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Instant effects decay: re-examining the impact of information intervention on consumers' food date label cognition and food waste behavior

RESEARCH ARTICLE

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Abstract

The global food waste crisis has emerged as a pressing sustainability challenge, an accurate understanding of food date labels presents a critical opportunity for reducing global food waste. However, current empirical research has paid limited attention to this pathway due to challenges in data acquisition, and longitudinal evidence remains particularly scarce. To address this research gap, this study collects three-stage balanced panel data (N=1,206) tracking consumers' food date label cognition and food waste behaviors over 1.5 years, and yields three key findings: (1) Information interventions maintain significant effectiveness during the follow-up period, with persistent cognition differences between intervention and control groups; (2) while impactful, intervention effects exhibit notable temporal decay, suggesting the need for periodic reinforcement to sustain label cognitive and food waste behavioral changes; (3) intervention strategies should prioritize three key demographics: consumers in warmer southern regions (where food perishability is higher), female consumers (typically responsible for household food management), and focusing on perishable foods may offer particularly effective pathways for reducing food waste. These findings provide empirical evidence for designing more effective, sustained intervention programs to improve date label interpreting and reduce food waste to achieve United Nations Sustainable Development Goal 12.3 "Halve Food Waste" before 2030.

Keywords: Difference-in-Differences (DID), experimental economics, follow-up survey, food date label, food waste behavior
JEL-code: Q18

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1. Introduction

The global food waste crisis has emerged as a pressing sustainability challenge, with scholars documenting its escalating severity (Aschemann-Witzel *et al.*, 2015; Block *et al.*, 2022; De Gorter *et al.*, 2021). The Food and Agriculture Organization of the United Nations (FAO, 2011) estimates that approximately one-third of global food production – equivalent to 1.3 billion tons annually – is lost or wasted. Within the food supply chain, the consumption stage represents the most substantial component of waste generation (FUSIONS, 2016; UNEP, 2021). A critical and often overlooked driver of this waste is consumer misunderstanding of food date labels. Food labeling systems serve as crucial information intermediaries between producers and consumers (Graham *et al.,* 2012; Malek *et al.*, 2020), yet the current heterogeneity in date label terminology has created widespread consumer confusion (Wilson and Miao, 2025). Research indicates that consumers frequently conflate quality indicators (e.g., "best before" dates) with safety thresholds (Kosa *et al.*, 2007; Newsome *et al.*, 2014), leading to the premature waste of edible food as a precautionary measure. This misinterpretation constitutes an important cause of global food waste (Davenport *et al.*, 2019; Verghese *et al.*, 2015; Waste and Resources Action Programme, 2011). In the United States alone, the U.S. Food and Drug Administration (FDA) reports that over 90% of consumers discard food prematurely due to label misinterpretations, accounting for approximately 20% of national food waste (FDA, 2019).

In response, improving consumer comprehension of food date labels has emerged as a promising strategy for household-level waste reduction. From a public policy standpoint, anti-food-waste messaging has been widely adopted. Governments and organizations globally have implemented various awareness campaigns as central components of food waste reduction initiatives (Aschemann-Witzel *et al.*, 2017; Neubig and Roosen, 2024; United States Environmental Protection Agency, 2019). These efforts often rely on voluntary engagement, yet their effectiveness remains insufficiently examined (Nisa *et al.*, 2022). Preliminary findings suggest that well-designed messaging campaigns can positively influence consumers' awareness and motivation, ultimately contributing to decreased food waste (Reynolds *et al.*, 2019; Zamri *et al.*, 2020). Furthermore, recent research highlights the critical role of information intermediaries; for instance, Dai and Gong (2024) demonstrate that food retailers and restaurants can significantly shape consumer conservation behaviors through strategically crafted messaging. At a more specific level, several studies have employed informational interventions targeting date label comprehension directly. Turvey *et al.* (2021) found that providing interpretive statements significantly improved consumer understanding of 'best if used by' labels, increasing correct identification rates from 64.0% to 82.0%. Similarly, Gong *et al.* (2022) demonstrated that sensory-based assurances about product characteristics (e.g., normal color, smell, and proper storage conditions) substantially enhanced consumers' willingness to consume yogurt one day past its expiration date. Most notably, Cheng *et al.*'s (2025) groundbreaking study in transitional economy provides empirical evidence that clarifying the meaning of food date labels not only improves consumers' accurate interpretation but also strengthens their waste-reduction intentions.

Despite these valuable contributions, several critical research gaps remain. First, existing interventions primarily focus on modifying label cognition while neglecting to robustly examine subsequent actual food waste behaviors and their causal relationships. Second, although some studies have assessed intervention effects on both cognition and behaviors, their reliance on short-term methodologies limits findings to the instant post-intervention phase, often capturing intentions rather than actual behaviors. Third, there is a complete absence of long-term efficacy assessments, a significant limitation given the well-documented intention-behavior gap. Longitudinal studies are urgently needed to track the dynamic effects of interventions over time. Fourth, current evidence is disproportionately drawn from developed economies, leaving transitional economies substantially underrepresented and hindering the understanding of context-specific mechanisms. Furthermore, existing research has heavily focused on perishable foods (particularly dairy products), although some studies have been conducted on non-perishable foods (Choi *et al.*, 2022), there are relatively few comparative studies that incorporate the two within the same analytical framework for comparative analysis.

To address these gaps, this study employs a unique three-stage longitudinal design, combining baseline (pre-intervention) and post-intervention data from a 2023 online information intervention experiment in China – a representative transitional economy – with a follow-up survey conducted after a 1.5-year interval in 2024. Focusing on milk (perishable) and cookies (non-perishable) consumption patterns, this research examines the sustained impacts and temporal dynamics of informational interventions on consumers' label interpretation and actual food waste behaviors. This study makes three key contributions: First, it pioneers the use of multi-stage longitudinal data to simultaneously track the evolving effects of interventions on both cognitive and behavioral outcomes, overcoming the limitations of previous short-term assessments. Second, by analyzing behavioral trajectories over an extended timeframe, it provides novel insights into the persistence of intervention effects. Third, the findings offer robust empirical evidence for developing effective, long-term strategies to reduce household food waste. These contributions significantly advance understanding in behavioral and food economics, particularly regarding the intention-behavior gap, while directly informing policy measures aimed a achieving UN Sustainable Development Goal 12.3 "halving per capita global food waste at retail and consumer levels by 2030."

The paper proceeds as follows: Section 2 details the experimental design, including sampling procedures, data collection, variable construction, and analytical methods. Section 3 presents the core empirical findings, robustness checks, and heterogeneity analyses. Section 4 discusses the results further, proposes the limitations, suggests future research directions, and outlines practical implications. Section 5 concludes the article.

2. Methods

2.1 Sampling strategy

In China, processed foods are categorized as either bulk or prepackaged, with the latter being standardized, quantitatively uniform products displaying consistent labeling on shelves. Importantly, mandatory date labeling regulations apply only to prepackaged foods. Given evidence that consumer understanding of date labels may vary by product perishability (Toma *et al.*, 2020), the survey initially included two representative food types: perishable (milk) and non-perishable (cookies). Detailed rationale for selecting these products and the original survey locations is provided in Cheng *et al.* (2025). To maintain temporal consistency in follow-up surveys and improve sample representativeness, analysis is restricted to data from eastern China (Beijing and Guangzhou). This approach also addresses regional variations in response rates between initial and follow-up surveys, thereby enhancing the reliability of observed trends.

