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Full length article

Unintended effect of refrigerator usage on household food waste: Evidence from rural China

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ABSTRACT

The rapid spread of refrigerators in rural China has significantly increased, yet their impact on household food waste remains unclear. This study investigates the impact of refrigerator usage on household food waste in rural China, employing an endogenous switching regression model and counterfactual analysis based on the China Health and Nutrition Survey (CHNS) data from 2004, 2006, and 2009. Although refrigeration significantly enhances food preservation conditions, our findings indicate that it may paradoxically increase household food waste. Specifically, refrigerator usage is associated with a 24.35 % rise in food waste and a 29.29 % increase in calorie loss among refrigerating households. This effect diminishes over time and is moderated by higher household income, greater dietary knowledge, and increased education levels of food decision-maker. The quantity of stored food at home serves as a mediating factor: refrigerators encourage greater storage, thereby increasing food waste. By deepening our understanding of the refrigerator-food waste nexus in rural areas, this study provides crucial insights for policy formulation aimed at mitigating household food waste for China and other developing countries experiencing similar trends in rising refrigerator adoption and food waste challenges.

1. Introduction

Food waste is a widespread and increasingly urgent global problem (Girotto et al., 2015; Davenport et al. 2019). Generally, food waste is defined as unintended losses of food produced for human consumption occurring in the distribution and consumption stages of the food supply chain (Ganglbauer et al. 2013; HLPE 2014; Tassinari et al. 2023). Increasing food waste has serious negative implications for food security, the global environment, the climate, water and land resources, nutritional health, and the economy (Conrad et al. 2018; Dorward 2012; Graham-Rowe et al. 2014; Munesue et al. 2015; Parizeau et al. 2015; Thyberg and Tonjes 2016; Usubiaga et al. 2018; Rao et al. 2023). In 2018, the Food and Agriculture Organization (FAO) estimated that the quantity of annual food waste reached 0.97 billion tons, accounting for 17 % of the total food available to consumers (FAO 2019). At the same time, 10.8 % of the world's population (or 821.6 million) is still hungry, with Asia accounting for 62.5 % of the total in 2018 (FAO 2019). Therefore, reducing food waste is commonly seen as a critical component of food security as well as global environmental sustainability (Wang et al. 2018) and helps achieve Sustainable Development Goal 2-Zero Hunger (UN 2021).

Household food waste refers to food waste that occurs between when food reaches the consumer and when it is consumed (HLPE 2014; Alexander et al. 2017). Previous studies also indicate that the food waste generated at the household level represents approximately half the total food loss and waste in developed countries, making this stratum one of the greatest contributors to this problem (Stancu et al. 2016; Heller 2019). For instance, household food waste was found to account for approximately half of the total food waste in the UK (Monier et al. 2010), and it is also the largest contributor in Switzerland (Beretta et al. 2013). Although household food waste in developed countries has stabilized, the increase in food waste in low- and middle-income countries is

Abbreviations: CHNS, China Health and Nutrition Survey; ESR, Endogenous switching regression model; ATT, Average treatment effect; DKI, Dietary knowledge index; HFW, Quantity of household food waste over 3 days (g); PFW, Quantity of household food waste per capita over 3 days (g); HCL, Household calories loss over 3 days (kcal); PCL, Calories loss per capita over 3 days (kcal).

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responsible for the majority of the growth observed in food waste (FAO 2011; Lin et al. 2011; Xu et al. 2018; FAO 2019). With economic growth, households in developing countries are expected to generate an increasing volume of food waste (Alexander et al. 2017; Gojard et al. 2021; Ding et al. 2022). Several studies have explored the factors related to household food waste, such as household income, household size, dietary knowledge, food donation policies and other factors, that play important roles in household food waste (Yu and Jacnicke 2020; Parfitt et al. 2010; Busetti 2019; Min et al. 2021; Rickard et al. 2023; De et al. 2020).

In fact, the most direct household food waste is expired, leftover or spoiled, while this food waste can be further attributed to individuals purchasing excessive amounts of food and using unsuitable or insufficient storage practices (Koivupuro et al. 2012; Porpino et al. 2015). Household food storage conditions have generally improved since the application of refrigerators in families; however, improved food storage conditions have also affected household food waste in two ways (Holsteijn and Kemna 2018; Marklinder and Erikkson 2015; James et al. 2017). On the one hand, foods can be stored in the refrigerator to extend their shelf life by lowering their temperature (Barthd et al. 2009; Gojard et al. 2021), while leftovers can also be consumed later after being placed in refrigerators (Gojard et al. 2021), thereby reducing the waste of these foods. However, food storage in refrigerators may also lead to food waste due to inadequate refrigerator temperatures, incorrect food handling or overbuying (Williams et al. 2012; Marklinder and Erikkson 2015; James et al. 2017).

While refrigerators are used globally (Rao and Ummel. 2017; Park et al. 2019), the effects of the improved food storage conditions provided by refrigerator usage on household food waste remain ambiguous. Most of the previous studies on the use of refrigerators in developing countries have focused on the impact of refrigerators on household food consumption and nutrient intake (Heard et al., 2020; Martinez 2021). To date, few studies have focused on the impact of refrigerator usage on household food waste in developing countries. For example, Qi et al. (2020) use the 1991–2009 waves of the CHNS and find a negative and significant association between food waste per capita and refrigerator ownership, with the effect size diminishing over time. Luo et al. (2021) and Li et al. (2021) showed that the use of refrigerators has an insignificant impact on household food waste, suggesting that refrigerator usage is not always effective at reducing food waste. Additionally, Carolan (2021) reported that the quantity of food wasted was strongly correlated with the number of refrigerators that they owned. Overall, the findings on the connection between refrigerator usage and household food waste remain mixed despite the empirical evidence. This may be attributed to that multiple linear regression model and tobit model regression in the empirical studies fail to adequately address the endogeneity issues associated with refrigerator usage (Qi et al., 2020; Luo et al., 2021; Li et al., 2021). Specifically, the endogeneity concerns of refrigerator usage may stem from several sources. First, reverse causality could be at play, where refrigerator usage and household food waste may influence each other. Additionally, unobserved heterogeneity among household decision-makers may simultaneously affect both refrigerator usage and food waste. Second, sample selection bias may arise, as households that use refrigerators might differ systematically from those that do not, potentially leading to skewed results. That is, the estimated impact of refrigerator usage on household food waste may be biased due to these endogeneity concerns.

The objective of this study is to explore the impact of improving household food storage conditions on household food waste by analyzing the case of refrigerator usage in rural China. The reasons we investigate rural China are threefold. First, China, the world's most populous country, is undergoing dramatic societal changes due to rapid economic growth, with food sustainability and food waste emerging as widespread concerns (Xue et al. 2021; Li et al. 2022). Given that rural areas in China are home to a significant portion of the population, any changes in rural household food waste would have significant consequences (Song et al. 2015). Second, with the growth of household income and the improvement in people's living standards, the food storage conditions of households in rural China have improved due to the use of refrigerators (Qi et al. 2020; Luo et al. 2021; Li et al. 2021). Unfortunately, it is unclear whether and to what extent refrigerator usage affects household food waste in rural China. Third, as the largest developing country in the world, the empirical evidence on household food waste in rural China could have important reference implications for other developing countries.

To achieve this objective, this study proposes a simple model of household food waste to assist in understanding the possible impact of food storage conditions on household food waste and the underlying mechanism involved. Then, the endogenous switching regression (ESR) model was applied to the CHNS data from 2004, 2006, and 2009. A counterfactual analysis is employed to estimate the treatment effects of refrigerator usage on the quantity of household food waste and calorie loss. These methods can address the issue of sample selection bias caused by both observable and unobservable factors (Lokshin and Sajaia 2004; Lokshin and Sajaia 2011). Moreover, a series of heterogeneity analyses were conducted to detect the differences in the treatment effects of refrigerator usage on household food waste and calorie loss by income, education level and dietary knowledge. We also test the robustness of the main findings by employing a subsample of household food waste and calorie loss of high-value food. A mechanism analysis is carried out to examine whether the quantity of available food at home is a potential mechanism through which refrigerator usage influences household food waste.

This paper contributes to the literature in three ways. First, this study supplements the empirical evidence on the determinants of household food waste in developing countries (Xu et al. 2020; Li et al. 2021; Ding et al. 2022). In addition, compared to past studies, this study measures household food waste by using both the volume of food waste and the loss of calories (Hall et al. 2009; Min et al. 2021; Ding et al. 2022), which provides broader insight into the issue of food waste (Bellemare et al. 2017). Second, this study not only estimates the effects of refrigerator usage on household food waste but also further explores the potential channels of these effects, while other studies have not explored the mechanism (Luo et al. 2021; Li et al. 2021). Third, the findings reveal that household food waste appears to be an unexpected consequence of improved household food storage conditions in terms of refrigerator usage among rural residents in developing countries, adding to the literature regarding the impacts of improved food storage conditions (Holsteijn and Kemna 2018; Gojard et al. 2021). Moreover, the findings have important implications for policy design to reduce household food waste in the context of increasing refrigerator usage among rural residents in developing countries.

The rest of the paper is structured as follows. In Section 2, a simple theoretical model is developed to derive the impact of improved food storage conditions on household food waste, and the theoretical hypotheses are proposed. Section 3 states the empirical strategies used to test the hypotheses. The data sources and descriptive statistics are presented in Section 4. Section 5 reports and discusses the estimation results, while the final section presents the conclusions and policy recommendations of this study.

2. Theoretical framework

We propose a simple model of household food waste to assist in understanding the possible impact of refrigerator usage on household food waste and the underlying mechanism involved. First, assume that the quantity of household food waste (w) can be expressed as a function of the total quantity of food available for eating (Q) in a household:

$$w = \rho Q \tag{1}$$

where ρ ($\rho>0$) is the waste ratio of the total food available. Note that ρ reflects the food utility ability of a household and can be determined by the socioeconomic characteristics of the household and the food decision maker (Z). ρ can be written as:

$$\rho = f(Z) \tag{2}$$

The total quantity of food available for eating, Q, is also affected by the vector Z and refrigerator usage (r) in the household. Thus, Q can be further expressed as a function of r and Z, that is:

$$Q = g(r, Z) \tag{3}$$

By incorporating functions (2) and (3) into (1), the quantity of household food waste is further expressed as follows:

$$w = f(Z) * g(r, Z) \tag{4}$$

Hence, the impact of r on w can be obtained as follows:

$$\frac{\partial w}{\partial r} = \frac{\partial w}{\partial g} * \frac{\partial g}{\partial r} \tag{5}$$

Eq. (5) indicates that r can affect w by influencing Q. When $f(Z)>0$, the quantity of household food waste (w) should be positively correlated with the amount of available food at home (Q); that is, $\frac{\partial w}{\partial g}>0$. According to previous studies (Hand and Shove 2007; Holsteijn and Kemna 2018), improvements in household food storage conditions, such as the use of refrigerators (r), can result in an increase in stored food at home, that is, $\frac{\partial g}{\partial r}>0$. Thus, $\frac{\partial w}{\partial r} > 0$ can be derived.

