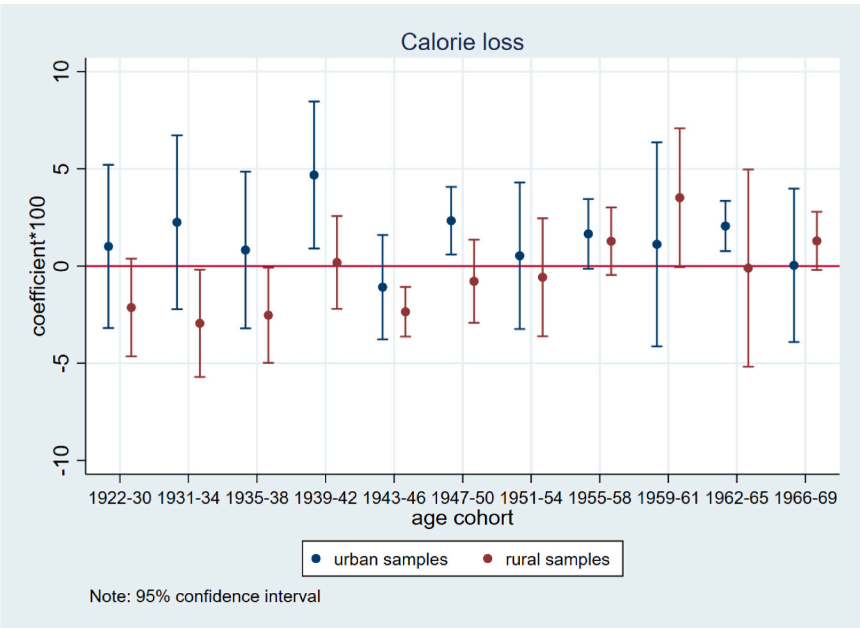
Fig. 3. The distribution of famine survivors.
Note: We restrict data to households whose heads were born before 1962 and famine survivors here refer to the household heads.
(Source: Authors' calculation using the CHNS data (2004–2009).)

6.3.2. Attrition analysis

Research about the impacts of famine always faces the challenge of selection bias in the identification strategy. That is, the observed samples are selected from the famine (Chen & Zhou, 2007; Meng et al., 2015). For example, if people who were healthier were more likely to survive during the famine, on average, they may also tend to have a longer longevity. In addition, empirical studies have shown that elderly people are less likely to discard food (Smith & Landry, 2020; Stancu et al., 2016). In caveat, if famine survivors are mainly elderly, the true effect of the 1959–1961 Great Famine on household food waste and calorie loss per capita could be overestimated.