The second-round questionnaire survey was conducted in 2024 via Questionnaire Star (https://www.wjx.cn), targeting all participants from the first-round 2023 survey (with 1.5 years interval between the two round surveys). Survey distribution and data collection followed quality control protocols, including the platform's participant screening mechanism based on an integrity score system (Lin and Guan, 2021). Unique identifiers ensure initial randomization and longitudinal tracking, while the platform restrict submissions to one per participant. It should be noted that, similar to commonly used online survey sample services, this study required the survey company to randomly assign participants into control and intervention groups, as well as milk and cookies sample groups during the first-round survey in 2023. Since the survey company maintains a large client pool, this randomization process was implemented by the company. In the second-round survey in 2024, we actually distributed the tracking survey to all valid participants who had previously completed the 2023 first-round survey. At this stage, participants remained blinded to their group assignment (control vs. intervention). To ensure data quality, attention-check questions are implemented. Although we initially aimed to track as many participants from the first-round survey as possible in the second-round follow-up, the actual valid sample tracking rate reached only 29.67% due to a low follow-up response rate and rigorous data validation screening. After integrating the second-round responses with two prior datasets, the final sample include 426 valid observations from two cities, forming a balanced three-stage panel data (1,278 total observations). To minimize food-type selection bias, 72 observations from non-consumers of milk or cookies

(24 participants across stages) are excluded, resulting in a final analytical sample of 1,206 observations (402 per stage).

2.2 Experiment design

Building on stimulus-organism-response (SOR) theory applications in food waste research (Talwar *et al.*, 2022), in the first-round survey, we delivered the information intervention content about the actual meaning of China's quality-guaranteed date labels by directly displaying it on participants' screens. The text stated: 'Quality-guaranteed date label – A quality indicator indicates food's optimal taste and flavor, which shares the same meaning as the best before date.' This content was presented on a dedicated page that separated the Stage 1 data collection from the Stage 2 survey data. Specifically, the page preceded the Stage 2 survey and followed the Stage 1 data collection. For detailed experimental protocols from earlier phases are available in Cheng *et al.* (2025). To ensure methodological consistency, the follow-up survey adhered to three key principles: (1) Participant continuity, only first-round participants are recruited; (2) Longitudinal tracking, original food-type assignments (milk or cookies) are retained; (3) Intervention consistency, group classifications (control vs. intervention) remain unchanged. The study specifically examines China's most common date label – the quality-guaranteed date – as a unified terminology. Since the initial intervention precisely mirrors China's official definition (a quality indicator indicates food's optimal taste and flavor, which shares the same meaning as the best before date), the analysis centers on the post-intervention shifts in consumer cognition, and the behavioral changes in food waste linked to this labeling.

Specifically, considering the control group did not receive information intervention, this study employs a differentiated assessment approach between intervention and control groups. The intervention group completes a two-stage evaluation process that first requires to report current comprehension of China's regulatory definition for the quality-guaranteed date label and their present food disposal behavior, followed by recalling the quality-guaranteed date label's definition from the initial intervention and the food discarding intentions/behaviors based on the label definition. To maintain the neutrality of the questionnaire, the word "waste" does not appear in the questionnaire survey, and "discard" is used. For the control group, which received no prior intervention, data collection focuses exclusively on current understanding of the quality-guaranteed date label and actual food discarding behaviors. Due to the inherent challenges of longitudinal data collection, the study maintains baseline demographic and household characteristics from the first-round survey rather than reassessing these variables. This methodological approach serves multiple purposes: streamlining questionnaire administration, enhancing data quality, maintaining survey feasibility, and preserving longitudinal comparability across study stages. The specific experimental flowchart is shown in Figure 1.

2.3 The definition of the food waste behavior

This study operationalizes food waste according to the FAO's (FAO, 2011) definition as the disposal of edible food portions (excluding inedible parts), consistent with Cheng *et al.*'s (2025) operational criteria. Since China's quality-guaranteed date label is functionally equivalent to the "best before" date, discarding food near these labeled dates represents food waste behavior. The survey measures this behavior through a 16-point scale where participants report their food discarding dates relative to the labeled quality-guaranteed date: negative values (−5 to −1) indicate days before expiration (e.g., −5=5 days prior the expiration date), zero (0) represents the exact expiration date, and positive values (+1 to +10) denote days after expiration (e.g., +10=10 days after the expiration date). Higher values on this scale demonstrate longer consumption periods, reflecting greater tolerance of foods and consequently reducing food waste (Cheng *et al.*, 2025).

Notably, this study makes a distinct methodological contribution by capturing participants' actual food waste dates following information intervention, rather than measuring waste intentions as examined in previous research (Cheng *et al.*, 2025). This approach effectively addresses the intention-behavior gap prevalent

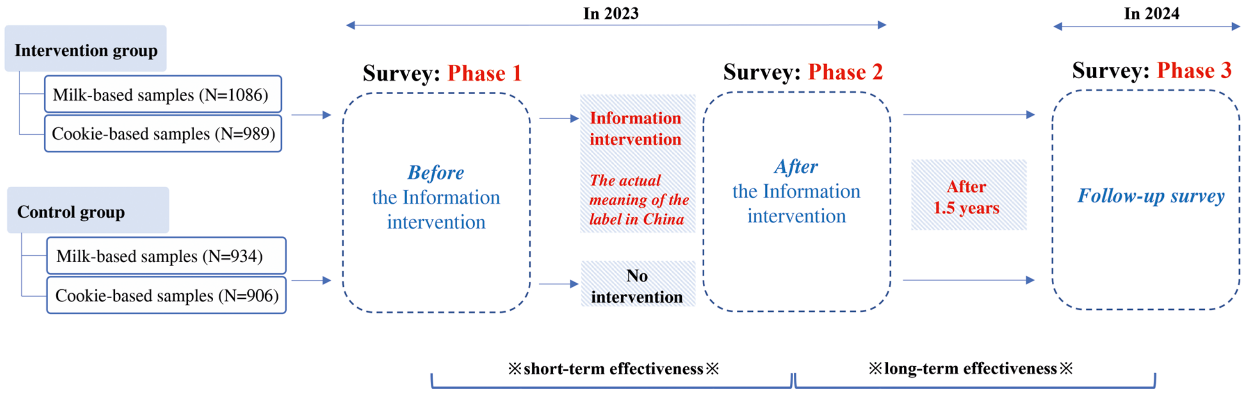

Figure 1. Experimental flowchart.

in the previous study (Chang *et al.*, 2021). For the intervention group, the survey systematically records: (a) food waste dates based on recalled prior intervention content, and (b) food waste dates reflecting current label interpretation. Considering the potential gap between recalled and current comprehension states, the latter measure (b) is particularly valuable as it likely represents more authentic behavior rather than intention. However, throughout the analysis, this study will consistently employ the term "behavior" to ensure conceptual clarity and maintain terminological precision.

2.4 Descriptive statistical analysis of core variables and control variables

The longitudinal analysis demonstrates a significant weakening in consumers' interpretation of the quality-guaranteed date label following the information intervention (see Table 1). The intervention group exhibits a marked decline in correct label interpretation, dropping from 61.40 to 41.23%. Interestingly, the control group also shows cognitive changes, which will be analyzed in detail in the section on self-learning effects. Regarding food waste behavior, findings reveal that consumers commonly discard food after the labeled quality-guaranteed date (date>0) in both survey periods. The intervention's effectiveness in reducing food waste weakens over time, mirroring the observed decline in label interpretation. This effect manifests as progressively earlier food waste behavior, ultimately resulting in increased food waste. Since we have already examined the net short-term effects of the information intervention from Stage 1 to Stage 2 based on the full sample in previous research Cheng *et al*. (2025), the content in Table 1 here only represents the three stages panel data (successfully followed up) used for analysis in this study and does not delve into the impact effects from Stage 1 to Stage 2 in detail.

Table 2 presents the demographic characteristics of the longitudinal sample from Beijing and Guangzhou, drawn from the 2023 baseline survey. The sample consists of 60.45% male participants with a mean age of 32.55 years, consistent with China's general internet user population.[1] Notably, 83.58% hold bachelor's degrees – significantly higher than national internet user averages – reflecting the inherent selection biases of online survey methodologies (Talwar *et al.*, 2022). With an average monthly per capita disposable income of 5921 CNY, the sample represents urban internet users' economic profile.[2,3] Collectively, while skewed toward young, educated males, it remains representative of this key demographic for studying urban consumption patterns.