Based on the above simple derivations, we propose two hypotheses:

Hypothesis 1. The use of refrigerators will increase household food waste.

Hypothesis 2. The quantity of stored food at home is a mechanism through which refrigerator usage affects household food waste.

3. Empirical strategy

To test the two proposed theoretical hypotheses, we further employ endogenous switching regression (ESR) and counterfactual analysis. According to previous studies (Di Falco et al. 2011; Huang et al. 2015; Khanal et al. 2018; Liu et al. 2021), the ESR model is used to address the potential sample selection bias arising from unobservables when estimating the causal effects of refrigerator usage on household food waste, while counterfactual analysis can be used to assess the impact of refrigerator usage on rural household food waste by calculating the average treatment effect on the treated (ATT).

3.1. Endogenous switching regression model

According to Lokshin and Sajaia (2004, 2011), the ESR model for the use of refrigerators in a rural household can be written as follows:

$$D_i = Z_i\alpha + \mu_i \text{ with } D_i = \begin{cases} 1 \; if \; D_i > 0 \\ 0 \; othewise \end{cases} \tag{6}$$

where D_i is a binary variable that equals 1 if rural household i chooses to use a refrigerator and 0 otherwise; Z_i is a vector of socioeconomic characteristic variables of the household that may affect the refrigerator usage decision; α is a vector of parameters to be estimated; and μ_i is an error term that is assumed to be normally and independently distributed with zero mean variance σ^2.

Based on the choice of refrigerator usage among rural households described above, two regime equations are further given to explain the outcomes of interest: HFW, PFW, HCL, and PCL. Specifically, the two regressions are defined as follows:

$$\text{Regime 1 (use refrigerator)}: Y_{iA} = \alpha_{iA}X_{iA} + \varepsilon_{iA} \; if \; D_i = 1 \tag{7a}$$

$$\text{Regime 2 (nonuse refrigerator)}: Y_{iN} = \alpha_{iN}X_{iN} + \varepsilon_{iN} \; if \; D_i = 0 \tag{7b}$$

where Y_{iA} and Y_{iN} are outcome variables representing the food waste of households using refrigerators and households not using refrigerators, respectively; X_{iA} and X_{iN} refer to vectors of exogenous variables; α_{iA} and α_{iN} are parameters to be estimated; and ε_{iA} and ε_{iN} are error terms.

The ESR model addresses the selection bias arising from unobservable factors by calculating inverse mill ratios (IMRs) after estimating Eq. (6) and including them in Eqs. (7a) and (7b). Here, Eqs. (8a) and (8b) can be rewritten as follows:

$$Y_{iA} = \alpha_{iA}X_{iA} + \sigma_{\mu A}\theta_{iA} + \omega_{iA} \; if \; D_i = 1 \tag{8a}$$

$$Y_{iN} = \alpha_{iN}X_{iN} + \sigma_{\mu N}\theta_{iN} + \omega_{iN} \; if \; D_i = 0 \tag{8b}$$

where Y_{iA}, Y_{iN}, X_{iA} and X_{iN} are defined as above; θ_{iA} and θ_{iN} are IMRs, which are used to capture selection bias arising from unobservable factors; $\sigma_{\mu A}$ and $\sigma_{\mu N}$ are the covariance terms, which are defined as $\sigma_{\mu A} = \text{cov}(\mu_i, \varepsilon_{iA})$ and $\sigma_{\mu N} = \text{cov}(\mu_i, \varepsilon_{iN})$, respectively; and ω_{iA} and ω_{iN} are error terms with conditional zero means. The selection of Eq. (6) and the outcomes of Eqs. (8a) and (8b) are estimated simultaneously using the FIML estimator. The ESR model uses correlation coefficients $\rho_{\mu A}(\sigma_{\mu A}/\sigma_\mu\sigma_A)$ and $\rho_{\mu N}(\sigma_{\mu N}/\sigma_\mu\sigma_N)$ to identify the existence of selection bias arising from unobservable factors (Kumar et al., 2020; Li et al., 2020). Specifically, selection bias associated with unobservable factors exists if $\rho_{\mu A}$ and/or $\rho_{\mu N}$ is significantly different from zero.

3.2. Estimating the treatment effects of refrigerator usage

The regression results of the ESR model reveal the differential effects of various factors on the quantity of food waste consumed by households using refrigerators compared to those not using refrigerators. Based on the estimation results, a counterfactual analysis framework is used to estimate the average treatment effect on the treated (ATT) effect of refrigerator usage on food waste in rural households by comparing the quantity of food wasted in households using refrigerators under real and counterfactual scenarios (Lokshin and Sajaia 2004; Lokshin and Sajaia 2011; Liu et al. 2021).

In the observable scenario, the expected values of the outcome variables for refrigerator usage can be specified as follows:

$$E(Y_{iA}|D = 1) = \alpha_{iA}X_i + \sigma_{\mu A}\theta_{iA} \tag{9a}$$

In the counterfactual scenario, the expected values of the outcome variables for refrigerator usage that were not used can be expressed as follows:

$$E(Y_{iN}|D=0) = \alpha_{iN}X_i + \sigma_{\mu N}\theta_{iA} \quad (9b)$$

Following Lokshin and Sajaia (2004) and Liu et al. (2021), the ATT can be derived by calculating the difference in outcomes between Eqs. (9a) and (9b):

$$ATT = E(Y_{iA}|D=1) - E(Y_{iN}|D=0) = X_i(\alpha_{iA} - \alpha_{iN}) + \theta_{iA}(\sigma_{\mu A} - \sigma_{\mu N}) \quad (10)$$

3.3. Instrumental variables

To identify the ESR model, it is important that at least one variable serves as an identifying instrument in Z_i when Eq. (1) is used but does not appear in X_i when Eqs. (7a) and (7b) are used (Lokshin and Sajaia 2004; Lokshin and Sajaia 2011). In this study, the price of electricity in the village is chosen as the instrumental variable[1] (IV). A valid IV should satisfy both the correlation condition and the exclusive restriction. First, the IV meets the relevance condition. Previous research has demonstrated that the price of electricity can impact the decision to use a refrigerator (Han et al. 2019; Jin 2007; Jin 2019). Second, the IV indeed satisfies the exclusive restriction condition. The monopoly property of the electricity price ensures its exogeneity for household food waste, while the electricity price does not have a direct impact on household food waste. The falsification test is used to check the validity of this instrumental variable (Di Falco et al. 2011). The results of the falsification test (Table A1 in the Appendix) show that the IV significantly increases the probability of using refrigerators, while it has no significant impact on household food waste when refrigerators are not used. This finding suggests that the price of electricity in the village serves as a valid instrumental variable for refrigerator usage.[2]

4. Data and descriptive statistics

4.1. Data sources and samples

The data used in this paper were obtained from the China Health and Nutrition Survey (CHNS), which is an international collaborative project undertaken by the National Institute of Nutrition and Food Safety at the China Centers for Disease Control and Prevention and the Carolina Population Center and University of North Carolina at Chapel Hill. The survey is longitudinal and includes ten waves covering 1989–2015. Each survey took place over a 7-day period, and the data were collected by using a face-to-face questionnaire. The CHNS provides detailed data on target families and their members as well as their communities, and the modules used in each survey remain as similar as possible. The module about food and nutrition collects detailed information on household food consumption.[3] Additionally, in three waves (2004, 2006, and 2009), this survey included a module on food waste, which has been widely used in previous studies (Min et al. 2021; Ding et al., 2022) .[4] During the 2004–2009 waves, the CHNS collected data in 9 provinces[5]: Liaoning, Heilongjiang, Jiangsu, Shandong, Henan, Hubei, Hunan, Guangxi, and Guizhou. Through further cleaning of the data, we obtained unbalanced panel data with complete information for 8019 rural households.[6] Specifically, there were 2545, 2697, and 2779 sample households in 2004, 2006, and 2009, respectively.

4.2. Variables

4.2.1. Food waste and calorie loss

Numerous studies have validated the reliability of the quality of food waste modules in the CHNS (Qi et al. 2021; Min et al. 2021). In this paper, we used two groups of measurements of food waste from rural households. The first group of measures of household food waste includes total food waste (g) in the observed three days and food waste per capita per day (g). The CHNS collected detailed food consumption information on three consecutive days randomly selected from Monday to Sunday to ensure the quality of the data. Additionally, for each of the food items consumed at home, the survey also recorded how much of it was wasted in grams. This allowed us to obtain the first set of dependent variables. Note that, this study considered only food waste at home within the three consecutive days and did not consider food waste away from home or food purchased within three days of the survey but waste after those three days.

The second group of dependent variables measures the extent of food waste in rural households in terms of nutrient loss. A previous study argued that it was unreasonable to simply add the quantities of the various foods wasted (Koester 2015); the nutrient composition of food contains calories, proteins, fats, carbohydrates, and other nutrients, with

[1] China adopts a tiered tariff for residential electricity consumption. According to national statistics, except for Shanxi Province, where the price of electricity is approximately 0.4 yuan per kilowatt-hour, the price of rural electricity in a considerable number of provinces is 0.6 to 0.8 yuan, with a high of 2 to 3 yuan, and the average price of electricity is 0.78 yuan, much higher than the average urban price of 0.42 yuan. The average tariff level is much higher than the average urban tariff of 0.42 yuan, and the cost of electricity in rural areas is relatively high.

[2] In addition, electricity prices are an essential input cost for food production and retail, and it is reasonable to assume that fluctuations in electricity prices could have an impact on food prices. Notably, in China, electricity prices are categorized as residential, commercial, industrial, and agricultural production. The prices of commercial and agricultural production electricity are the primary factors that influence the production cost and price of food due to the nature of their respective usage. However, regarding this article, the term electricity price refers to residential electricity, which exclusively impacts households' use of refrigerators and does not directly influence local food prices.

[3] Some studies have calculated household food consumption by the amount of food prepared and consumed by households on a daily basis (Min et al. 2021). Moreover, the relationship between food intake and body mass index (BMI) is used to calculate food waste by arguing that not consuming all the food consumed would result in the body not achieving the expected BMI (Yu 2018).

[4] This study focuses on the household food waste and calorie loss. To calculate the household calorie loss in rural China, we need to employ the Food Composition Table (FCT). The Food Composition Table (FCT) for China was updated in 2002, and a newer version of FCT was used during the 2004 survey. To ensure the consistence of food waste and calorie data, this study ultimately selected data from the years 2004, 2006, and 2009 to analyze the impact of refrigerator use on household food waste and calorie loss.