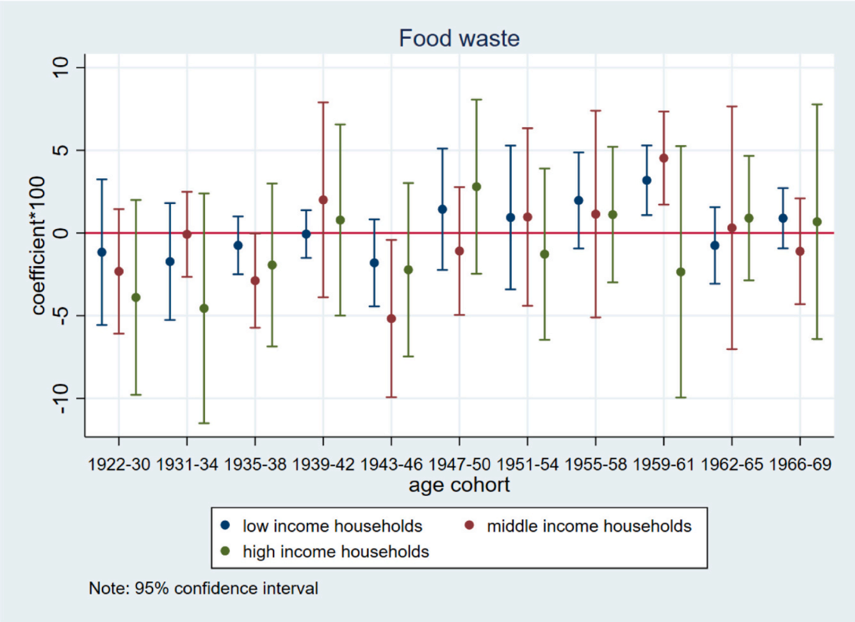


A. Heterogeneous impacts of famine experiences on household food waste per capita

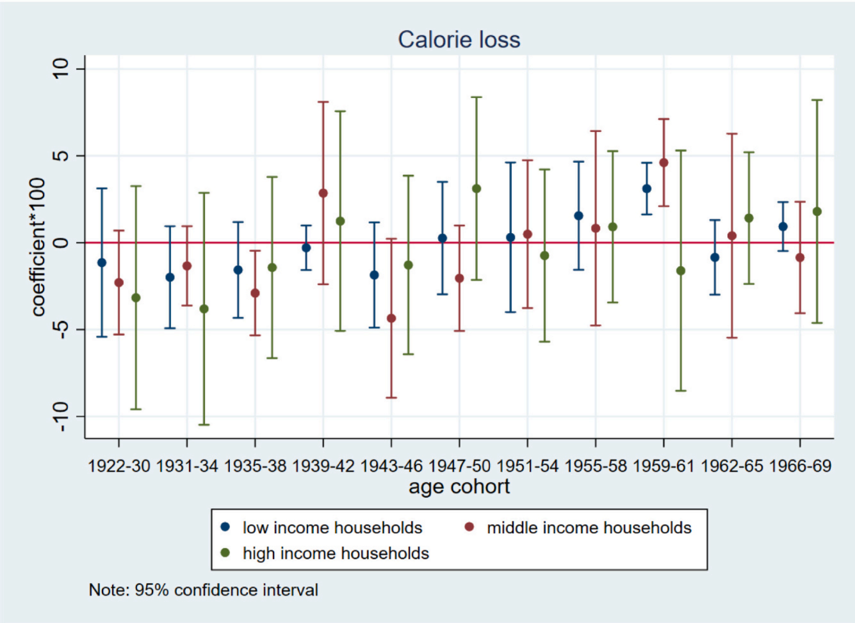


B. Heterogeneous impacts of famine experiences on household calorie loss per capita

Fig. 4. Heterogeneous effects of famine experiences by residence.
Note: We estimate the effects of household samples by residence separately. The points in the figure represent the estimated effects of famine experiences on household food waste and calorie loss per capita, controlling for the full sets of cohort fixed effects, birthplace fixed effects, survey year fixed effects and time trend. The error bars represent the 95% confidence intervals.
(Source: Authors' calculation using the CHNS data (2004–2009).)



A. Heterogeneous impacts of famine experiences on household food waste per capita



B. Heterogeneous impacts of famine experiences on household calorie loss per capita

Fig. 5. Heterogeneous effects of famine experiences by household income per capita.
Note: We estimate the effects of household samples with different household income levels separately. The points in the figure represent the estimated effects of famine experiences on household food waste and calorie loss per capita, controlling for the full sets of cohort fixed effects, birthplace fixed effects, survey year fixed effects and time trend. The error bars represent the 95% confidence intervals.
(Source: Authors' calculation using the CHNS data (2004–2009).)

Fig. 3 presents the distribution of the household heads who were famine survivors by birth years and age cohorts (born before 1962), suggesting that the sample size does not decrease monotonically with the birth year or age cohorts. The sample size reaches its peak in 1951–54 and 1955–58 cohorts, while there is a plummet during the 1959–1961 Great Famine, which is also in line with existing evidences (Ashton et al., 1984; Gørgens et al., 2012; Lin & Yang, 1998). This suggests that the age distribution caused by selection bias cannot be mistakenly interpreted as the effect of the 1959–1961 Great Famine on household food waste behaviors.

6.4. Heterogeneity analysis

6.4.1. Rural-urban difference

In this part, we explore two potential heterogeneous effects of early life famine experiences on household food waste behaviors. First, we investigate whether the impact of early life famine experiences varies by household heads' residence status. We conduct OLS estimations separately by the residence status of the household head in the survey year, while the regression specifications remain the same as the baseline estimations. The estimated coefficients of interest are displayed in Fig. 4. There is a clear pattern in which the main effects of early life famine experiences are prominent for rural households whose heads were born before 1946. In particular, the 1959–1961 Great Famine has a significant effect on the reduction of household food waste and calorie loss per capita for households residing in rural areas for those born in 1922–30, 1931–34, 1935–38 and 1943–46, but is insignificant for their urban counterparts.

There are several possible reasons why early life famine experience tends to entail a salient effect on the reduction of food waste and calorie loss for rural residents compared to urban residents. First, the death rate in rural areas was much higher than that in urban areas during the famine, indicating that famine mainly affected rural residents (Kim et al., 2014; Lin & Yang, 2000). Over-procurement of grain from rural areas in favor of urban residents deteriorate famine intensity in rural areas (Meng & Qian, 2009). Second, a large number of rural households consume considerable amounts of food that they produce themselves (Park, 2006; Sibhatu & Qaim, 2018). Evidence shows that this pattern can lead to deviations in the "pre-committed quantity", which is often larger than the quantity the household needs to consume and, in turn, may lead to more food waste (Huang, Antonides, Kuhlgatz, & Nie, 2018; Piggott, 2003). Another plausible explanation is that households living in urban areas have higher education levels and dietary knowledge, which indicates that these households are more likely to have scientific and reasonable dietary habits and to be more rational in their food consumption-waste decisions (Min et al., 2021).

Instead, urban residents seem to be spared the famine experience effect. That is, famine exposure appears to have significantly positive effects on household food waste in later life for urban households whose heads were born in 1939–42, 1947–50 and 1955–58, while the estimated coefficients are negative or insignificantly positive for their rural counterparts. The possible reason may be that the positive effects of dining out on food waste offset the negative effects of the 1959–1961 Great Famine in the city. Urban residents have more opportunities to dine out compared with rural counterparts, which is often accompanied by more food waste (Xu et al., 2020). In addition, the opportunity cost of time for producing meals at home in cities may also account for the positive effects for urban households (Bai, Wahl, Lohmar, & Huang, 2010; Becker, 1965).

6.4.2. Heterogeneous effects by household income

We examine the heterogeneous effects by dividing household income per capita in the survey years into three terciles. The results are presented in Fig. 5. Interestingly, we find that the early life famine experience effects on household food waste behavior in later life are mainly restricted to households in the middle-income group. Among this group, in particular, the 1959–1961 Great Famine has significant effects on the reduction of household food waste and calorie loss in later life for those born in 1935–38 and 1943–46 but insignificant effects for their low-income and high-income counterparts. The results indicate that early life famine experience effects on household food waste behavior in later life are unequally distributed among households with different income levels.