[1] https://www.cnnic.net.cn/NMediaFile/2024/0325/MAIN1711355296414FIQ9XKZV63.pdf
[2] https://www.cac.gov.cn/2021-02/03/c_1613923423079314.htm
[3] http://big5.www.gov.cn/gate/big5/www.gov.cn/lianbo/bumen/202404/content_6945489.htm

Table 1. Descriptive statistical analysis of key variables

Variable	Cognition (%)				Behavior (date)			
	Stage 1	**Stage 2**	**Stage 3**	**Diff.**	**Stage 1**	**Stage 2**	**Stage 3**	**Diff.**
Intervention group	26.75%	61.40%	41.23%	***	0.27	1.86	0.81	***
Number of observations	228	228	228		228	228	228	
Control group	16.67%	10.34%	29.31%	***	0.46	0.47	0.60	
Number of observations	174	174	174		174	174	174	

*** p<0.01, ** p<0.05, * p<0.1. The significance here represents the paired samples t-test results (Ha: diff!=0) of the corresponding cognition and behavior variables changes between the stage 2 and stage 3 to verify if there are any significant changes.

2.5 Econometric models

This study first examines consumers' cognition of the quality-guaranteed date label between the intervention and control groups using the data from the third-stage follow-up survey to verify whether the information intervention remains effective after 1.5 years. Given that the dependent variable is a binary dummy variable indicating whether the cognition of the quality-guaranteed date label is accurate or not, a logit model for empirical analysis is employed. The specific formula is presented below:

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 \text{Treat}_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

Where P_i denotes the probability of accurate cognition regarding the quality-guaranteed date label, while $1 - P_i$ represents the probability of inaccurate cognition. The subscript i indexes individual participants. Treat_i is a dummy variable equal to 1 for the intervention group (i.e., participants who received the information intervention in the first-round survey) and 0 for the control group (i.e., participants who did not receive the information intervention in the first-round survey). X_i denotes the vector of control variables, encompassing demographic characteristics, household variables, food consumption habits variables, label attitudes variables, food types, and region variable, consistent with those presented in Table 2. ε_i represents the random error term.

Second, this study employs the two-stage balance panel data of the stage 2 and stage 3 of the survey and the Difference-in-Differences (DID) model, a predominant method for evaluating policy implementation effects (Chen and Wu, 2015) to assess the changes in consumer cognition and food waste behavior during the follow-up period. This quasi-experimental approach combines within-subject and between-subject comparisons to evaluate the long-term net effects of the data in the second stage, namely instant cognition and behavior by the follow-up survey. The models are constructed as follows:

$$\text{Cognition}_{it} = \alpha_0 + \alpha_1 \text{ Treat}_i \times \text{Post}_t + \alpha_2 X_{it} + \lambda_i + \upsilon_t + \varepsilon_{it} \quad (2)$$

$$\text{Behavior}_{it} = \delta_0 + \delta_1 \text{ Treat}_i \times \text{Post}_t + \delta_2 X_{it} + \lambda_i + \upsilon_t + \varepsilon_{it} \quad (3)$$

Where t indexes the time period in the data series. Cognition_{it} denotes participant i's cognition of food date label at time t. Behavior_{it} represents participant i's food waste behavior at time t. Treat_i is a dummy variable indicating intervention or control group. $Post_t$ is a time dummy variable. The interaction term $\text{Treat}_i \times \text{Post}_t$ identifies the net effect. The primary parameters of interest are the coefficients α_1 and δ_1, which represent the net effect of cognitive and behavioral changes during the second and third periods, respectively. λ_i captures individual fixed effects, υ_t captures time fixed effects, and ε_{it} denotes the random error term.

Third, to precisely capture the dynamic evolution pattern of the information intervention's effects over time, study further employs a dynamic Difference-in-Differences (DID) model and the three-stage balanced panel data (including stage 1, stage 2 and stage 3). While the conventional DID model typically estimates a single

Table 2. Sample descriptive statistical analysis

Control variables	Description	Mean	SD
Demographic variables			
Age	Years old	32.55	7.47
Gender (n/%)	Female	159 (39.55%)	
	Male	243 (60.45%)	
Education level (n/%)	Below bachelor degree	66 (16.42%)	
	Bachelor degree	286 (71.14%)	
	Above bachelor degree	50 (12.44%)	
Risk attitude	Risk aversion=−1; Risk neutral=0; Risk preference=1		
Household variables			
Household population	The number of living family members.	3.11	1.26
Number of elderly people	The number of elderly living family members (over 65 years old).	0.35	0.69
Number of children	The number of children living with family members (below 18 years old).	0.68	0.63
Health state	Whether all living family members are healthy (including the participant)? (No=0; Yes=1)	0.50	0.50
Per capita disposable income	Yuan (CNY, Chinese currency unit) per month	5,921	4,353
Food consumption habits variables			
Planned	I always have a plan when purchasing food (7-point Likert scale: Strongly disagree=1; Neutral=4; Strongly agree=7)	5.57	1.06
Freshness requirement	The freshness requirements for food when purchasing (0–4 continuous integer variable, no requirement=0; the highest requirement=4)	2.05	0.96
Purchasing frequency	1–11 continuous integer variables increase frequency as the number increases.	8.89	1.90
Label attitudes variables			
Perception of FDL usefulness	FDL is meaningful (7-point Likert scale: Strongly disagree=1; Neutral=4; Strongly agree=7)	6.02	1.00
Dependence on the FDL	I judge whether the food is still edible by myself, not relying on the FDL (7-point Likert scale: Strongly disagree=1; Neutral=4; Strongly agree=7)	2.57	1.42
Food types			
	Milk-based samples	231 (57.46%)	
	Cookie-based samples	171 (42.54%)	
Region variable			
	Beijing City	223 (55.47%)	
	Guangzhou City	179 (44.53%)	
Number of participants		402	

1 CNY=0.1408 USD (March 2023). FDL, food date labeling. According to the criteria set by the National Bureau of Statistics of China, the eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan.

average treatment effect, which fails to distinguish heterogeneous effects across distinct post-intervention periods. The Dynamic DID specification, by introducing a series of time-varying indicator variables relative to the intervention timing, allows for the clear construction of the complete trajectory of intervention effects over time (Ferrara *et al.*, 2012; Wang and Zhou, 2025). The specific formulas are as follows:

$$\text{Cognition}_{it} = \gamma_0 + \gamma_1 \text{Treat}_i \times \text{Post}_t^0 + \gamma_2 \text{Treat}_i \times \text{Post}_t^1 + \gamma_3 X_{it} + \lambda_i + \upsilon_t + \varepsilon_{it} \tag{4}$$

$$\text{Behavior}_{it} = \chi_0 + \chi_1 \text{Treat}_i \times \text{Post}_t^0 + \chi_2 \text{Treat}_i \times \text{Post}_t^1 + \chi_3 X_{it} + \lambda_i + \upsilon_t + \varepsilon_{it} \tag{5}$$

Specifically, within the model specification, research defines the event time variable. Event-period dummy variables are included in the regression: Post_t^0 (representing the short-term, post-intervention period) and Post_t^1 (representing the long-term, post-intervention period). The coefficient γ_1 (χ_1) estimates the short-term intervention effect, while γ_2 (χ_2) estimates the long-term intervention effect. Both coefficients quantify the difference-in-differences in the outcome variables between the intervention and control groups relative to the pre-intervention baseline. By directly comparing the magnitude, statistical significance, and directional change between γ_1 and γ_2 (χ_1 and χ_2), the study assesses the change pattern of the information intervention effect from the short-term to long-term. The definitions of all other symbols are consistent with those established for the standard DID model specification.

3. Results

3.1 Validation of Information Intervention Effectiveness

Baseline regression analysis

The information intervention demonstrates persistent statistical significance in its treatment effects. As evidenced by the descriptive statistics in Table 1, participants in the intervention group exhibit a significantly higher accuracy rate in interpreting the quality-guaranteed date label during follow-up assessments compared to the control group. This observed effect is further substantiated through econometric modeling analysis. The Logit regression results (Table 3, column (1)) derived from third-stage follow-up data confirm the sustained statistical significance of the intervention effect. Specifically, the intervention group shows a 0.672 unit increase in log-odds for correct label interpretation relative to the control condition. Converting to the corresponding odds ratio $e^{0.672} \approx 1.958$, indicates significantly greater probability of accurate interpretation in intervention group.