[5] Although the CHNS is not a nationally representative dataset in China, these 9 sample provinces vary widely regarding geography, economic development, public resources, and health indicators and host approximately 45% of China's total population.

[6] This study's focus on rural areas is justified by several key considerations. First, we chose to focus on rural areas because the rural market still holds significant research value and practical importance in terms of refrigerator penetration. Although the prevalence of refrigerators in rural areas has seen a significant increase in recent years, there is still a gap when compared to urban areas. We believe it is necessary to conduct an in-depth study of rural areas separately. Second, the penetration rate of refrigerators in urban areas is already very high. According to relevant data, the overall refrigerator ownership rate in urban households across China has reached 90%, with some large and medium-sized cities' refrigerator markets nearing saturation. In this context, the primary demand in the urban refrigerator market has shifted from penetration to replacement, which is in stark contrast to the demand in rural areas, where the focus is still on broadening access. Therefore, studying rural areas as a distinct subject enables a more precise understanding of the impacts of refrigerator usage.

calories being widely considered a major nutritional indicator (Tian and Yu 2015). Thus, the calculated caloric intake of diverse wasted foods appears to be a better indicator. We used food codes for discarded food, as well as information from the Chinese food consumption table on the nutrient makeup of various foods (Tian and Yu 2015; Yang et al. 2002), to calculate the caloric units of food wasted. Total food waste (g) and food waste per day (g) were converted into the nutritional content of the wasted food in terms of calories.

Table A2 reports the descriptive statistics of the four dependent variables. On average, each household wasted approximately 315 g of food over the three days of the survey, resulting in a caloric loss of approximately 323 kcal. Accordingly, the food waste per capita over the three days was approximately 130 g, and the per capita calorie loss was 135 kcal. The per capita food waste over the three days of the survey can be translated to 15.5 kg/person/year, which is lower than the average food waste and loss estimated by FAO (2011) for consumers in Japan, Korea, and China (73 kg/person/year) and higher than that in South and Southeast Asia (11 kg/person/year). These differences are acceptable given the differences in the statistical methods used. While the quantity of food waste seems small, it is quite alarming given the large population in rural China.

4.2.2. *Refrigerator usage*

While refrigerators were popularized in most developed countries before the 1990s, their use expanded in China after the reform. Fig. A1 shows the increasing trend of the refrigerator usage rate among the CHNS sample households, consistent with the official statistics reported in the Chinese Statistical Yearbook (2002, 2021). According to Fig. A1, the percentage of families with refrigerators is increasing in both urban and rural regions. In urban areas, it increased from 30.3 % in 1989 to 97.4 % in 2015, while in rural areas, it increased from 3.8 % in 1989 to 87.3 % in 2015. The penetration of refrigerators in rural China continuously lags behind that in urban China. Moreover, the results show that in 2004, 2006, and 2009, the proportions of households using refrigerators in rural China were 22.6 %, 30.2 %, and 50 %, respectively. By 2015, just over 80 % of the rural households were using refrigerators.

Fig. A2 shows the differences in the mean values of household food waste and calorie loss between households with and without refrigerator usage. The results suggest that households using refrigerators, on average, had significantly greater food waste and calorie loss than households that did not use refrigerators. These descriptive statistical results are consistent with our hypothesis.

4.2.3. *Other control variables*

Table 1 lists the definitions and summary statistics of the control variables used in our analysis. According to previous studies (e.g., Min et al. 2021; Xu et al., 2020; Qi et al. 2021), the individual characteristics of food decision maker include gender, age, educational attainment, and work status. The household food decision maker dietary knowledge index (DKI) was generated from the nine questions used in the CHNS (Min et al. 2021; Ren et al. 2019). Table A3 provides more detail regarding these questions. The higher the DKI score is, the greater the participants' knowledge of nutritional intake. The family characteristics included the equivalent family size and the family structure by age cohort. The possession of air conditioner proxies is a variable of household assets. We also control for the net income per capita at 2015 constant prices and employ the logarithm form of net income in the empirical study to control for potential heteroscedasticity of the income variable (Min et al. 2021). The prices of four types of foods, including beans, poultry, vegetables, and oil, at the village level are also used as control variables.[7]

The last column of Table 1 reports the differences in the mean values of these control variables between households with and without refrigerators. The results of the mean comparison tests further suggest that the differences in most variables are significant, revealing the possible correlations between these variables and the use of a refrigerator. Moreover, the results indicate the observed confounder effect of an imbalance of characteristics between households with and without refrigerator use, implying the existence of sample selection bias related to refrigerator use. Thus, when estimating the impact of refrigerator usage, we must address the sample selection issue.

5. Estimation results and discussion

Table 2 reports the estimation results of the four ESR models for household food waste (HFW, PFW) and calorie loss (HCL, PCL) .[8] A pseudo-fixed-effects estimator (MK) approach is used to control for possible bias that may arise from unobserved heterogeneity and omitted time-varying variables[9] (Mundlak 1978; Cameron and Trivedi, 2005; Wooldridge 2010; Ren et al. 2019). Here, the mean values of all covariates are included in the estimation as additional explanatory variables. Year fixed effects are also included in the estimation to capture time-varying heterogeneity, while a set of variables of food prices at the village level are used to control for the food market effect. Moreover, the standard errors are clustered at the household level to address the correlation of refrigerator usage for a household in different years.

Table 2 reports the estimations of the ESR. For all four ESR models, the selection equations are the same; for simplicity, we report only the results of the selection equation in column 1 of Table 2. In each model, there are two outcome equations, which represent the food waste or calorie loss for households using a refrigerator and households not using a refrigerator. The bottom of Table 2 shows that the Wald test of joint independence of the equations is significantly different from zero, confirming the validity of the joint estimation of the selection equation and the outcome equations. A significant IMR or Rho 0/1 indicates the presence of selection bias. These statistical tests confirm the appropriateness of using the ESR model to estimate the impacts of refrigerator usage on household food waste and calorie loss.

5.1. *Estimation results of refrigerator usage*

The first column in Table 2 presents the estimation results of the selection equation for refrigerator usage; the results reveal several significant variables influencing the refrigerator usage of rural households. Specifically, the coefficient of the gender variable is significantly

[7] The village questionnaire reports a total of four prices, including beans, poultry, vegetables, and oil.

[8] To address potential multicollinearity concerns, we conducted Variance Inflation Factor (VIF) tests for all control variables before the empirical analysis. The VIF is a commonly used indicator to assess the severity of multicollinearity, with a value greater than 10 typically indicating serious multicollinearity among variables. In this analysis, all control variables had VIF values <5, which suggests that multicollinearity among the variables is within an acceptable range and will not significantly bias the results of the regression analysis.

[9] The pseudo fixed-effects estimator (MK) approach offers several advantages. First, it allows us to control for time-constant unobserved heterogeneity by including the vector of time-averaged variables, similar to fixed-effects model (FE) (Mundlak 1978; Wooldridge 2010). This provides better control and avoids the problem of incidental parameters that arises in nonlinear models. Another advantage of using the MK approach is that it allows us to measure the effects of time-constant independent variables just as in a traditional random-effects environment (Mundlak 1978; Ren et al. 2019). Considering that the adjustments in refrigerator usage and other control variables are relatively small in 2004, 2006, and 2009 for some samples, the use of FE models may result in sample omission and thereby interfere with the results of the model estimation. Therefore, this study employs a pseudo-fixed-effects estimator within the ESR model to assess the effects of refrigerator usage on food waste in rural households.

Table 1
Statistics for other control variables.

Variables	Definition and assignment	Mean			Mean difference (1–0)
		Full sample	No-use	Use	
Characteristics of the food decision maker					
Gender	Gender of the personal characteristic (1=Male; 0=Female)	0.223 (0.417)	0.246 (0.006)	0.193 (0.007)	−0.053***
Age	Age of the personal characteristic (Years)	49.20 (13.44)	50.21 (0.206)	47.84 (0.214)	−2.367***
Education	Years of education (Years)	7.094 (3.758)	6.182 (0.053)	8.323 (0.062)	2.141***
Work status	Whether he or she is working (1=Yes; 0=No)	0.634 (0.482)	0.667 (0.007)	0.590 (0.008)	−0.077***
DKI	Dietary knowledge index	4.005 (2.821)	3.461 (0.041)	4.738 (0.047)	1.277***
Household characteristics					
Proportion (≤14)	Proportion of household members aged 14 and under	10.58 (15.04)	10.70 (0.227)	10.42 (0.248)	−0.277
Proportion (≥60)	Proportion of household members aged 60 and above	17.47 (29.02)	20.30 (0.461)	13.65 (0.429)	−6.657***
Family size	Number of household members aged 60 and above	2.537 (0.875)	2.545 (0.013)	2.526 (0.014)	−0.019
Log (income)	Natural logarithm of family income per capita inflated to 2015 (Yuan)	8.665 (2.049)	8.393 (0.295)	9.031 (0.035)	0.638***
Air conditioner	Whether the family have an air conditioner	0.129 (0.335)	0.022 (0.002)	0.273 (0.008)	0.251***
Village characteristics					
UDI	Urbanization development index	57.63 (17.80)	51.43 (0.222)	66.01 (0.305)	14.59***
Chicken price	Price of chicken at the village level (Yuan/Jin[a])	18.59 (5.995)	18.75 (0.091)	18.38 (0.098)	−0.36***
Vegetables price	Price of vegetables at the village level (Yuan/Jin[a])	1.291 (0.561)	1.211 (0.008)	1.398 (0.010)	0.187***
Beans price	Price of beans at the village level (Yuan/Jin[a])	4.942 (1.598)	4.862 (1.592)	5.049 (1.601)	0.187***
Oil price	Price of oil at the village level (Yuan/Jin[a])	7.160 (1.242)	7.129 (0.018)	7.202 (0.022)	0.073***
Supermarket	Whether the village has a supermarket within 5 km	0.717 (0.450)	0.640 (0.480)	0.822 (0.382)	0.183***
Electricity	Price of electricity at the village level (Yuan/Kw-h)	0.742 (0.195)	0.753 (0.003)	0.727 (0.003)	−0.026***
Observations		8019	4607	3412	

Note: The significance levels of 1 %, 5 % and 10 % are denoted by ***, **, and *, respectively
[a] : 1 Jin=0.5 kg.

Table 2
Estimation results of refrigerator usage and household food waste using the ESR.