In general, changes in income can often translate into large changes in household food consumption behaviors (Behrman & Deolalikar, 1987; Skoufias, Di Maro, González-Cossio, & Ramirez, 2011). Households in the middle income quantile are in a diet transition period when they substitute away from cheap calorie-dense staples toward more expensive nutrient-dense foods (Meng, Gong, & Wang, 2009). In contrast, households in the low income quantile mainly rely on staple foods and the resulting lack of dietary diversity (Min et al., 2021). Those poorest individuals are more at risk of becoming hungry again and thus eat more and waste less as a type of precautionary measure (Kesternich et al., 2015).

Existing evidence has shown that high-income households tend to waste a relatively larger amount of food in the developed countries, which seems not true in the context of our study (Barrera & Hertel, 2021; Zhou & Yu, 2015). Our data illustrates that the average amount of household food waste per capita in low-, middle-, and high-income households is about 117, 134 and 128 g, respectively; while the average amount of household food consumption per capita in these three groups is about 3455, 3766 and 3890 g respectively. This suggests that household consumption per capita is a monotonically increasing function of income, while household food waste per capita shows an inverted U-shape.

6.5. Mechanism analysis

Why does early life famine experience exert long-term effects on household food waste behaviors in later life, especially for cohorts exposed to famine during prime-age adulthood? Memory utility theory argues that current utility depends not only on current consumption but also on memory utility produced by past consumption (Bao, Dai, & Yu, 2018; Gilboa, Postlewaite, & Samuelson, 2016). Individuals who experienced the 1959–1961 Great Famine during adolescence were deeply impressed by hunger and had episodic fear memories of food shortages, which induced higher memory utility. Here, the role of memory utility is consistent with the role of

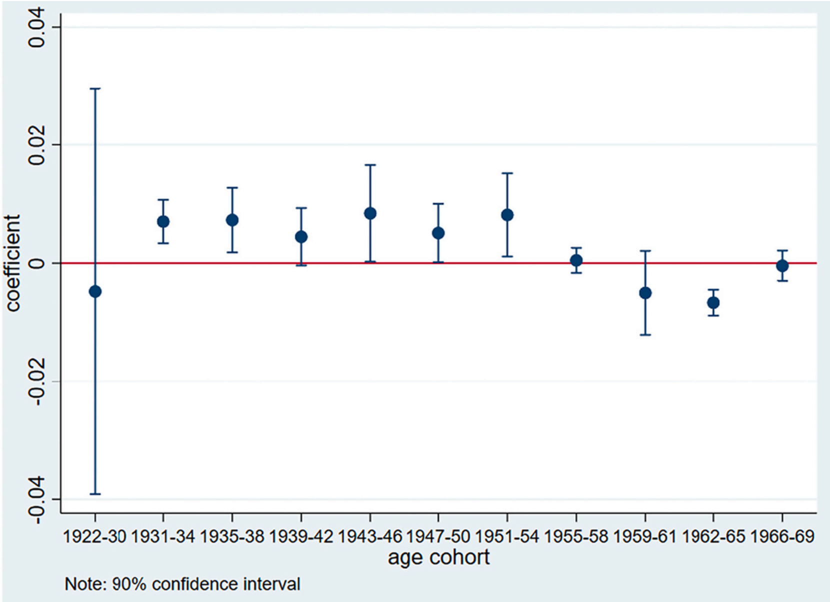


Fig. 6. Mechanism analysis.
Note: The points in the figure represent the estimated effects of famine experiences on the household saving rate, controlling for the full sets of cohort fixed effects, birthplace fixed effects and the time trend. Standard errors are calculated using the wild cluster bootstrap method.
(Source: Authors' calculation using the CFPS data (2010).)

experience value in the theoretical model in Section 3. Even if current household income or wealth is greatly improved, the frugal habits formed during adolescence continue to influence consumption behavior. Here, we employ the household saving rate to identify the possible mechanism and to explain why adolescent famine experiences contribute the most to household food waste behavior in later life.

To construct a variable for the household saving rate, we use the 2010 wave of China Family Panel Studies (CFPS), which has rich and detailed financial information on household income, disposable income, and different types of consumption expenditure.[11] To reduce the sensitivity of the regression results to outliers, we refer to the methods of Chamon and Prasad (2010), who define the household saving rate as the natural logarithm of household disposable income divided by household consumption expenditure.[12] Moreover, we retain the birthplace provinces used in the baseline regression analysis of the CHNS data.[13] Descriptive statistics for this part are reported in Appendix Table A6.

In Fig. 6, we plot the effects of famine experiences on household saving rates across all age cohorts. There is a strong positive correlation between famine severity and the household saving rate for most cohorts exposed to famine. Specifically, the 1959–1961 Great Famine had a significantly positive effect on household saving rates for prime-age adults who were exposed to the famine. This provides a possible explanation for the effect of early life famine experience on the reduction of household food waste in later life: cohorts that experienced the 1959–1961 Great Famine during adolescence developed a deep memory of the famine that influenced their saving rates through "famine memory utility" (Cui et al., 2020). This indicates that these age cohorts tend to have stronger risk aversion as well as stronger precautionary saving motivations and behaviors, helping to reduce food waste in late life (Gilboa et al., 2016; Kahneman & Tversky, 1979, 1988). Exposure to famine in late childhood can have salient effects on preference formation, consistent with behavioral economic evidence (Cheng & Zhang, 2011; Kesternich et al., 2015).