Robustness tests

To ensure the reliability of the findings, three complementary methodological approaches are implemented: (1) Sample restriction analysis. To address potential confounding effects arising from food-type selection, the analysis re-includes the participants who reported not consuming milk or cookies and conducts model regression (N=426). As demonstrated in column (2) of Table 3, the intervention effect maintains statistical significance in the new sample, with coefficient magnitudes comparable to the baseline results. (2) Linear Probability Model (LPM) specification. The robustness is further verified through LPM estimation. Column (3) of Table 3 reveals that the intervention group exhibits a 14.2 percentage-point increase in accurate interpretation probability of the quality-guaranteed date label relative to the control group, consistent with the Logit model estimates. (3) Propensity Score Matching (PSM). Although we followed the principle of a randomized controlled trial using informational intervention in the first-round survey and distributed follow-up questionnaires to all participants from the first-round, considering the effective tracking rate for responses was less than 30%, it is difficult to ensure that the follow-up survey remains randomized, as whether participants decide to take part in the second-round is beyond the control of both the survey company and us, the research designers. This non-random response behavior may introduce selection bias – meaning

Table 3. Baseline regression results and robustness tests of the Logit model

Variable	(1) *Y*	(2) *Y*	(3) LPM	(4) PSM_N	(5) PSM_K
Treat	0.672***	0.712***	0.142**		
	(0.258)	(0.253)	(0.055)		
$Treat_N$				0.766**	
				(0.322)	
$Treat_K$					0.669***
					(0.260)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	−0.640	−0.480	0.364	−1.680	−1.096
	(1.581)	(1.567)	(0.353)	(1.960)	(1.755)
ATT	–	–	–	1.77	2.48
Pseudo R^2/R^2	0.052	0.054	0.065	0.070	0.054
No. of observations	402	426	402	291	386

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. PSM_N stands for nearest neighbor matching and PSM_K stands for kernel matching.

that respondents who completed the follow-up survey might systematically differ from those who dropped out (as preliminarily indicated in the Stage 1 data in Table 1). Therefore, we employed PSM to simulate a randomized experimental setting, reducing the group imbalance caused by non-random follow-up survey to approximate random assignment conditions (Zhang *et al.*, 2022). The analysis employs two distinct matching algorithms nearest-neighbor matching and kernel matching. Common support regions are visualized in Figure 2a,c, with covariate balance distributions presented in Figure 2b,d. Post-matching diagnostic tests reveals standardized biases approaching zero confirm matching effectiveness (Deng *et al.*, 2024). Subsequent regression analyses on the matched samples produce statistically consistent treatment effects (columns (4–5), Table 3). The robustness of these results across matching specifications provides strong evidence for the validity of primary findings.

Heterogeneity analysis

The research result is systematically evaluated across three dimensions of heterogeneity: Regional variation. In the second-round of follow-up, this study focused on conducting a heterogeneity analysis between Beijing and Guangzhou in the eastern region, based on the following rationale: First, due to low questionnaire response rates in tracking participants in the central and western regions, we prioritized in-depth follow-up in the eastern region where higher response rates and data quality could be ensured. More importantly, consumers' misunderstanding of food date labels leading to food waste are likely influenced by regional climatic conditions (e.g., annual temperature, humidity). Even within the eastern region, notable variations in temperature and humidity across cities may further affect food storage conditions, consumer cognition or behavior, especially Beijing and Guangzhou, which have obvious north-south differences, thus contributing to heterogeneous intervention effects. Although only two cities are included at this stage, Beijing and Guangzhou represent temperate monsoon and subtropical monsoon climates, respectively, with significant differences in average annual temperature and seasonal variations. Geographically stratified analyses (Table 4, columns (1–2)) confirm statistically significant treatment effects in all sampled eastern Chinese cities, despite the study's regional limitation to eastern China due to tracking constraints in western/central regions. The consistent effects across urban populations suggest broad applicability of the intervention within developed eastern areas.

Gender-specific effects. While existing studies have indicated that women report discarding more food (Visschers *et al*., 2016), this study further explores potential variations in consumers' label cognition between

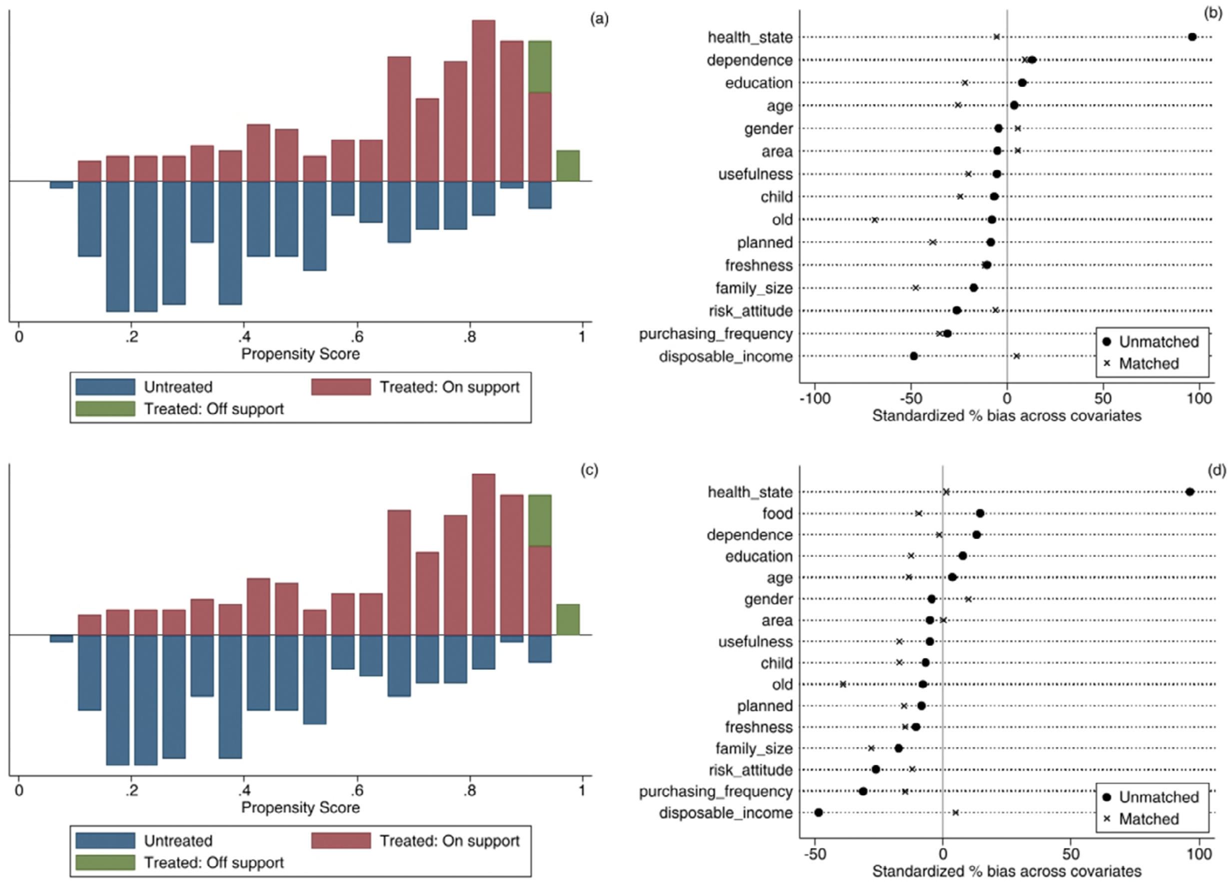

Figure 2. Common support domains (a) and nearest neighbor matching (b); Common support domains (c) and kernel matching results (d) for the Logit model.