Variables	Refrigerator usage	Log(HFW)		Log(PFW)		Log(HCL)		Log(PCL)	
		Use	Nonuse	Use	Nonuse	Use	Nonuse	Use	Nonuse
Gender	−0.108* (0.065)	−0.081 (0.186)	0.106(0.159)	−0.058 (0.161)	0.080 (0.137)	−0.080 (0.181)	0.099 (0.155)	−0.059 (0.156)	0.086 (0.136)
Age	−0.005 (0.003)	−0.003 (0.009)	−0.011 (0.007)	−0.004 (0.008)	−0.008 (0.006)	−0.002 (0.009)	−0.011 (0.007)	−0.003 (0.008)	−0.008 (0.006)
Education	0.021* (0.011)	−0.024 (0.033)	0.020(0.027)	−0.020 (0.028)	0.016 (0.023)	−0.028 (0.032)	0.021 (0.026)	−0.025 (0.027)	0.015 (0.023)
Work status	0.032 (0.057)	0.109 (0.164)	0.066(0.141)	0.086(0.141)	0.068 (0.122)	0.101 (0.159)	−0.008 (0.137)	0.080 (0.138)	−0.007 (0.120)
DKI	0.012 (0.010)	−0.048* (0.029)	−0.030 (0.023)	−0.040 (0.025)	−0.022 (0.020)	−0.042 (0.028)	−0.027 (0.023)	−0.035 (0.024)	−0.021 (0.020)
Family size	0.060 (0.049)	0.120 (0.145)	0.311*** (0.112)	−0.129 (0.125)	0.030 (0.097)	0.145 (0.141)	0.300*** (0.109)	−0.097 (0.122)	0.021 (0.096)
Proportion (≤14)	0.003 (0.003)	0.008 (0.007)	0.000 (0.006)	0.006 (0.006)	−0.000 (0.005)	0.009 (0.007)	−0.001 (0.006)	0.008 (0.006)	−0.001 (0.005)
Proportion (≥60)	−0.002 (0.002)	0.003 (0.006)	−0.000 (0.004)	0.003(0.005)	−0.000 (0.003)	0.003 (0.006)	−0.002 (0.004)	0.002 (0.005)	−0.002 (0.003)
Log (income)	0.000 (0.012)	−0.011 (0.034)	0.073** (0.031)	−0.008 (0.029)	0.061** (0.027)	−0.002 (0.033)	0.064** (0.030)	0.001 (0.029)	0.053** (0.026)
Air conditioner	0.604*** (0.098)	−0.031 (0.239)	0.325(0.382)	0.023(0.199)	0.210 (0.331)	−0.005 (0.221)	0.139 (0.382)	0.047 (0.188)	−0.066 (0.342)
UDI	0.002 (0.004)	−0.011 (0.010)	0.015*(0.008)	−0.011 (0.009)	0.011 (0.007)	−0.010 (0.010)	0.017** (0.008)	−0.010 (0.009)	0.012* (0.007)
Supermarket	−0.005 (0.057)	−0.176 (0.183)	−0.350*** (0.129)	−0.117 (0.157)	−0.275** (0.112)	−0.071 (0.177)	−0.230* (0.125)	−0.018 (0.153)	−0.153 (0.110)
Prices	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled
MK estimator	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled
Year	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled	controlled
Electricity (IV)	−0.824*** (0.104)								
Constant	−3.332*** (0.243)	2.224* (1.284)	1.202** (0.601)	2.157** (0.983)	1.656*** (0.523)	1.456(1.027)	0.365(0.605)	1.401* (0.831)	0.985* (0.552)
Lns_1/ Lns_0		0.997*** (0.025)	0.982*** (0.012)	0.846*** (0.021)	0.839*** (0.013)	0.967*** (0.020)	0.955*** (0.013)	0.821*** (0.018)	0.827*** (0.020)
rho0/rho1		−0.298* (0.163)	−0.139 (0.100)	−0.277** (0.136)	−0.183* (0.104)	−0.295** (0.121)	−0.160 (0.123)	−0.270** (0.107)	−0.290** (0.146)
Wald test		5.39* (p value=0.07)		6.44** (p value=0.04)		6.43** (p value=0.04)		8.02** (p value=0.01)	
Log likelihood		−23,093.70		−21,915.61		−,22,860.82		−,21,725.71	
Observations	8019	3412	4607	3412	4607	3412	4607	3412	4607

Note: Robust standard errors in parentheses are clustered at the household level; significance level *<0.10, **<0.05 and ***<0.01.

negative, suggesting that a household with a female head tends to be more willing to use refrigerators than a household with a male head. This could be because refrigerator usage can save time from daily grocery shopping, which enables households to derive greater utility from its usage, especially in traditional households, where women are more likely to take care of housework (Alesina et al. 2013; Dhanaraj et al. 2018; Debnath et al. 2019). In line with the findings of Pham (2021), the education levels of household heads have a significant and positive effect on the use of refrigerators. A household with an air conditioner is more likely to use a refrigerator, consistent with the findings of previous studies (Matsumoto, 2016). As expected, IVs have a significant negative impact on refrigerator usage in rural households, demonstrating that households in villages with relatively high electricity prices are less likely to use refrigerators (Han et al. 2019; Jin 2019).

5.2. Estimation results of household food waste and calorie loss

Columns 3, 4, 5 and 6 of Table 2 show the estimation results of household food waste (HFW, PFW) and calorie loss (HCL, PCL) between households with and without refrigerator usage. The results show that the significant variables affecting household food waste (calorie loss) differ between households with and without refrigerator usage, suggesting that the factors related to household food waste and calorie loss are heterogeneous. The DKI of food decision maker is negatively correlated with food waste for households using refrigerators. This result is reasonable, as a food decision maker with a higher DKI may make better use of a refrigerator and therefore waste less food. However, the insignificant effect of the DKI on household food waste for a household not using a refrigerator is also reasonable because the impacts of the DKI on household food waste are heterogeneous for households with different incomes (Min et al. 2021).

For households that do not use refrigerators, family size has a significant and positive impact on household food waste, consistent with the findings of previous studies (Parfitt et al. 2010). Generally, a household with more family members prepares more food and thereby might have more leftovers that are likely to be wasted in a context with poor food storage conditions, as in the absence of a refrigerator. In line with the findings of Parfitt et al. (2010), household income significantly and positively affects household food waste and calorie loss. This result is reasonable, as a household with a higher income normally pays more attention to higher household dietary diversity and nutrient intake (Yu and Jacnicke 2020), thereby allowing excess food to be wasted when a refrigerator is lacking.

Similarly, in the urbanization and development process proxied by the index of the located village, a household not using a refrigerator is likely to waste more food (Parfitt et al. 2010; Thyberg and Tonjes 2016). Nevertheless, the supermarket variable has a negative impact on household food waste. This may be because the improved food availability due to supermarkets leads rural households to prepare fewer foods at home and thereby waste fewer foods (Cuffey et al. 2023).

5.3. Treatment effects of refrigerator usage on household food waste and calorie loss

Based on the estimation results of the ESR models, a counterfactual analysis could be conducted to simulate the treatment effect of refrigerator usage on household food waste and calorie loss. Following Eq. (10), the ATTs of refrigerator usage on household food waste and calorie loss are calculated (Table A7). The significant and positive ATTs shown in Fig. A3 reveal that refrigerator usage could lead to more household food waste, and these findings are consistent with the conclusions of Carolan (2021), confirming our first hypothesis. This mechanism analysis provides a reasonable explanation of how refrigerator usage affects household food waste in rural China through the possibility of storing excess food.

Specifically, for households using refrigerators, refrigerator usage could increase household food waste by 24.35 %, food waste per capita by 35.12 %, household calorie loss by 29.29 % and calorie loss per capita by 70.73 %. Obviously, refrigerator usage could lead to more food waste and calorie loss per capita than at the household level. This is possibly due to the heterogeneity of family size. Moreover, refrigerator usage led to more calorie loss than food waste, regardless of the per capita or household level. A possible reason is that refrigerator usage may change food decision makers' food purchasing behavior and lead to the waste of more high-calorie foods.

5.4. Heterogeneity analysis

To further understand the impact of refrigerator usage on food waste and calorie loss among households with different characteristics, a series of heterogeneity analyses were conducted. First, considering that rural residents with different education levels may vary in their capacity to use refrigerators, we detect the heterogeneous impacts of refrigerator usage on household food waste among residents with different education levels. According to the years of education of the food decision maker in a household, the sample households are divided into three groups (Table A8). Based on the ESR models, we further calculate the ATTs of refrigerator usage on household food waste and calorie loss for the three groups. The results shown in Fig. 1 suggest heterogeneous impacts of refrigerator usage on household food waste and calorie loss. There is a lower ATT of refrigerator usage on household food waste and calorie loss for households whose food decision maker has a higher education level. The possible explanations are higher levels of education, better food storage behavior, and a weakening of the impact of refrigerator usage on household food waste (Secondi et al. 2015; Holsteijn and Kemna 2018).

Second, refrigerator usage may have different effects on household food waste and calorie loss among residents with different DKI values (Min et al. 2021). As shown in Table A8, the sample households are divided into three groups according to the DKI of food decision makers. Fig. 2 reports the estimated ATTs of refrigerator usage on household food waste and calorie loss. A food decision maker with a higher DKI could have lower household food waste and calorie loss. This result implies that promoting household decision makers' DKI could efficiently reduce household food waste and calorie loss.

Third, with rural economic development in China, the household income of rural residents has been increasing, from an average per capita income of 2253 yuan in 2000 to 23,119 yuan in 2024. In this context, it is necessary to test whether refrigerator usage has different effects on household food waste and calorie loss among households with different income levels (Table A8). As shown in Fig. 3, for all income groups, ATTs are always significantly positive, but refrigerator usage has a greater impact on household food waste and calorie loss for lower-income households. This may be attributed to the fact that refrigerator usage enables lower-income households to store more food at home (Holsteijn and Kemna, 2018; Cuffey et al., 2023). However, it seems to differ from previous assumption that higher-income households are more likely to store larger quantities of food at home (Jribi et al., 2020). This can be explained by the inverted U-shaped relationship between household income and the quantity of food stored and consumption at home (Ren et al., 2019; Porpino et al., 2015; Toma, 2014). In the study period, the household income levels in rural China remain relatively low and didn't reach the turning point. Accordingly, lower-income rural households are more likely to store larger quantities of food at home and thereby leading to more food wasted.

Finally, considering that residents may better utilize refrigerators with increasing use time, we investigate the heterogeneous effects of refrigerator usage on food waste and calorie loss in different years. Fig. 4 shows that the ATTs of refrigerator usage on food waste and calorie loss were the highest in 2004, followed by 2006, and the lowest in 2009. This implies that an increase in refrigerator usage experience may reduce the food waste and calorie loss that refrigerator usage leads to.