7. Conclusion and discussion

This paper builds the link between the 1959–1961 Great Famine and the observed food waste behavior of Chinese households in recent years. We argue that the 1959–1961 Great Famine may have a persistent effect and constitute one important explanation for the heterogeneous food waste behavior of Chinese households. The results reveal that other things being equal, individuals who

[11] The CHNS survey did not record enough information to support this test.
[12] Household disposable income does not include lump sum income such as compensation for demolition and land expropriation, and household consumption expenditure does not include the housing purchase expenditure. Considering that expenditures for medical care and education fluctuate greatly from year to year, this paper excludes these two special expenditures when calculating the household consumption expenditure.
[13] The CFPS 2012–2016 survey data exclude the consumption expenditure of family members who do not live at home but have economic ties with the family. Theoretically, the CFPS data of 2012–2016 cannot be used to accurately calculate the household consumption expenditure and household savings rate. Therefore, the mechanism analysis in this paper uses only the 2010 wave of the CFPS.

experienced the 1959–1961 Great Famine during adolescence show higher motivation to waste less food under the cohort-DID estimation framework. A possible explanation is that experiences in late childhood can profoundly influence the formation of consumers' preferences and consumption habits. As the generation that suffered from famine is gradually fading away, it can be plausibly expected that food waste will worsen in the future if no interventions are taken.

In contrast to the severe food loss and waste problems worldwide, there are still a large number of people in extreme poverty who lack access to adequate nutrition. At the time of this writing, the COVID-19 pandemic remains a serious threat to food security, nutrition and livelihood. Broadly speaking, this paper may shed light on how to improve the resilience of the food system when faced with extreme events. Although this paper focuses on a famine event in only one country, the results can also contribute to the understanding of the long-term consequences on economic behaviors of many types of economic shocks such as extreme climate events and pandemic outbreaks in other countries and can provide insights on how policymakers can implement feasible intervention programs to reduce food waste.

Declarations of interest

None.

Acknowledgments

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Appendix

Table A1
Robustness check by Tobit regression.

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(CLP)	IHS_CLP
	(1)	(2)	(3)	(4)
EDR_cohort2230	−0.038*	−0.043*	−0.032	−0.037
	(0.009)	(0.010)	(0.010)	(0.011)
	(0.022)	(0.024)	(0.020)	(0.023)
EDR_cohort3134	−0.031	−0.035	−0.033*	−0.038*
	(0.018)	(0.020)	(0.017)	(0.020)
	(0.019)	(0.022)	(0.018)	(0.021)
EDR_cohort3538	−0.027	−0.031	−0.029*	−0.033*
	(0.009)	(0.010)	(0.010)	(0.011)
	(0.019)	(0.021)	(0.017)	(0.019)
EDR_cohort3942	0.011	0.013	0.014	0.015
	(0.011)	(0.012)	(0.010)	(0.012)
	(0.016)	(0.017)	(0.015)	(0.017)
EDR_cohort4346	−0.042**	−0.048**	−0.037**	−0.042**
	(0.008)	(0.009)	(0.008)	(0.009)
	(0.017)	(0.019)	(0.015)	(0.018)
EDR_cohort4750	0.014	0.016	0.008	0.009
	(0.012)	(0.014)	(0.012)	(0.014)
	(0.015)	(0.017)	(0.014)	(0.016)
EDR_cohort5154	0.005	0.006	0.003	0.003
	(0.013)	(0.015)	(0.012)	(0.014)
	(0.015)	(0.017)	(0.014)	(0.017)
EDR_cohort5558	0.026*	0.029*	0.022	0.025
	(0.012)	(0.014)	(0.011)	(0.012)
	(0.015)	(0.017)	(0.014)	(0.016)
EDR_cohort5961	0.028	0.031	0.031	0.034
	(0.016)	(0.018)	(0.016)	(0.018)
	(0.021)	(0.024)	(0.021)	(0.022)
EDR_cohort6265	0.011	0.013	0.013	0.014

(continued on next page)

Table A1 (*continued*)

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(CLP)	IHS_CLP
	(1)	(2)	(3)	(4)
	(0.030)	(0.034)	(0.025)	(0.028)
	(0.016)	(0.018)	(0.015)	(0.017)
EDR_cohort6669	0.004	0.003	0.008	0.009
	(0.006)	(0.006)	(0.005)	(0.006)
	(0.019)	(0.020)	(0.017)	(0.019)
Control Variables	Yes	Yes	Yes	Yes
Birth year fixed effects	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	9615	9615	9617	9617
Pseudo R^2	0.0193	0.0184	0.0199	0.0190
Wald chi2	937.27	908.08	980.73	1033.72
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Source: Authors' calculation using the CHNS data (2004–2009).
Note: We probe the robustness of the estimate accuracy by clustering the standard errors at the provincial level and bootstrapping the standard errors with 1000 replications. These two types of standard errors are reported in parentheses below the estimated coefficients. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Table A2
Robustness check using birth-year fixed effects.