Table 4. Heterogeneity analysis of the Logit model

Variable	**(1) Beijing**	**(2) Guangzhou**	**(3) Male**	**(4) Female**	**(5) Milk**	**(6) Cookies**
Treat	0.823**	0.700*	1.146***	0.561	0.525	0.991**
	(0.373)	(0.419)	(0.424)	(0.350)	(0.372)	(0.407)
Control variables-city	–	–	Yes	Yes	Yes	Yes
Control variables-gender	Yes	Yes	–	–	Yes	Yes
Control variables-food type	Yes	Yes	Yes	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−1.046	−0.797	−4.852*	1.584	−0.729	−1.725
	(2.029)	(2.832)	(2.713)	(2.044)	(2.280)	(2.447)
Pseudo R^2	0.082	0.105	0.119	0.085	0.062	0.086
No. of observations	223	179	159	243	231	171

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

genders after the intervention. Regressions (Table 4, columns (3–4)) reveal a pronounced gender disparity: while males exhibit sustained intervention effects, females show no statistically significant effects. The heterogeneity analysis reveals persistent effectiveness of the information intervention among male participants. This discrepancy may stem from differences in how men and women respond to information-based interventions. Men may tend to rely more on explicit external information cues for decision-making, making them more receptive to instructional information with this effect demonstrating greater persistence. In contrast, female consumers generally exercise more caution in food purchasing and consumption decisions, exhibiting higher sensitivity to food safety and health risks. Their pre-existing cognitive frameworks may be more entrenched, making one time intervention less effective in achieving lasting changes in their understanding. Furthermore, as women often assume primary responsibility for food procurement and household management, they accumulate more practical experience in food storage and handling. This experiential knowledge may contribute to the formation of relatively fixed interpretative patterns regarding labels, thereby fostering stronger cognitive resilience to external informational interventions.

Food perishability heterogeneity. Given that the comparison between perishable and non-perishable foods constitutes a crucial aspect of this research, we hereby investigate this potential heterogeneous effect by conducting separate regression analyses. The intervention demonstrates significantly stronger effects for non-perishable items (cookies) compared to perishables (milk) (Table 4, columns (5–6)). This divergence likely stems from consumers' heightened receptiveness to non-perishable food interventions compared to perishables and higher perceived risks associated with perishable food expiration. Consequently, the findings highlight the necessity for tailored intervention strategies for perishable goods, differentiated gender-specific and regional-adaptation communication approaches.

3.2 Sustained effects on cognition and behavior

Baseline regression of the effect on cognition

Temporal decay of intervention effects on the label cognition. The longitudinal analysis reveals significant temporal decay in the effectiveness of information intervention for correcting consumers' interpreting of the quality-guaranteed date label. The analysis employs multiple analytical approaches to quantify this weakening pattern. First, two-stage DID analysis. Although descriptive statistics in Table 1 already indicate significantly reduced cognition accuracy of the quality-guaranteed date label among the intervention group, this decay is formally identified using two periods of balanced panel data separated by one and a half years and a DID specification. The model results identify a statistically significant decay effect in label interpretation accuracy (Table 5, column (1)), with a net weakening effect of 0.391.

Compared to the instant net effect of 0.465 on consumers' cognition of the quality-guaranteed date label after intervention observed in the intervention group of Cheng *et al.* (2025), the analysis further use dynamic DID framework with three-stage follow-up data to investigate the long-term rate of cognitive weakening among these followed-up consumers, and results are reported in column (2) of Table 5. By taking the difference between the two regression coefficients (did_0 and did_1, representing the instant effect after the intervention and the long-term effect of follow-up, respectively), the study also obtains a net weakening effect of 0.391 for cognitive data. Furthermore, by calculating the decay rate, the results show that consumers' cognition of the quality-guaranteed date label during the follow-up survey weakens by 95.53% compared to their cognition after the intervention instantly.

Baseline regression of the effect on food waste behavior

The longitudinal analysis reveals a significant weakening in the intervention's effectiveness on modifying food waste behaviors related to the quality-guaranteed date label. While descriptive statistics results in Table 1 demonstrate that consumers in the intervention group modify their food waste dates forward under

Table 5. Baseline regression results and robustness tests of the DID model (cognition)

Variable	(1) *Y*	(2) *Y*	(3) *Y*	(4) PSM_N	(5) PSM_K
did	−0.391***		−0.380***		
	(0.062)		(0.060)		
did_0		0.410***			
		(0.057)			
did_1		0.018			
		(0.062)			
did_N				−0.350***	
				(0.077)	
did_K					−0.388***
					(0.063)
Control variables	Yes	Yes	Yes	Yes	Yes
Constant	0.070	0.155	0.084	−0.093	0.029
	(0.236)	(0.192)	(0.230)	(0.299)	(0.262)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
ATT	–	–	–	6.38	8.19
R^2	0.173	0.151	0.172	0.168	0.171
No. of observations	804	1,206	852	582	772

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. PSM_N stands for nearest neighbor matching and PSM_K stands for kernel matching.

the quality-guaranteed date label, the research further verify the net decay effect on behavioral outcomes through econometrics. The baseline DID estimation (Table 6, column (1)) demonstrates that the intervention significantly advanced food waste dates by 1.186 days under the quality-guaranteed date label. Similarly, the research employs dynamics analysis and the dynamic DID framework (Table 6, column (2)) reveals the net weakening effect for food waste date advancement is 1.186 days, consistent with the main regression results, and the decay rate is 74.77%, which is slightly lower than the decay rate of cognition.

Robustness tests

Four robustness tests are implemented to validate the reliability of findings. (1) Sample restriction analysis. Out of considerations consistent with those given above, the analysis re-includes the participants who reported not consuming milk or cookies and conducts model regression (N=852). Results yield consistent cognition effects (Table 5, column (3)) and robust behavioral impacts (Table 6, column (3)), which confirm the intervention's generalizability across diverse consumer segments. (2) PSM-DID estimation. The combination of PSM with DID methodology widely adopted for policy impact assessments (Fu *et al.*, 2021; Deng *et al.*, 2024). This dual methodology addresses both observable and time-invariant unobservable confounders, effectively creating quasi-experimental conditions. The research uses Nearest neighbor and kernel matching to match samples with the treat dummy variable. Common support domains for cognition visualized in Figure 3a,c, with matched covariates documented in Figure 3b,d. Behavioral common support is visualized in Figure 4a, with corresponding covariates in Figure 4b. Post-matching covariate balances approach zero, indicating sufficient matching quality. Subsequent regressions on matched samples – cognition outcomes in columns (4–5) of Table 5 and behavioral outcomes in column (4) of Table 6, yield coefficients statistically significant at the 1% level. These estimates align with baseline results, further confirming robustness. (3) Placebo test. To rule out spurious correlations, the research conducts 1000 randomized placebo tests for both cognition and behavioral outcomes. The kernel density plots in Figure 5a,b display the null distribution

Table 6. Baseline regression results and robustness tests of the DID model (behavior)

Variable	**(1)** ***Y***	**(2)** ***Y***	**(3)** ***Y***	**(4)** **PSM_K**	**(5)** **$Y_{milk/cookies}$**	**(6)** **Y_{food}**
did	−1.186**		−1.089**		0.615***	0.662***
	(0.472)		(0.461)		(0.081)	(0.082)
did_0		1.586***				
		(0.454)				
did_1		0.400				
		(0.439)				
did'				−1.157**		
				(0.474)		
Control variables	Yes	Yes	Yes	Yes		
Constant	−1.673	−2.366	−1.492	−2.455	0.058	−0.372
	(1.886)	(1.449)	(1.844)	(2.020)	(0.306)	(0.306)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
ATT	–	–	–	2.06	–	–
R^2	0.107	0.118	0.092	0.112	0.220	0.263
No. of observations	804	1206	852	772	804	804

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. PSM_K, kernel matching.

of coefficients generated through randomization, with the mass tightly clustered around zero and approximate normality. indicating that random factors exert no influence on cognition or behavior (Deng *et al.*, 2024), thereby reinforcing the robustness of the estimates. (4) Alternative dependent variables. To address potential measurement limitations, the research reconceptualize the dependent variables using self-reported behavioral changes captured through the second and third stage surveys. Participants assess their food waste patterns on milk (or cookies) and aggregate food types using a standardized three-point scale (increased=1, unchanged=0, decreased=−1, compared with the previous period of time). This alternative specification serves two critical purposes: it controls for recall bias through relative self-assessment, and tests effect generalizability beyond specific food items. As shown in columns (5–6) of Table 6, the regression analyses yield consistent evidence of behavioral reversion, with statistically significant increases in self-reported waste during long-term follow-up. Notably, this pattern holds for both the studied products and broader food categories, suggesting the observed decay effect reflects genuine behavioral change rather than measurement artifacts. The convergence of results across operationalizations strengthens conclusions regarding the intervention's temporal decay.