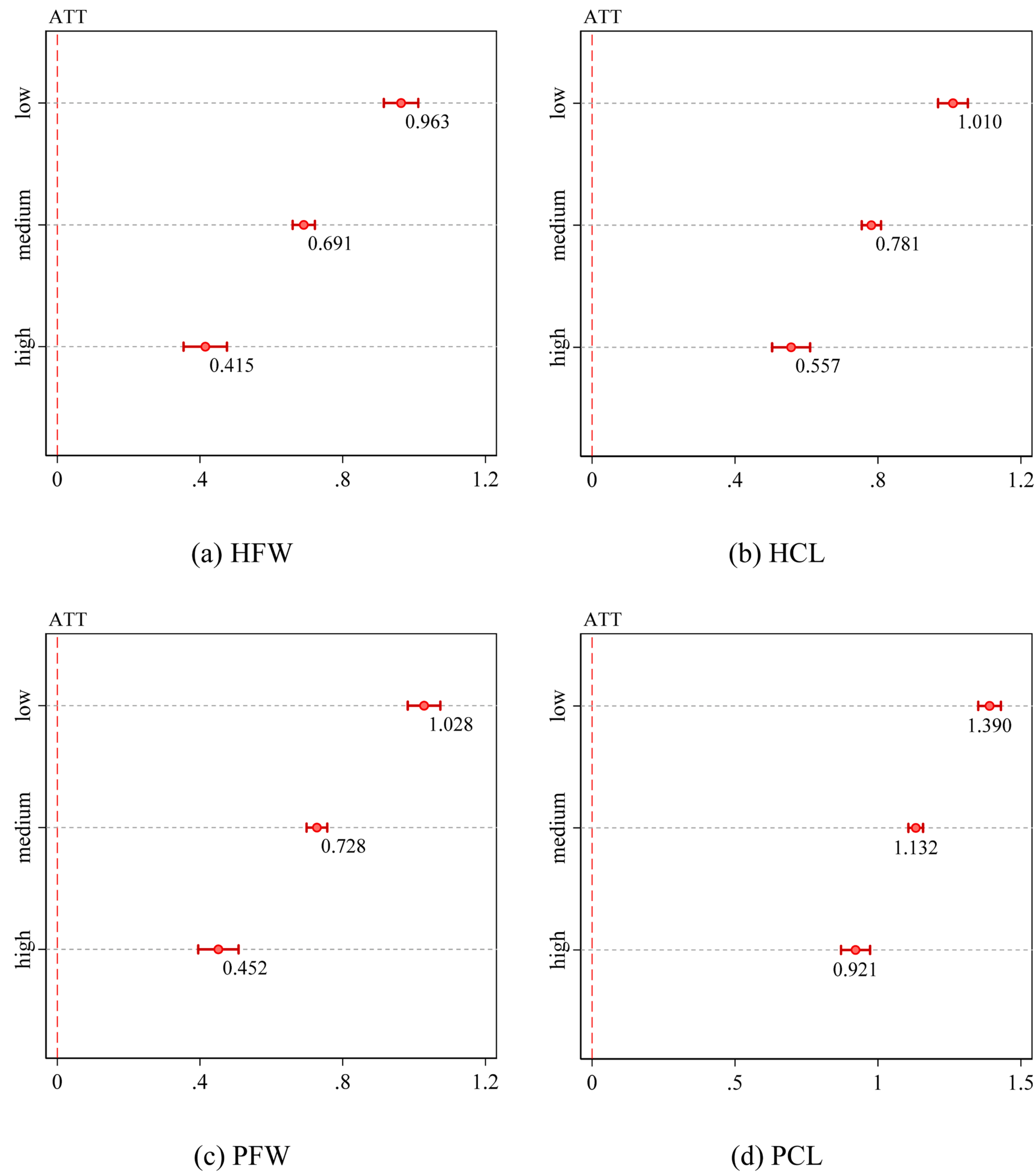

Fig. 1. Treatment effects of refrigerator usage on household food waste by education.

5.5. Mechanism analysis

This section seeks to shed light on the potential channels through which refrigerator usage positively affects household food waste in rural China. Due to improvements in food storage conditions, it is common for individuals to purchase and cook more items than they require (Brizi 2021; Jribi et al. 2020). However, the freshness of other goods whose quality degrades with time, such as fruits and vegetables, is sometimes difficult to guarantee in refrigerators. Additionally, if overprepared fresh meat or seafood is not properly stored in a refrigerator, food waste can ensue. Therefore, we posit that the quantity of available food at home is a possible channel through which refrigerator usage affects household food waste and calorie loss. Based on the ESR model and a counterfactual analysis, we further estimate the ATTs of refrigerator usage on the quantity of stored food at home.

As shown in Table A9, there are significantly positive ATTs of

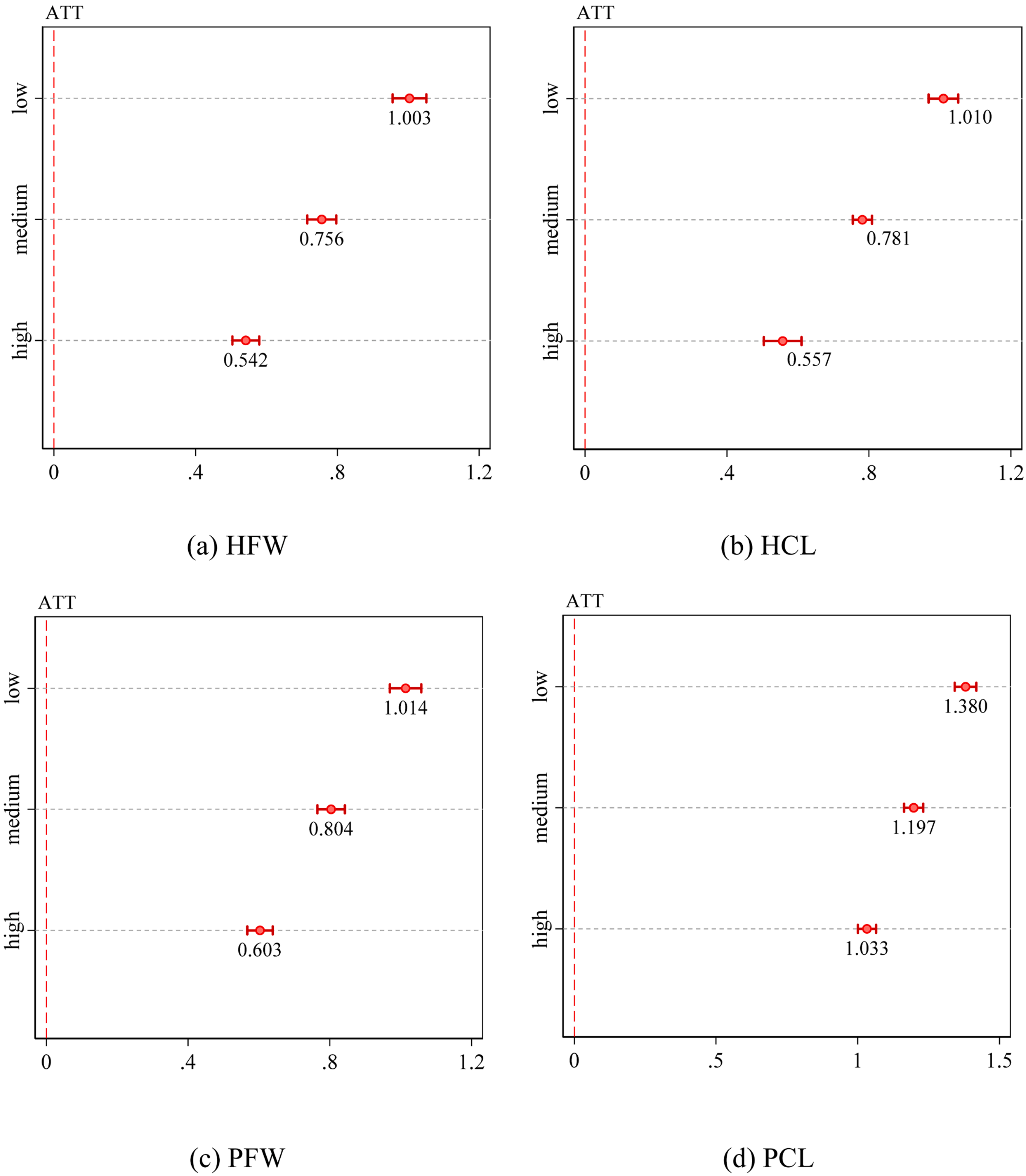

Fig. 2. Treatment effects of refrigerator usage on household food waste by DKI.

refrigerator usage on the quantity of available food at home. For households using refrigerators, refrigerator usage significantly increased the quantity of available food at home by 9.53 %. The results imply that hypothesis 2 cannot be rejected; i.e., refrigerator usage can increase household food waste by increasing the quantity of stored food at home. Hence, household food storage quantity is a key channel through which refrigerator usage impacts household food waste in rural China.

5.6. *Robustness tests*

We conduct two robustness checks to show the stability of our main findings reported in Table A10 and Table A11. First, residents in China tend to increase their consumption of high-value food, such as meat, seafood, and fruit (Yu and Abler 2009). We use a subsample focused on the food waste and calorie loss of high-value food to re-estimate the