	Food waste		Calorie loss	
	Log(FWP)	IHS_FWP	Log(CLP)	IHS_CLP
	(1)	(2)	(3)	(4)
EDR_cohort2230	−0.024**	−0.028**	−0.017**	−0.020**
	(0.007)	(0.008)	(0.007)	(0.008)
	[0.001]	[0.001]	[0.020]	[0.012]
EDR_cohort3134	−0.019	−0.022	−0.018	−0.021*
	(0.010)	(0.012)	(0.010)	(0.011)
	[0.070]	[0.065]	[0.065]	[0.054]
EDR_cohort3538	−0.017**	−0.019**	−0.017**	−0.019**
	(0.005)	(0.006)	(0.006)	(0.006)
	[0.001]	[0.001]	[0.003]	[0.002]
EDR_cohort3942	0.007	0.007	0.009	0.010
	(0.007)	(0.008)	(0.006)	(0.007)
	[0.347]	[0.363]	[0.141]	[0.153]
EDR_cohort4346	−0.024***	−0.028***	−0.019**	−0.023***
	(0.006)	(0.006)	(0.006)	(0.007)
	[0.000]	[0.000]	[0.001]	[0.001]
EDR_cohort4750	0.009	0.010	0.004	0.005
	(0.008)	(0.009)	(0.008)	(0.009)
	[0.216]	[0.233]	[0.574]	[0.561]
EDR_cohort5154	0.003	0.003	0.001	0.001
	(0.009)	(0.010)	(0.009)	(0.010)
	[0.768]	[0.795]	[0.871]	[0.893]
EDR_cohort5558	0.015*	0.017*	0.013*	0.015*
	(0.008)	(0.009)	(0.006)	(0.007)
	[0.044]	[0.043]	[0.040]	[0.037]
EDR_cohort5961	0.018	0.020	0.021*	0.023*
	(0.011)	(0.012)	(0.011)	(0.012)
	[0.090]	[0.093]	[0.059]	[0.061]
EDR_cohort6265	0.005	0.005	0.007	0.007
	(0.018)	(0.020)	(0.013)	(0.015)
	[0.792]	[0.785]	[0.611]	[0.623]
EDR_cohort6669	0.005	0.005	0.009***	0.010***
	(0.003)	(0.004)	(0.003)	(0.003)
	[0.172]	[0.196]	[0.000]	[0.000]
Control Variables	Yes	Yes	Yes	Yes
Birth year fixed effects	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Observations	9615	9615	9617	9617
R^2	0.0853	0.0846	0.0864	0.0859

Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Table A3
The number of migration households and non-migration households.

Birthplace of household head	Household samples	
	Frequency	Percent
Non-migration households		
Liaoning	1085	11.04
Heilongjiang	1029	10.47
Jiangsu	1104	11.23
Shandong	1046	10.64
Henan	1043	10.61
Hubei	982	9.99
Hunan	1087	11.06
Guangxi	1094	11.13
Guizhou	1102	11.21
Migration households	256	2.60
Total	9828	100.00

Source: Authors' calculation using the CHNS data (2004–2009).

Table A4
Heterogeneity analysis by residence.

	Food waste				Calorie loss			
	Log(FWP)		IHS_FWP		Log(CLP)		IHS_CLP	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EDR_cohort2230	0.009	−0.026**	0.009	−0.029**	0.010	−0.018	0.010	−0.021*
	(0.026)	(0.012)	(0.029)	(0.013)	(0.019)	(0.011)	(0.021)	(0.013)
	[0.729]	[0.029]	[0.754]	[0.030]	[0.602]	[0.110]	[0.638]	[0.096]
EDR_cohort3134	0.021	−0.028**	0.024	−0.032**	0.020	−0.025**	0.023	−0.030**
	(0.019)	(0.014)	(0.021)	(0.016)	(0.021)	(0.012)	(0.023)	(0.014)
	[0.253]	[0.043]	[0.250]	[0.044]	[0.333]	[0.040]	[0.324]	[0.036]
EDR_cohort3538	0.004	−0.020**	0.004	−0.022**	0.008	−0.022**	0.008	−0.025**
	(0.019)	(0.009)	(0.022)	(0.010)	(0.018)	(0.011)	(0.021)	(0.012)
	[0.831]	[0.023]	[0.861]	[0.019]	[0.657]	[0.048]	[0.689]	[0.043]
EDR_cohort3942	0.038*	−0.000	0.043**	−0.000	0.042**	0.002	0.047**	0.002
	(0.020)	(0.012)	(0.021)	(0.013)	(0.017)	(0.011)	(0.019)	(0.012)
	[0.051]	[0.994]	[0.045]	[0.986]	[0.017]	[0.861]	[0.015]	[0.881]
EDR_cohort4346	−0.012	−0.025***	−0.015	−0.028***	−0.009	−0.020***	−0.011	−0.024***
	(0.014)	(0.005)	(0.016)	(0.005)	(0.012)	(0.006)	(0.014)	(0.007)
	[0.391]	[0.000]	[0.350]	[0.000]	[0.444]	[0.001]	[0.427]	[0.000]
EDR_cohort4750	0.027***	−0.002	0.030***	−0.002	0.020***	−0.007	0.023***	−0.008
	(0.009)	(0.010)	(0.010)	(0.012)	(0.008)	(0.010)	(0.009)	(0.011)
	[0.003]	[0.869]	[0.003]	[0.866]	[0.008]	[0.454]	[0.009]	[0.472]
EDR_cohort5154	0.010	−0.004	0.011	−0.004	0.005	−0.005	0.005	−0.006
	(0.021)	(0.017)	(0.024)	(0.019)	(0.017)	(0.014)	(0.019)	(0.015)
	[0.621]	[0.821]	[0.654]	[0.814]	[0.766]	[0.714]	[0.783]	[0.708]
EDR_cohort5558	0.018*	0.015	0.019*	0.017	0.015*	0.011	0.017*	0.013
	(0.010)	(0.010)	(0.011)	(0.012)	(0.008)	(0.008)	(0.009)	(0.009)
	[0.085]	[0.153]	[0.088]	[0.148]	[0.070]	[0.157]	[0.070]	[0.150]
EDR_cohort5961	0.006	0.033*	0.006	0.037*	0.010	0.031**	0.011	0.035*
	(0.029)	(0.019)	(0.032)	(0.021)	(0.023)	(0.016)	(0.027)	(0.018)
	[0.838]	[0.073]	[0.848]	[0.072]	[0.670]	[0.049]	[0.677]	[0.054]
EDR_cohort6265	0.015**	0.001	0.016*	0.002	0.019***	−0.002	0.021***	−0.001
	(0.007)	(0.027)	(0.009)	(0.030)	(0.005)	(0.023)	(0.007)	(0.026)
	[0.037]	[0.975]	[0.057]	[0.957]	[0.001]	[0.945]	[0.002]	[0.967]
EDR_cohort6669	−0.003	0.008	−0.005	0.009	0.001	0.012*	0.000	0.013*
	(0.022)	(0.006)	(0.024)	(0.007)	(0.018)	(0.007)	(0.020)	(0.008)
	[0.883]	[0.171]	[0.848]	[0.196]	[0.952]	[0.078]	[0.986]	[0.091]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(continued on next page)