Heterogeneity analysis of intervention effect decay

Consistent with the three-dimensional heterogeneity analytical framework described above, this section examines how the decay of intervention effects varies across demographic and behavioral dimensions. The regression analyses (Tables 7 and 8) reveal key findings regarding cognitive and behavioral outcomes. For cognition decay in Table 7, for the one hand, the weakening of cognitive intervention effects exhibits statistically significant consistency across all subsamples – spanning regional, gender, and food-type stratifications. This universal decay pattern indicates that the weakening in information sustain is not context-specific but rather a generalized phenomenon across consumer subgroups. For the other hand, the pervasive nature of this decay suggests that one-time informational interventions are insufficient to sustain long-term cognition correction. The non-permanence of consumer understanding underscores the need for complementary reinforcement mechanisms and optimized intervention frequency to maintain label comprehension accuracy.

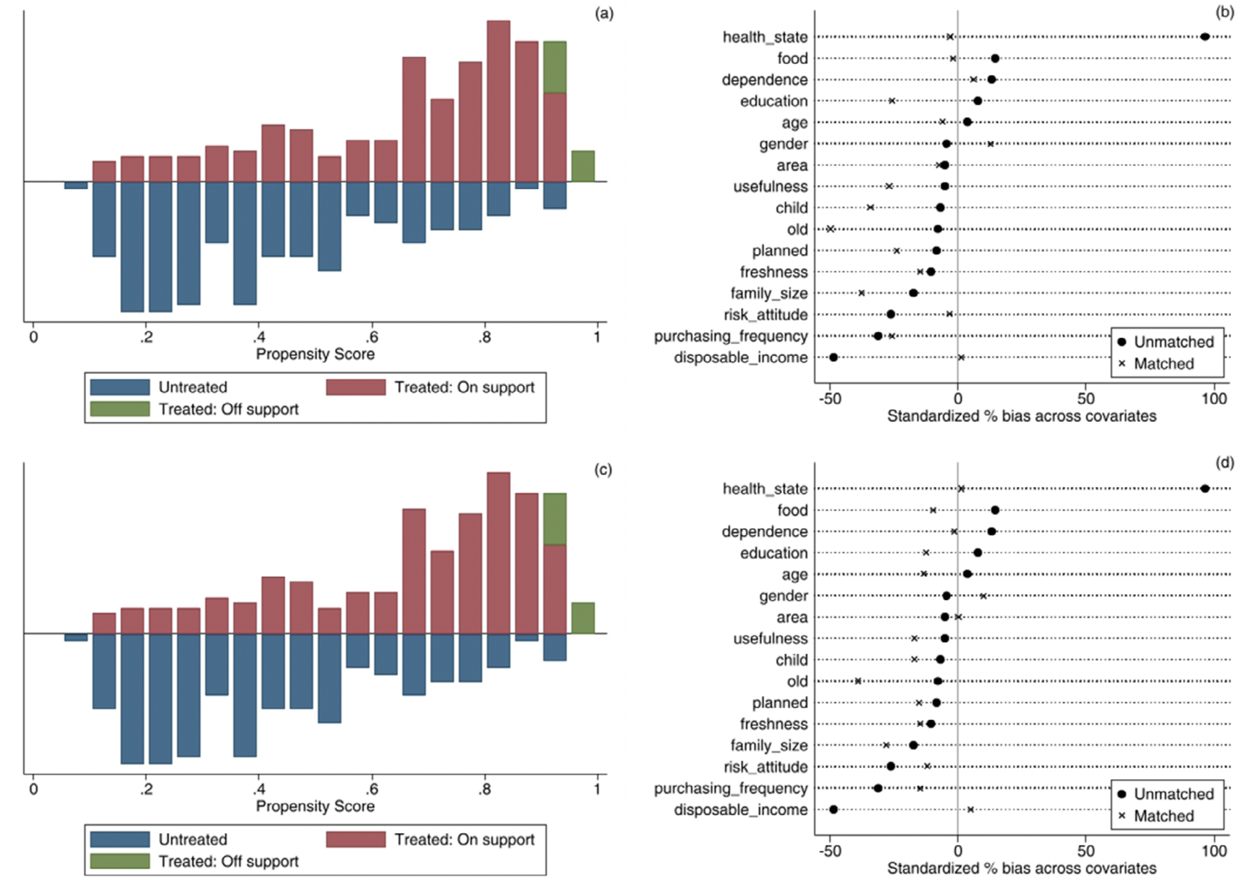

Figure 3. Common support domains (a) and nearest neighbor matching (b); Common support domains (c) and kernel matching results (d) for the DID model (cognition).

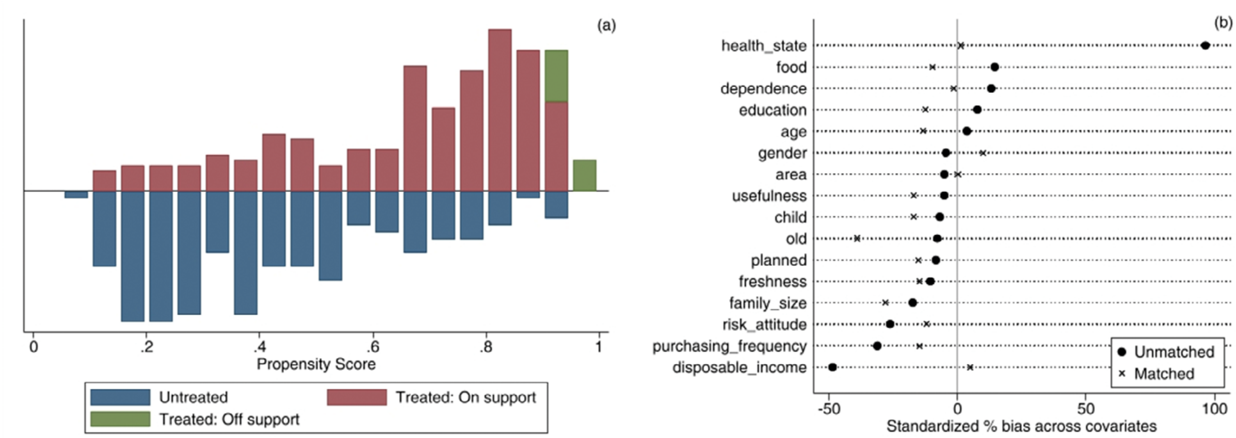

Figure 4. Common support domains (a) and kernel matching results (b) for the DID model (behavior).

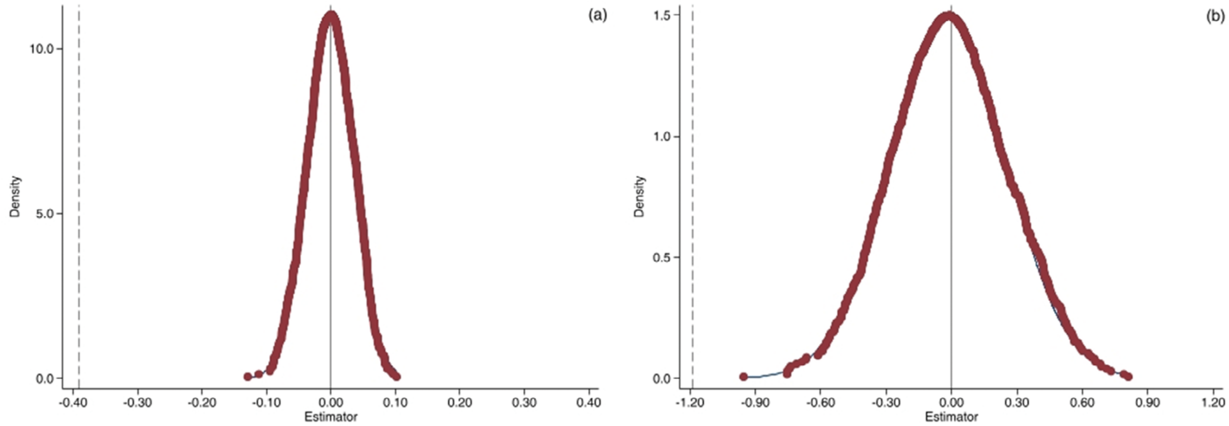

Figure 5. Density curve of simulated coefficients: (a, b) corresponds to the cognitive change and the food waste behavior change, respectively.