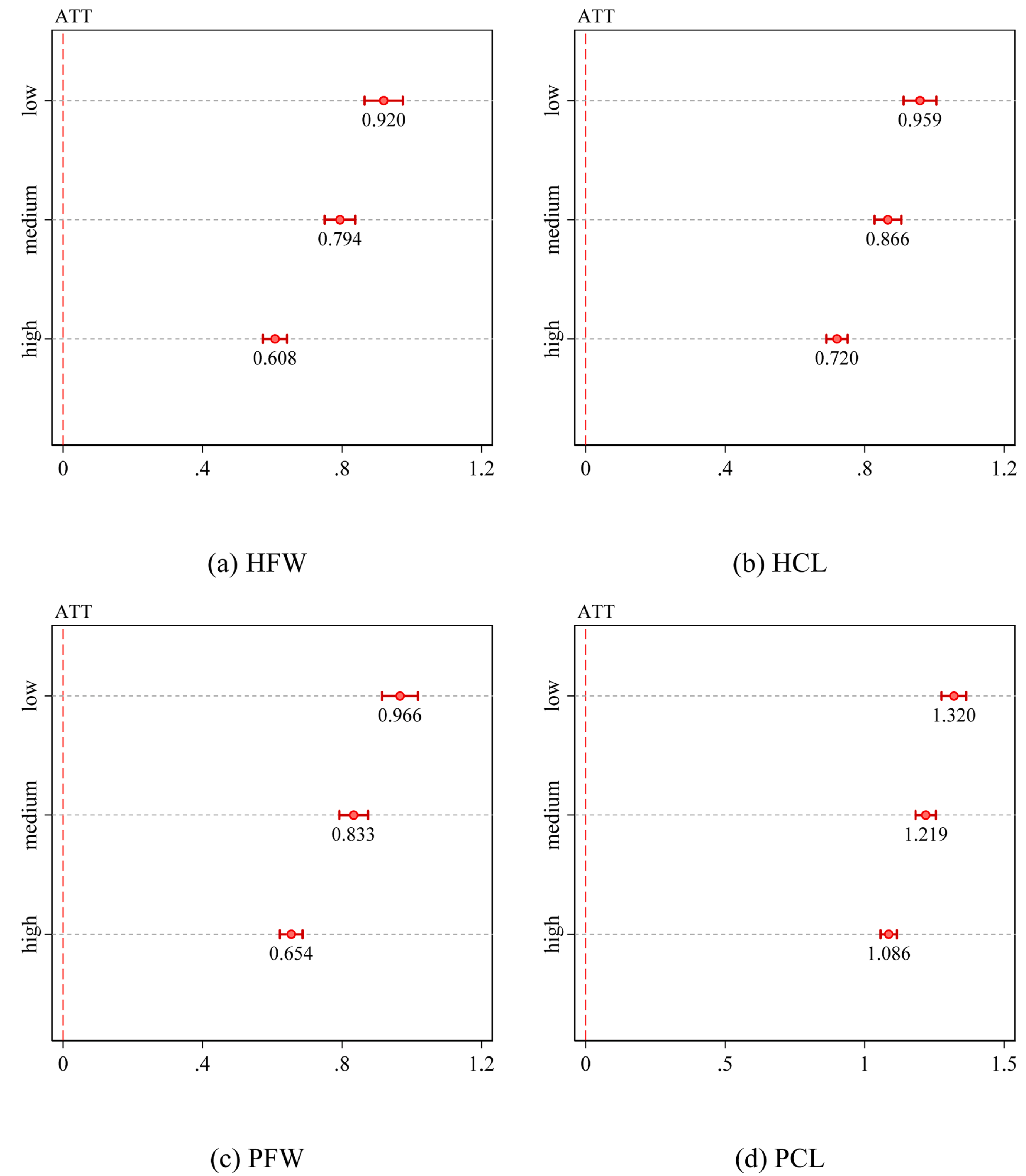

Fig. 3. Treatment effects of refrigerator usage on household food waste by income.

impacts of refrigerator usage on household food waste and calorie loss by using ESR and counterfactual analysis. The results reported in Fig. A4 show significant and positive ATTs of refrigerator usage on household food waste and calorie loss, consistent with the main findings.

Second, we use an alternative estimation method to test whether the main findings depend on the estimation methods. Like in the ESR model, the treatment effects (TE) model enables us to address selectivity bias arising from both observed and unobserved heterogeneity. Another advantage of the TE model is that it can estimate the direct effect of refrigerator usage on rural household food waste and calorie loss (Maddala 1983; Wooldridge 2010). Therefore, we employ the TE model to test the robustness of the basic results. The results reported in

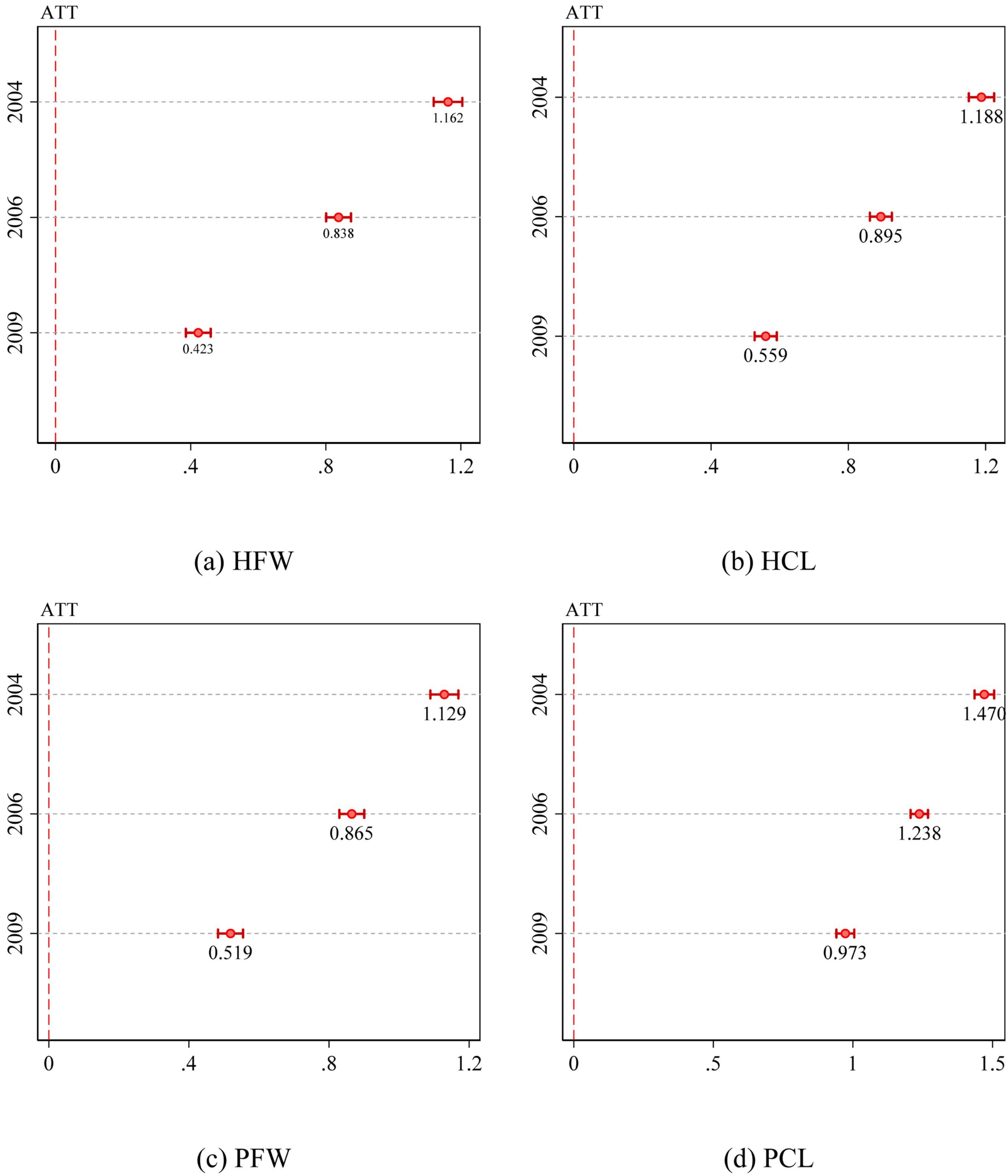

Fig. 4. Treatment effects of refrigerator usage on household food waste by year.

Table A11 show significant and positive effects of refrigerator usage on household food waste and calorie loss, in line with our main findings. Hence, the findings that refrigerator usage could lead to more food waste and calorie loss at home in rural China are robust and stable.

6. Concluding remarks

This study assessed the impacts of refrigerator usage on household food waste and calorie loss in rural China. Based on the panel data of the CHNS, ESR models are employed to control for potential sample selection bias and estimate the ATTs of refrigerator usage on household food waste and calorie loss. The results indicate that refrigerator usage could increase household food waste by 24.35 % and calorie loss by 29.29 %. The main impact channel through which refrigerator usage affects household food waste is the quantity of stored food at home. For households with a lower DKI, a lower education level, and a lower household income, refrigerator usage could lead to more household food waste and calorie loss.

The findings of this study have important practical significance for reducing household food waste in rural China and other developing countries with similar situations. As refrigerator usage becomes increasingly prevalent in developing countries, strategies to reduce rural household food waste should be closely aligned with the expansion of refrigerator usage. First, it is crucial to address the issue of over-storage refrigerators. Media channels, including television and the internet, can be utilized to disseminate tips on food planning for rural households using refrigerators and urge them to avoid overbuying and storing food (Smith and Landry 2021). Additionally, governments should enhance public knowledge on effective refrigerator use, such as conducting routine checks to identify expired or spoiled food and organizing perishable items for rational consumption (Priefer et al., 2016). Second, policymakers should design targeted policies to optimize refrigerator usage and reduce food waste among rural populations. For instance, community education programs could be implemented to teach food storage techniques and refrigerator management, particularly for residents with lower education levels. Simultaneously, stricter labeling standards should be enforced on food packaging to display storage instructions and expiration dates (Messer et al., 2017; Rickard et al., 2023). To support low-income families, subsidies could be provided to help them upgrade to smarter refrigerators with advanced temperature control and storage features, which can significantly reduce food waste. Moreover, to reduce over–purchasing local grocery stores should offer smaller-sized or flexible packaging options for low-income families (Berger and van Helvoirt, 2018). Finally, policymakers should consider synergistic measures to mitigate the increase in household food waste due to refrigerator usage. For instance, improving rural food markets including wet market can play a vital role in reducing the need for excessive home food storage. Developing rural food markets, such as increasing access to fresh produce, providing better storage and transport facilities, and promoting efficient supply chains, is recommended (Cuffey et al., 2023). These improvements can help reduce the reliance on excessive food storage in refrigerators at home and minimize the chances of food going to waste.

Finally, we would like to point out some limitations of this study. The CHNS data have several advantages, including the good representativeness with a long panel and a three-day record dietary approach. To some extent, this dataset is uniquely suitable for analyzing the evolution of household food consumption and food waste in China (Huang and Tian, 2019; Qi et al., 2020). However, some limitations need to be noted. Firstly, the data from the CHNS collected in 2004, 2006, and 2009 were used in this study. Obviously, the data are quite old, but it facilitates us to explore the impacts of improvements in food storage conditions on household food waste and calorie loss in a developing economy given that the refrigerator usage increased from 22.60 % to 50 %. These findings have reference implications for other developing countries in South Asia or Africa. Secondly, the study may underestimate the quantity of food waste, as the CHNS data do not account for the waste of food away from home. With rapid urbanization and rising incomes, dining out and food delivery services have become increasingly prevalent, contributing to a significant portion of food waste (Xu et al., 2020; Wang et al., 2022; Zhao et al., 2024). Ignoring this aspect may lead to an underestimation of the overall food waste issue. In future studies, more related research should be conducted using panel data and a timely and representative dataset to analyze the food waste including those wasted at home and food away from home.

CRediT authorship contribution statement

Longqiang Zhao: Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Shi Min:** Writing – review & editing, Validation, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Xiaobing Wang:** Writing – review & editing, Validation, Data curation. **Xiaohua Yu:** Writing – review & editing, Investigation.

Declaration of competing interest

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

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Appendix A

Table A1
Falsification test for the validity of the proposed IV for refrigerator usage.