Table A4 (*continued*)

	Food waste				Calorie loss			
	Log(FWP)		IHS_FWP		Log(CLP)		IHS_CLP	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	3149	6466	3149	6466	3156	6466	3156	6461
R^2	0.1365	0.1582	0.1351	0.1561	0.1223	0.1649	0.1223	0.1634

Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Table A5
Heterogeneity analysis by household income per capita.

	Food waste						Calorie loss					
	Log(FWP)			IHS_FWP			Log(CLP)			IHS_CLP		
	Low income	Middle income	High income	Low income	Middle income	High income	Low income	Middle income	High income	Low income	Middle income	High income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EDR_cohort2230	−0.011	−0.021	−0.034	−0.012	−0.023	−0.039	−0.011	−0.020	−0.026	−0.011	−0.023	−0.032
	(0.020)	(0.017)	(0.027)	(0.022)	(0.019)	(0.030)	(0.019)	(0.013)	(0.029)	(0.022)	(0.015)	(0.033)
	[0.588]	[0.232]	[0.202]	[0.607]	[0.227]	[0.195]	[0.583]	[0.143]	[0.371]	[0.599]	[0.133]	[0.334]
EDR_cohort3134	−0.015	−0.002	−0.039	−0.017	−0.001	−0.046	−0.017	−0.012	−0.032	−0.020	−0.013	−0.038
	(0.016)	(0.012)	(0.031)	(0.018)	(0.013)	(0.035)	(0.013)	(0.010)	(0.030)	(0.015)	(0.012)	(0.034)
	[0.358]	[0.880]	[0.213]	[0.339]	[0.952]	[0.199]	[0.188]	[0.235]	[0.296]	[0.184]	[0.252]	[0.264]
EDR_cohort3538	−0.007	−0.026**	−0.016	−0.007	−0.029**	−0.019	−0.015	−0.026**	−0.011	−0.016	−0.029**	−0.014
	(0.008)	(0.013)	(0.022)	(0.009)	(0.015)	(0.025)	(0.013)	(0.011)	(0.023)	(0.014)	(0.012)	(0.027)
	[0.343]	[0.046]	[0.473]	[0.403]	[0.048]	[0.442]	[0.241]	[0.018]	[0.643]	[0.265]	[0.020]	[0.592]
EDR_cohort3942	−0.000	0.018	0.007	−0.001	0.020	0.008	−0.003	0.026	0.011	−0.003	0.029	0.012
	(0.006)	(0.027)	(0.027)	(0.007)	(0.030)	(0.029)	(0.006)	(0.024)	(0.029)	(0.007)	(0.027)	(0.032)
	[0.980]	[0.490]	[0.803]	[0.932]	[0.505]	[0.790]	[0.650]	[0.261]	[0.703]	[0.655]	[0.286]	[0.700]
EDR_cohort4346	−0.016	−0.046**	−0.018	−0.018	−0.052**	−0.022	−0.016	−0.038*	−0.010	−0.019	−0.043*	−0.013
	(0.012)	(0.021)	(0.024)	(0.013)	(0.024)	(0.027)	(0.014)	(0.020)	(0.023)	(0.015)	(0.023)	(0.026)
	[0.200]	[0.032]	[0.441]	[0.179]	[0.033]	[0.406]	[0.249]	[0.064]	[0.675]	[0.229]	[0.063]	[0.624]
EDR_cohort4750	0.013	−0.010	0.026	0.014	−0.011	0.028	0.002	−0.019	0.028	0.003	−0.020	0.031
	(0.017)	(0.018)	(0.024)	(0.019)	(0.020)	(0.027)	(0.014)	(0.014)	(0.024)	(0.017)	(0.015)	(0.027)
	[0.429]	[0.579]	[0.287]	[0.442]	[0.582]	[0.297]	[0.906]	[0.171]	[0.240]	[0.872]	[0.186]	[0.246]
EDR_cohort5154	0.009	0.008	−0.010	0.009	0.010	−0.013	0.003	0.004	−0.005	0.003	0.005	−0.007
	(0.020)	(0.025)	(0.024)	(0.022)	(0.027)	(0.026)	(0.020)	(0.019)	(0.023)	(0.022)	(0.022)	(0.025)
	[0.647]	[0.741]	[0.662]	[0.671]	[0.723]	[0.629]	[0.893]	[0.833]	[0.815]	[0.889]	[0.821]	[0.770]
EDR_cohort5558	0.018	0.010	0.010	0.020	0.011	0.011	0.013	0.007	0.008	0.016	0.008	0.009
	(0.013)	(0.028)	(0.019)	(0.015)	(0.032)	(0.021)	(0.014)	(0.025)	(0.020)	(0.016)	(0.029)	(0.022)
	[0.192]	[0.727]	[0.590]	[0.183]	[0.720]	[0.593]	[0.346]	[0.777]	[0.697]	[0.328]	[0.771]	[0.681]
EDR_cohort5961	0.029***	0.040***	−0.021	0.032***	0.045***	−0.023	0.028***	0.041***	−0.014	0.031***	0.046***	−0.016
	(0.010)	(0.012)	(0.034)	(0.011)	(0.014)	(0.039)	(0.007)	(0.011)	(0.030)	(0.008)	(0.013)	(0.035)
	[0.003]	[0.001]	[0.538]	[0.003]	[0.002]	[0.545]	[0.000]	[0.000]	[0.646]	[0.000]	[0.000]	[0.648]
EDR_cohort6265	−0.007	0.002	0.008	−0.007	0.003	0.009	−0.008	0.004	0.013	−0.008	0.004	0.014
	(0.011)	(0.033)	(0.017)	(0.012)	(0.037)	(0.019)	(0.010)	(0.026)	(0.017)	(0.011)	(0.030)	(0.019)
	[0.491]	[0.941]	[0.620]	[0.527]	[0.933]	[0.639]	[0.408]	[0.892]	[0.449]	[0.441]	[0.894]	[0.463]
EDR_cohort6669	0.009	−0.010	0.007	0.009	−0.011	0.007	0.009	−0.008	0.017	0.009	−0.009	0.018
	(0.008)	(0.014)	(0.032)	(0.009)	(0.016)	(0.036)	(0.006)	(0.014)	(0.029)	(0.007)	(0.016)	(0.033)
	[0.298]	[0.494]	[0.836]	[0.335]	[0.499]	[0.851]	[0.172]	[0.588]	[0.552]	[0.196]	[0.602]	[0.583]
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birthplace fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3195	3200	3220	3195	3200	3220	3191	3204	3222	3191	3204	3222
R^2	0.1210	0.0885	0.0822	0.1203	0.0883	0.0808	0.1211	0.0926	0.0801	0.1209	0.0919	0.0794