Table 7. Heterogeneity analysis of the DID model (cognition)

Variable	**(1) Beijing**	**(2) Guangzhou**	**(3) Male**	**(4) Female**	**(5) Milk**	**(6) Cookies**
Treat	−0.364***	−0.425***	−0.314***	−0.442***	−0.349***	−0.439***
	(0.082)	(0.092)	(0.098)	(0.079)	(0.083)	(0.092)
Control variables-city	–	–	Yes	Yes	Yes	Yes
Control variables-gender	Yes	Yes	–	–	Yes	Yes
Control variables-food type	Yes	Yes	Yes	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.215	−0.252	−0.340	0.381	0.389	−0.321
	(0.296)	(0.389)	(0.392)	(0.303)	(0.363)	(0.338)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.198	0.212	0.193	0.207	0.156	0.248
No. of observations	446	358	318	486	462	342

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

For the decay patterns in food waste behavior, regression analyses (Table 8) reveal significant spatial, demographic, and product-based heterogeneity in the weakening of intervention effects on food waste behavior. First, geographically, consumers in Guangzhou – characterized by subtropical climates with higher average temperatures compared to Beijing – exhibit a significant advancement in waste date, whereas no significant change occurred in Beijing, suggesting thermal stress amplifies spoilage concerns and accelerates behavioral reversion. Second, this decay is significant among the female group, likely due to their greater risk aversion and traditional roles in household food safety management. Third, product-level differences aligned with perishability. The type of milk (highly perishable) shows a significant weakening (earlier waste date) compared to nonperishable cookies, reflecting a risk mitigation strategy where cognitive decay intensifies precautionary behavior for spoilage-prone items.

Table 8. Heterogeneity analysis of the DID model (behavior)

Variable	**(1) Beijing**	**(2) Guangzhou**	**(3) Male**	**(4) Female**	**(5) Milk**	**(6) Cookies**
Treat	−0.930	−1.491**	−1.188	−1.195**	−1.186**	−1.049
	(0.618)	(0.716)	(0.738)	(0.604)	(0.572)	(0.811)
Control variables-city	–	–	Yes	Yes	Yes	Yes
Control variables-gender	Yes	Yes	–	–	Yes	Yes
Control variables-food type	Yes	Yes	Yes	Yes	–	–
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.160	−5.322*	−3.125	0.919	2.079	−4.694*
	(2.417)	(2.992)	(3.289)	(2.308)	(2.557)	(2.753)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.133	0.117	0.127	0.136	0.137	0.132
No. of observations	446	358	318	486	462	342

Robust standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

4. Discussion

4.1 Further exploration of the results

Self-learning effects

Self-learning effects among consumers may represent another theoretically significant phenomenon observed in this study. Data from the control group in Table 1 reveal a significant improvement in accurate cognition of the quality-guaranteed date label after one and a half years – despite no exposure to information intervention. This trend aligns with the self-learning effect documented in prior literature (Schmitt, 2024). Empirical support comes from survey responses: 86.78% of control group participants report paying greater attention to date labels in daily consumption following initial survey. This behavioral adaptation suggests that consumers may actively utilize autonomous learning channels to enhance their understanding of labeling systems. Similarly, while no statistically significant change occurred in food waste behavior, the mean waste date in the control group shifts later relative to baseline. This shift corresponds with survey evidence, where 83.91% of participants report increased awareness of food waste issues in their daily routines. These findings imply that heightened consumer attention to date labels serves as a key mechanism for cognitive improvement. Thus, the survey without the information interventions may also have long-term effects: indirect stimulation of attentional engagement, prompting autonomous information-seeking and deliberative processing, which may gradually reshape subsequent behavioral patterns.

Memory decay and cognitive internalization

Similarly, intriguing patterns emerge within the intervention group. The follow-up survey measures participants' interpretation of the quality-guaranteed date label and food waste behaviors in two methods. Participants are asked to interpret current Chinese regulatory specifications for the label, and recall the definition provided during the prior information intervention. Despite the alignment between the intervention's definition and regulatory standards, the results reveal a statistically significant divergence. 53.51% of participants correctly identify regulatory specifications as referring to food quality and sensory attributes, and their actual food waste behavior indicated 1–2 days post-expiration during daily consumption. However, only 41.23% accurately recall the intervention's content. Among these individuals, the intended waste behaviors suggest waste on or within one day post-expiration. These findings imply that follow-up surveys assessing intervention effects largely measure memory retention rather than internalized cognition or behavior. Even among participants with poor explicit recall, intervention content may have subtly influenced daily decision-making. Although minimal divergence exists between actual cognition/behaviors and the memory of the intervention content, such discrepancy remains noteworthy.

This discrepancy suggests that trust in the intervention source and content may moderate the relationship between retained intervention memory and actual cognition. Notably, comprehension of regulatory standards of the quality-guaranteed date label surpasses recall of intervention content, possibly due to heightened attentional engagement: 88.60% of intervention participants report increased focus on date labels post-survey (initial), and 84.21% pay greater attention to food waste – both exceeding the corresponding situations in the control group. Thus, information interventions may also function through dual pathways in the intervention group: direct cognitive-behavioral modification, and indirect attentional priming, fostering sustained engagement with labeling systems and autonomous knowledge acquisition.

Cognition-behavior gap

By comparing Tables 7 and 8, our study confirms a highly important finding that reveals a complex yet common phenomenon in behavioral intervention: changes in cognition do not always translate into changes in behavior (Chang *et al*., 2022). As shown in Table 7, we observed a comprehensive decay in consumers' cognition of the date label, yet Table 8 reveals heterogeneous changes in behavior. This discrepancy may be explained by the difference in decay rates between cognition and behavior. Since cognition is a relatively superficial mental construct, primarily acquired through memory and short-term persuasion (e.g., receiving new information) during intervention, without ongoing reinforcement, repetition, or integration into deeper beliefs, this new cognition is easily forgotten or overridden by pre-existing, deeply ingrained misconceptions. Hence, a broad decay in cognition over the long term may be a common occurrence. In contrast, behavior may be influenced by deeper, more stable factors such as habits, motivations, risk perceptions, and contextual cues. A one-time information intervention may not be sufficient to instantly alter long-established habits, but once behavior change is initiated, its effects may persist longer than cognition gains.

Since women are typically primarily responsible for household food purchasing and safety management, they tend to perceive higher responsibility and exhibit greater risk aversion regarding food safety. Although they may temporarily accept the new information after the intervention, in the long run, this understanding may be overpowered by a stronger force: the fear of "what if my family gets sick from food?" This potent social and psychological risk likely drives them to revert to more conservative behavioral patterns. Furthermore, the heterogeneous decay in food waste behavior across product types may stem from fundamental differences in consumers' perception of risk. For milk (perishable), which carries a high risk of microbial spoilage with visible and serious consequences, consumers maintain a strong safety mentality. Even when aware that the label refers to quality, the heuristic of "safety first" may eventually dominates again, leading to a rebound in waste behavior. In contrast, for cookies (non-perishable), the risks mainly involve sensory deterioration (e.g., staleness, sogginess) rather than safety issues. Consumers may tolerate higher levels of risk in such products. The new information provided by the intervention is more readily accepted and sustainably adopted into behavior, since acting on it does not entail serious negative consequences. Thus, waste reduction behavior is more likely to be maintained.