Variables	Refrigerator usage	For households that do not use a refrigerator			
		Log(HFW)	Log(PFW)	Log(HCL)	Log(PCL)
Electricity (*IV*)	−0.423***	0.302	0.255	0.167	0.125
	(0.105)	(0.198)	(0.170)	(0.192)	(0.166)
Control	Controlled	Controlled	Controlled	Controlled	Controlled

(*continued on next page*)

Table A1 (*continued*)

Variables	Refrigerator usage	For households that do not use a refrigerator			
		Log(HFW)	Log(PFW)	Log(HCL)	Log(PCL)
Year FE	Controlled	Controlled	Controlled	Controlled	Controlled
MK estimator	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	−2.304***	0.843***	1.245***	0.142***	0.545***
	(0.222)	(0.416)	(0.358)	(0.404)	(0.350)
Observations	3412	4607	4607	4607	4607

Note: Robust standard errors in parentheses are clustered at the household level; significance level * < 0.10, ** < 0.05, *** < 0.01; control variables are consistent with Table 2.

Table A2
Definitions and descriptive statistics of the key variables.

Variable	Variable definition	Mean			
		Full sample	2004	2006	2009
HFW	Quantity of household food waste over 3 days (g)	314.926	345.744	313.776	287.820
		(493.450)	(561.089)	(474.228)	(441.354)
PFW	Quantity of household food waste per capita over 3 days (g)	130.653	153.800	126.085	113.900
		(204.062)	(240.366)	(191.857)	(175.481)
HCL	Household calories loss over 3 days (kcal)	323.588	374.682	291.761	307.685
		(682.105)	(813.314)	(602.288)	(617.883)
PCL	Calories lossper capita over 3 days (kcal)	133.001	163.997	116.246	120.901
		(202.439)	(355.133)	(237.493)	(242.416)
Observations		8021	2545	2697	2779

Data source: Authors' calculations based on the CHNS data (2004–2009).

Table A3
Questions concerning dietary knowledge in the CHNS.

Do you strongly agree, agree, neutral, disagree, or strongly disagree with this statement?	True/False
Please note that the question is not asking about your actual habits.	
Q1: Choosing a diet with a lot of fresh fruit and vegetables is good for one's health	T
Q2: Eating a lot of sugar is good for one's health	F
Q3: Eating a variety of foods is good for one's health	T
Q4: Choosing a diet high in fat is good for one's health	F
Q5: Choosing a diet with a lot of staple foods (rice and rice products and wheat and wheat products) is not good for one's health	T
Q6: Consuming a lot of animal products daily (fish, poultry, egg, and lean meat) is good for one's health	F
Q7: Reducing the amount of fatty meat and animal fat in one's diet is good for one's health	T
Q8: Consuming milk and dairy products is good for one's health	T
Q9: Consuming beans and bean products is good for one's health	T
Index rules: 1 point was given for correct answers, −1 point for incorrect answers, and 0 points for other answers	

Table A4
Estimation results of the ESR for PFW.

Variables	Refrigerator usage	Log(PFW)	
		Use	Nonuse
Gender	−0.108*(0.065)	−0.058(0.161)	0.080(0.137)
Age	−0.005(0.003)	−0.004(0.008)	−0.008(0.006)
Education	0.021*(0.011)	−0.020(0.028)	0.016(0.023)
Work status	0.032(0.057)	0.086(0.141)	0.068(0.122)
DKI	0.012(0.010)	−0.040(0.025)	−0.022(0.020)
Family size	0.059(0.049)	−0.129(0.125)	0.030(0.097)
Proportion(≤14)	0.003(0.003)	0.006(0.006)	−0.000(0.005)
Proportion(≥60)	−0.002(0.002)	0.003(0.005)	−0.000(0.003)
Log(income)	0.000(0.012)	−0.008(0.029)	0.061**(0.027)
Air conditioner	0.605***(0.098)	0.023 (0.199)	0.210(0.331)
UDI	0.002(0.004)	−0.011(0.009)	0.011(0.007)
Supermarket	−0.004(0.057)	−0.117(0.157)	−0.275**(0.112)
Price	controlled	controlled	controlled
MK estimator	controlled	controlled	controlled
wave	controlled	controlled	controlled
Electricity (*IV*)	−0.826***(0.103)		
Constant	−3.324***(0.242)	2.157**(0.983)	1.656***(0.523)
Lns_1/ Lns_0		0.846***(0.021)	0.839***(0.013)
rho0/rho1		−0.277**(0.136)	−0.183* (0.104)
Wald test		6.44**(p value=0.04)	
Log likelihood		−2,1915.61	
Observations	8019	3412	4607

Note: Robust standard errors in parentheses are clustered at the household level; significance level *<0.10, **<0.05 and ***<0.01.

Table A5
Estimation results of the ESR for HCL.

Variables	Refrigerator usage	Log(HCL)	
		Use	Nonuse
Gender	−0.108*(0.065)	−0.080(0.181)	0.099(0.155)
Age	−0.005(0.003)	−0.002(0.009)	−0.011(0.007)
Education	0.020*(0.011)	−0.028(0.032)	0.021(0.026)
Work status	0.032(0.057)	0.101(0.159)	−0.008(0.137)
DKI	0.012(0.010)	−0.042(0.028)	−0.027(0.023)
Family size	0.060(0.049)	0.145(0.141)	0.300***(0.109)
Proportion(≤14)	0.003(0.003)	0.009(0.007)	−0.001(0.006)
Proportion(≥60)	−0.002(0.002)	0.003(0.006)	−0.002(0.004)
Log(income)	0.000(0.012)	−0.002(0.033)	0.064**(0.030)
Air-conditioner	0.605***(0.098)	−0.005(0.221)	0.139(0.382)
UDI	0.002(0.004)	−0.010(0.010)	0.017**(0.008)
Supermarket	−0.005(0.057)	−0.071(0.177)	−0.230*(0.125)
Price	controlled	controlled	controlled
MK estimator	controlled	controlled	controlled
wave	controlled	controlled	controlled
Electricity (*IV*)	−0.816***(0.104)		
Constant	−3.328***(0.244)	1.456(1.027)	0.365(0.605)
Lns_1/ Lns_0		0.967***(0.020)	0.955***(0.013)
rho0/rho1		−0.295**(0.121)	−0.160(0.123)
Wald test		6.43**(p value=0.04)	
Log likelihood		−2,2860.82	
Observations	8019	3412	4607

Note: Robust standard errors in parentheses are clustered at the household level; significance level *<0.10, **<0.05 and ***<0.01.

Table A6
Estimation results of the ESR for PCL.

Variables	Refrigerator usage	Log(PCL)	
		Use	Nonuse
Gender	−0.108*(0.065)	−0.059 (0.156)	0.086 (0.136)
Age	−0.005 (0.003)	−0.003 (0.008)	−0.008 (0.006)
Education	0.020*(0.011)	−0.025 (0.027)	0.015 (0.023)
Work status	0.030 (0.057)	0.080 (0.138)	−0.007 (0.120)
DKI	0.011 (0.010)	−0.035 (0.024)	−0.021 (0.020)
Family size	0.061 (0.049)	−0.097 (0.122)	0.021 (0.096)
Proportion (≤14)	0.003 (0.003)	0.008 (0.006)	−0.001 (0.005)
Proportion (≥60)	−0.002 (0.002)	0.002 (0.005)	−0.002 (0.003)
Log(income)	0.000 (0.012)	0.001 (0.029)	0.053**(0.026)
Air conditioner	0.606***(0.098)	0.047 (0.188)	−0.066 (0.342)
UDI	0.002 (0.004)	−0.010 (0.009)	0.012*(0.007)
Supermarket	−0.003 (0.057)	−0.018 (0.153)	−0.153(0.110)
Price	controlled	controlled	controlled
MK estimator	controlled	controlled	controlled
wave	controlled	controlled	controlled
Electricity (*IV*)	−0.825***(0.102)		
Constant	−3.292***(0.245)	1.401*(0.831)	0.985*(0.552)
Lns_1/ Lns_0		0.821***(0.018)	0.827***(0.020)
rho0/rho1		−0.270**(0.107)	−0.290** (0.146)
Wald test		8.02** (p value=0.01)	
Log likelihood		−2,1725.71	
Observations	8019	3412	4607

Note: Robust standard errors in parentheses are clustered at the household level; significance level *<0.10, **<0.05 and ***<0.01.

Table A7
ATT of refrigerator usage on household food waste and calorie loss.

Outcome variables	Mean outcomes		ATT	Change
	Refrigerator usage	Refrigerator nonuse		
log(HFW)	3.703 (0.016)	2.978 (0.017)	0.725*** (0.024)	24.3 5 %
log(PFW)	3.124 (0.014)	2.312 (0.015)	0.812*** (0.020)	35.1 2 %
log(HCL)	3.399 (0.016)	2.629 (0.018)	0.770*** (0.024)	29.2 9 %
log(PCL)	2.829 (0.013)	1.657 (0.016)	1.172*** (0.020)	70.7 3 %

Note: Standard deviations are presented in parentheses; significance level *** < 0.01, ** < 0.05, * < 0.10.

Table A8
Heterogeneous ATTs of refrigerator usage on household food waste and calorie loss.

Outcome variables	ATT			
	Log(HFW)	Log(HCL)	Log(PFW)	Log(PCL)
DKI				
Low (−2<DKI≤2)	1.003*** (0.024)	1.056*** (0.021)	1.014*** (0.023)	1.380*** (0.019)
medium (2<DKI≤5)	0.756*** (0.021)	0.837*** (0.018)	0.804*** (0.020)	1.197*** (0.017)
High (5<DKI≤9)	0.542*** (0.019)	0.650*** (0.017)	0.603*** (0.018)	1.033*** (0.016)
Income				
Low (0<lnincome≤8.50)	0.920*** (0.028)	0.959*** (0.024)	0.966*** (0.026)	1.320*** (0.023)
medium (8.50<lnincome≤9.34)	0.794*** (0.022)	0.866*** (0.019)	0.833*** (0.021)	1.219*** (0.018)
high (9.34<lnincome≤11.12)	0.608*** (0..018)	0.720*** (0.015)	0.654*** (0.017)	1.086*** (0.015)
Education				
Low (Age≤6)	0.963*** (0.025)	1.001*** (0.021)	1.028*** (0.023)	1.390*** (0.020)
Medium (6<Age≤10)	0.691*** (0.016)	0.781*** (0.014)	0.728*** (0.015)	1.132*** (0.013)
High (Age>10)	0.415*** (0.031)	0.557*** (0.027)	0.452*** (0.029)	0.921*** (0.026)
Year				
2004	1.162*** (0.022)	1.188*** (0.019)	1.129*** (0.020)	1.470*** (0.018)
2006	0.838*** (0.019)	0.895*** (0.016)	0.865*** (0.015)	1.238*** (0.016)
2009	0.423*** (0.019)	0.559*** (0.016)	0.519*** (0.018)	0.973*** (0.016)

Note: Standard deviations are presented in parentheses; significance level *** < 0.01, ** < 0.05, * < 0.10.

Table A9
ATT of refrigerator usage on the quantity of available food at home.