Source: Authors' calculation using the CHNS data (2004–2009).
Note: Standard errors clustered at the provincial level are reported in parentheses. Wild bootstrap p values are reported in square brackets. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Table A6
Descriptive statistics of the key variables in the mechanism analysis.

Variable	Definition	Full	Born in 1922–61	Born in 1962–77	Difference
		(1)	(2)	(3)	(3)–(2)
Dependent variable					
SR	Natural logarithm of household disposable income divided by household consumption expenditure	0.259 (0.713)	0.313 (0.741)	0.220 (0.689)	−0.093***
Characteristics of the household head					
Age	Age of the household head (years)	51.427 (11.451)	57.109 (4.895)	47.254 (12.990)	−9.855***
Gender	Gender of the household head (1 = male; 0 = female)	0.722 (0.448)	0.734 (0.442)	0.713 (0.452)	−0.021
Education	Years of education (years)	7.411 (4.248)	6.956 (4.321)	7.746 (4.164)	0.790***
Hukou	Registration (1 = urban; 0 = rural)	0.359 (0.480)	0.355 (0.479)	0.362 (0.481)	−0.007
Work status	Whether he/she is working (1 = yes; 0 = no)	0.562 (0.496)	0.495 (0.500)	0.611 (0.488)	0.116***
Household characteristics					
Log(income)	Natural logarithm of household disposable income last year (yuan)	10.078 (0.815)	10.060 (0.846)	10.091 (0.791)	0.031
Family size	Number of household members	3.718 (1.637)	3.785 (1.912)	3.669 (1.400)	−0.116**
Observations		3608	1528	2080	

Source: Authors' calculation using the CFPS data (2010).
Note: Standard errors are reported in parentheses. Differences are *t*-test results of means. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

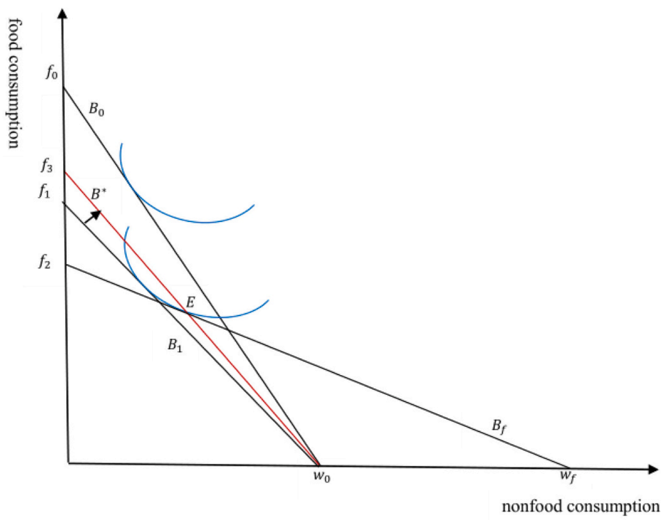
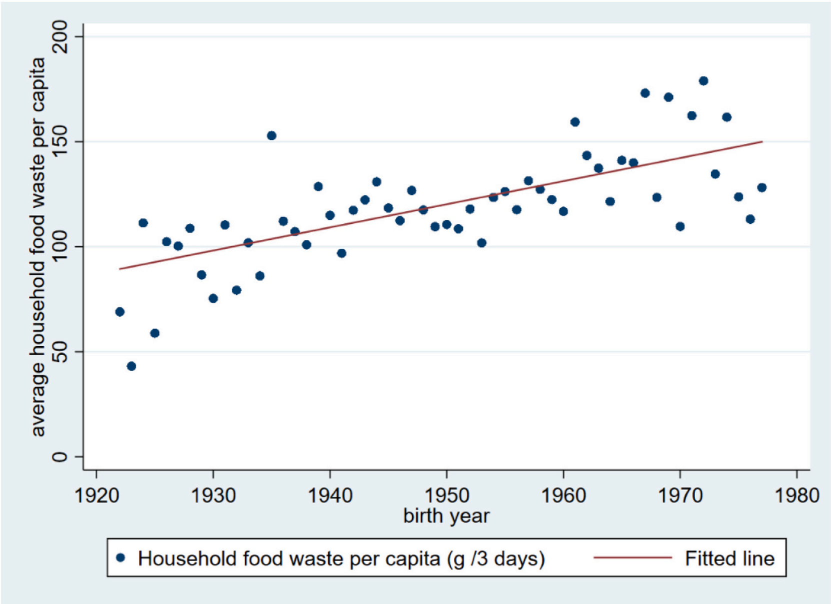
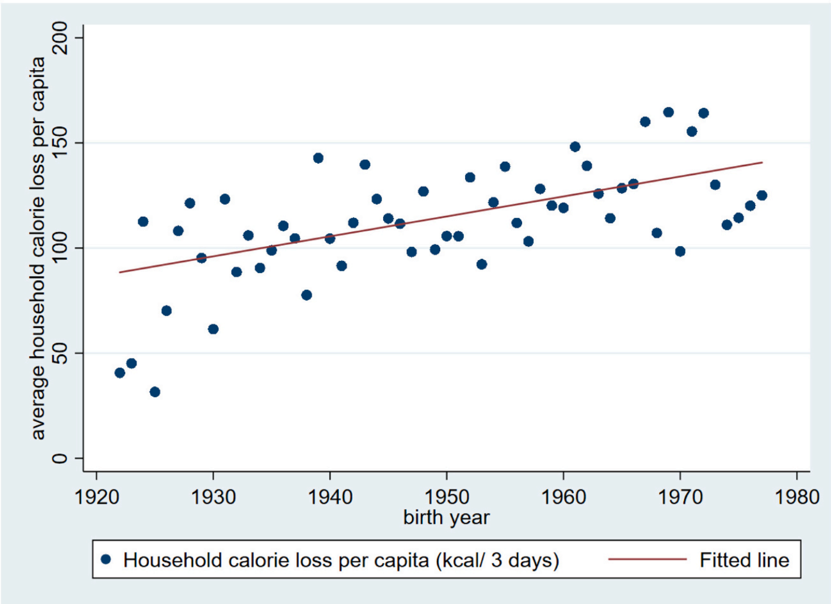


Fig. A1. Relationship between famine and food waste.
Notes: w_0f_0 represents the budget line with no food waste and no famine experience; w_0f_1 represents the budget line with food waste and no famine experience; w_ff_2 represents the "as if" budget line with food waste under famine experience; w_0f_3 represents the "real" budget line with food waste under famine experience.



A. Variations in household food waste per capita



B. Variations in household calorie loss per capita

Fig. A2. Household food waste and calorie loss per capita across birth years.
(Source: Authors' calculation using the CHNS data (2004–2009).)

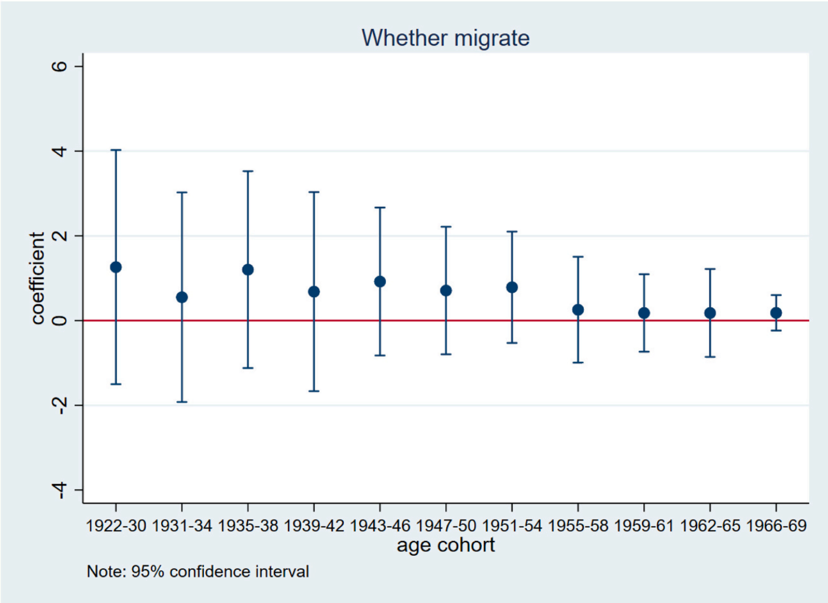


Fig. A3. Attrition analysis.
Note: The points in the figure represent the estimated effects on migration status, controlling for the full sets of cohort fixed effects, birthplace fixed effects, survey year fixed effects and time trend. Standard errors are calculated using the wild cluster bootstrap method. The error bars represent the 95% confidence intervals.
(Source: Authors' calculation using the CHNS data (2004–2009).)

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