Outcome variables	Mean outcomes		ATT	Change
	Refrigerator usage	Refrigerator nonuse		
Log(HFW2)	8.320 (0.006)	8.230 (0.006)	0.091*** (0.008)	9.5 3 %

Note: Standard deviations are presented in parentheses; significance level *** < 0.01, ** < 0.05, * < 0.10.

Table A10
ATT of refrigerator usage on household food waste and calorie loss for high-value food.

Outcome variables	Mean outcomes		ATT
	Refrigerator usage	Refrigerator nonuse	
log(HFW1)	3.352 (0.016)	2.697 (0.016)	0.654*** (0.023)
log(PFW1)	2.814 (0.014)	2.014 (0.014)	0.800*** (0.019)
log(HCL1)	2.823 (0.014)	2.506 (0.014)	0.317*** (0.020)
log(PCL1)	2.299 (0.012)	1.985 (0.011)	0.314*** (0.016)

Note: Standard deviations are presented in parentheses; significance level *** < 0.01, ** < 0.05, * < 0.10.

Table A11
Impacts of refrigerator usage on household food waste and calorie loss: Treatment effects model.

Variables	Treatment effects model		Treatment effects model		Treatment effects model		Treatment effects model	
	Refrigerator usage	Log(HFW)	Refrigerator usage	Log(PFW)	Refrigerator usage	Log(HCL)	Refrigerator usage	Log(PCL)
REF		0.810** (0.350)		0.828*** (0.305)		0.884** (0.372)		0.967*** (0.315)
Electricity (IV)	−0.818** (0.105)		−0.824*** (0.104)		−0.819*** (0.104)		−0.824*** (0.102)	
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Mundlak mean	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	−3.321** (0.242)	0.981** (0.464)	−3.321*** (0.242)	1.378*** (0.402)	−3.309*** (0.242)	0.263*** (0.458)	−3.302*** (0.242)	0.704*** (0.401)
Ath($\rho_{\mu\varepsilon}$)=0	−0.171***(0.078)		−0.205***(0.079)		−0.204**(0.086)		−0.260***(0.089)	
Ln(σ)	0.992*** (0.010)		0.8482*** (0.011)		0.965***(0.011)		0.829***(0.013)	
Wald test (rh0=0)	4.12** with Prob > chi2 = 0.042		5.53** with Prob > chi2 = 0.020		4.72** with Prob > chi2 = 0.003		6.69** with Prob > chi2 = 0.011	
Observations	8019		8019		8019		8019	

Note: Robust standard errors in parentheses are clustered at the household level; significance level *<0.10, **<0.05 and ***<0.01; control variables are consistent with those in Table 3.

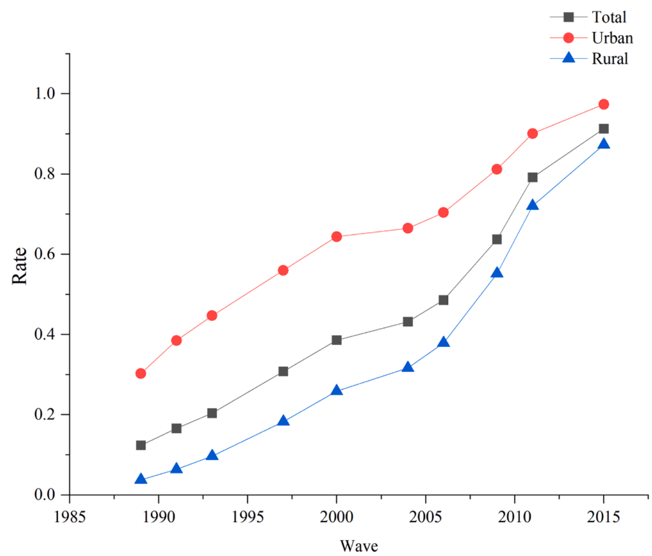

Fig. A1. The use rate of refrigerators among CHNS sample households.
Source: Authors' calculations based on the CHNS data (1989–2015).

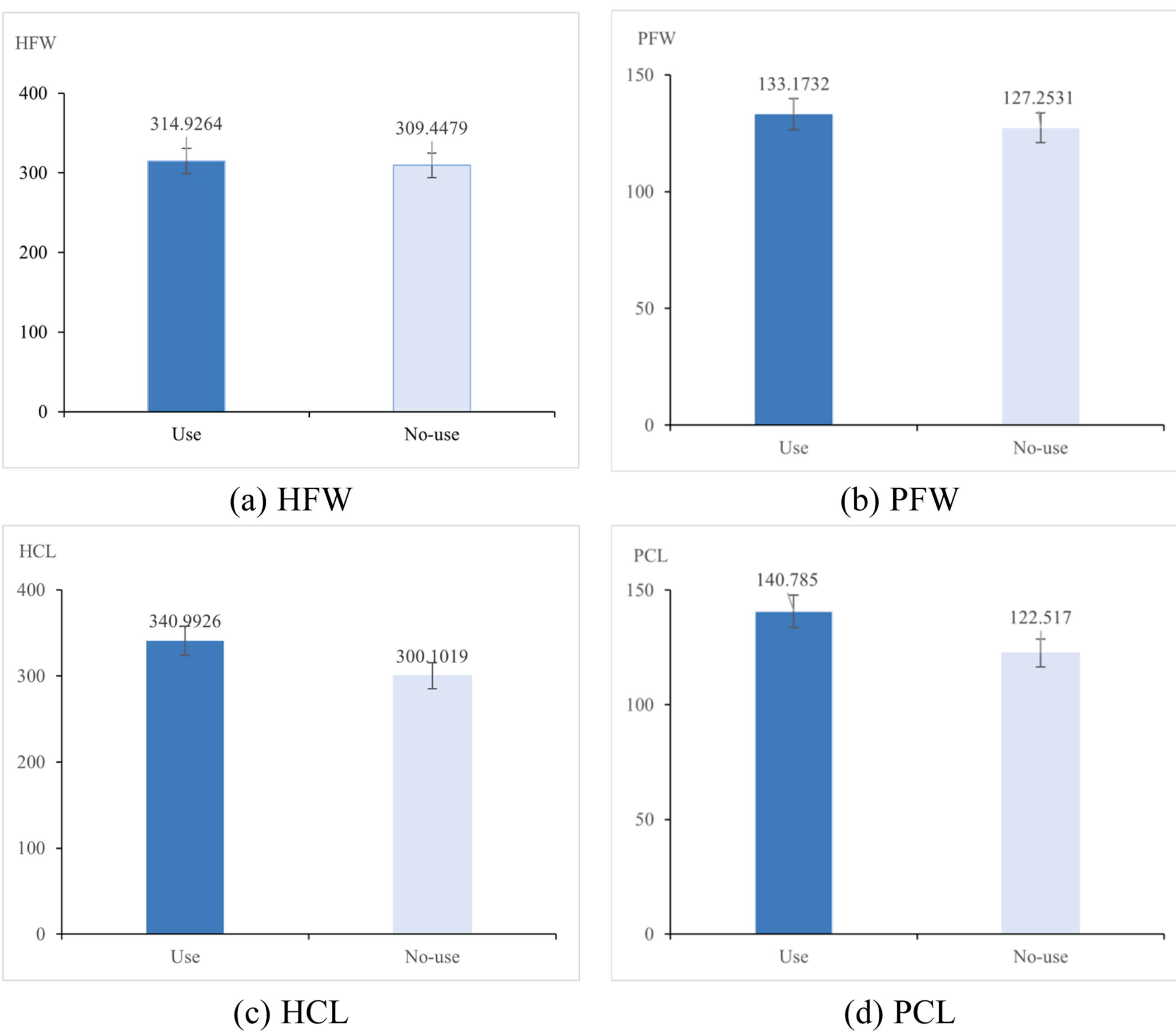

Fig. A2. Mean differences in household food waste and calorie loss between households with and without using refrigerator.

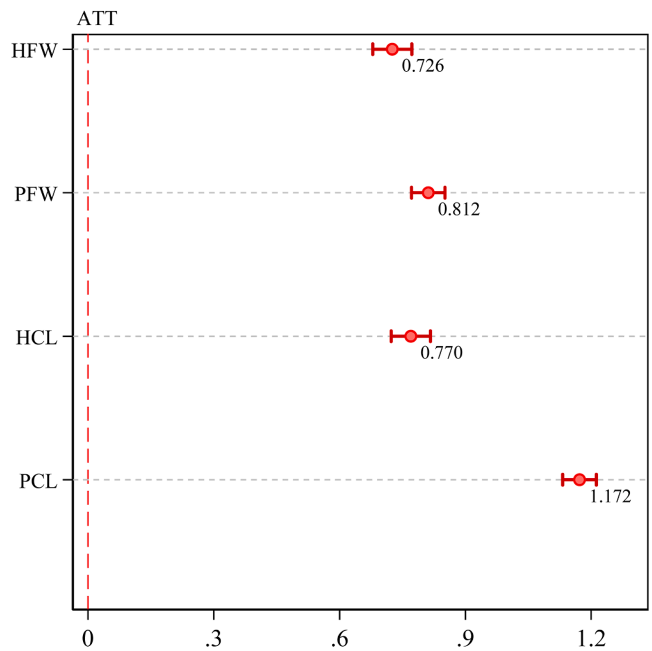

Fig. A3. Treatment effects of refrigerator usage on household food waste.

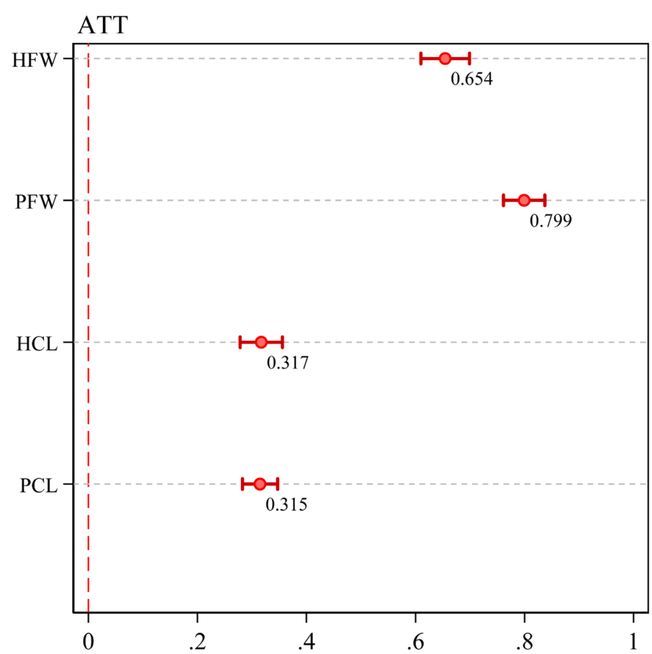

Fig. A4. Treatment effects of refrigerator usage on high-value food waste.

Data availability

Data will be made available on request.

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