Another interesting point we would like to further discuss regarding the types of food here is although, as mentioned in previous study (Cheng *et al*., 2025), the food date labels of both packaged milk and cookie products mostly indicate a duration of 3–6 months or longer, we must acknowledge that consumers may naturally exhibit greater caution toward perishable foods. This heightened vigilance, arguably an intuitive response, likely contributed to the observed rebound in milk waste behavior over the long term. Nevertheless, one central aim of our study was precisely to uncover and examine such differences. Moreover, while earlier research has demonstrated that both perishable and non-perishable foods show significant potential for short-term waste reduction following intervention (Cheng *et al*., 2025), this study underscores the importance of implementing reinforced messaging strategies specifically targeting perishable products to mitigate behavioral reversal in the long-term.

Effect of duration and dynamic intervention timing

A critical finding emerges from dynamic DID models analyzing both short- and long-term intervention effects: neither cognitive nor behavioral outcomes demonstrate statistically significant persistence under long period of time. Does this suggest that food waste reduction efforts are ineffective? Quite the contrary: (1) Short-term impacts matter. Even transient improvements in consumers' understanding of the date label. Measurable short-term reductions in food waste behaviors represent meaningful achievements. Cumulatively, these effects can yield substantial decreases in aggregate food waste over time. (2) Temporal thresholds for policy optimization. The findings empirically identify the point at which net intervention effects approach nullity, and the potential ways to sustain impact could through increasing intervention frequency before this threshold and conducting quantitative determination of efficacy half-life decay rates.

4.2 Limitations

While this study provides valuable insights, several limitations should be acknowledged. First, regional focus. Due to the huge differences in the difficulty of follow-up survey across central and western China, this study prioritizes analysis of the eastern region where the response rate is relatively high. However, given substantial regional disparities, future research should expand data collection to other regions to enable comprehensive comparative analysis. Second, label expression specificity. Although this research focuses on the quality-guaranteed date label (the most common form in China), different label expressions may yield varying intervention effects. Subsequent studies could examine how intervention efficacy differs across label types to optimize labeling strategies. Third, urban-rural representation. The study's urban focus represents a notable limitation, as rural populations likely differ in both cognition and food consumption habits. Future work could include rural samples to enable meaningful urban-rural comparisons and tailored intervention approaches. Fourth, temporal considerations. this study chose to follow up for one and a half years after the intervention, but this period may not represent the optimal interval for intervention reinforcement. Further research could map cognitive decay trajectories in greater detail, identify critical thresholds for secondary interventions and determine the most effective timing to sustain both correct label cognition and reduced food waste behaviors. Last but not least, although this study collected data through a professional online survey platform and employed random sampling to ensure the representativeness of the sample structure as much as possible, several limitations of this approach should be noted. (1) Participants in online platforms often exhibit self-selection characteristics, which may lead to self-selection bias – meaning that individuals with greater interest in food labeling or sustainable consumption topics may be more likely to participate in the survey, thereby affecting the external validity of the results. (2) Although we controlled for key demographic variables such as age, gender, and region, the online sample may still not fully represent the broader Chinese consumer population, particularly in areas with low internet penetration and among digitally disadvantaged groups such as the elderly and low-income populations. Future research could incorporate offline field experiments, community interventions, and other diverse methods to more comprehensively capture the true cognitive and behavioral patterns across different populations.

4.3 Policy implications

The research findings suggest four actionable policy directions for stakeholders. First, China should enhance enforcement of the Anti-Food Waste Law through systematic monitoring and public education campaigns, particularly regarding the quality-guaranteed date label. Second, current decay rate calculations reveal that the optimal retreatment window for maintaining efficacy occurs before the one and a half years interval used in this study. This suggests periodic reinforcement may preserve intervention effects, strategic retiming could enhance long-term outcomes and a sustained intervention system should be established, utilizing periodic reinforcement via social media, community outreach, and packaging labels at optimized intervals to actively improve the public's cognition level of food date labels and thus curb the resulting food waste. Third, interventions should be geographically and demographically tailored, such as increasing the frequency and intensity of popularization in southern China, focusing on special information attraction and intervention for female groups generally responsible for household food procurement. Also, perishable food as a food medium could be considered in the ongoing dissemination of information. Fourth, and importantly from an industry perspective, food manufacturers and retailers should be encouraged and potentially regulated to adopt more intuitive and differentiated date labeling practices, such as playing an active role in consumer education through QR codes, packaging inserts, or in-store campaigns that reinforce interpretative guidance. Furthermore, companies should align corporate social responsibility initiatives with targeted awareness programs, particularly aimed at female consumers who are key household decision-makers. Such initiatives not only contribute to waste reduction but also enhance brand trust and compliance with sustainability goals. To sum up, policy design should combine persistent, targeted approaches using dynamic strategies to solidify consumer cognition and maximize long-term food waste reduction, while engaging the food industry as a crucial partner in labeling reform and consumer outreach.

5. Conclusions

From a micro-level perspective, this paper employs balanced panel data from three stages of follow-up surveys (totaling 1,206 observations) to examine the longitudinal effectiveness of information interventions on Chinese consumers' cognition of the quality-guaranteed date label, identify the net effect of consumer cognition and food waste behavior change between the second stage after intervention and the third stage (follow-up survey), and also calculate the decay rate in cognition and behavior. The study yields three key findings: First, information interventions maintain significant effectiveness, as evidenced by persistent differences in date label cognition between intervention and control groups. Second, while impactful, intervention effects exhibit notable temporal decay, suggesting the need for periodic reinforcement to sustain cognitive and behavioral changes. Third, intervention strategies should prioritize three key demographics: consumers in warmer southern regions (where food perishability is higher), female consumers (typically responsible for household food management), and focusing on perishable foods may offer particularly effective pathways for reducing food waste. These findings provide empirical evidence for designing more effective, sustained intervention programs to improve date label understanding and reduce food waste.

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References

Aschemann-Witzel, J., I. De Hooge, P. Amani, T. Bech-Larsen and M. Oostindjer. 2015. Consumer-related food waste: causes and potential for action. *Sustainability* 7(6): 6457–6477.

Aschemann–Witzel, J., J. Jensen, M. Jensen and V. Kulikovskaja. 2017. Consumer behaviour towards price–reduced suboptimal foods in the supermarket and the relation to food waste in households. *Appetite* 116: 246–258.

Block, L., Vallen, B. and Paul Austin, M. 2022. Food waste (mis)takes: The role of (mis)perception and (mis)estimation. *Current Opinion in Psychology* 46: 101327.

Chang, Q., Yan, Y., Li, X.P., Zhang, C.Y., and Zhao, M.J. 2021. Why "Say one thing and do another"? A study on the deviation of willingness and behavior of farmers' ecological production. *Journal of Agrotechnical Economics* 4: 85–97.

Cheng S., Lu Y., Ren Y., Jiang Z. and Zhao M. 2025. Which food date label brings us the most excellent opportunity to reduce food waste? Evidence from a quasi-natural intervention experiment in urban China. *Agricultural and Food Economics* 13: 14.

Dai, J. and S. Gong. 2024. Sustainable messaging strategies and consumer food waste: The congruence effect between message framing and state anxiety. *Journal of Retailing and Consumer Services* 79: 103817.

Davenport, M., D. Qi, B. Roe. 2019. Food–related routines, product characteristics, and household food waste in the United States: A refrigerator–based pilot study. *Resources, Conservation and Recycling* 150: 104440.

de Gorter, H., D. Drabik, D.R. Just, C. Reynolds, G. Sethi. 2021. Analyzing the economics of food loss and waste reductions in a food supply chain. *Food Policy* 98:101953.

Deng, X., K. Niu, X. Xu, C. Li and L. Zhang. 2024. Does the closure of polluting enterprises improve rural livelihoods? Evidence from rural China. *Sustainable Development*: sd.2984.

Ferrara, L., A. Chong and S. Duryea. 2012. Soap Operas and Fertility: Evidence from Brazil. *American Economic Journal: Applied Economics* 4(4): 1–31.

Food and Agriculture Organization of the United Nations (FAO). 2011. Global food losses and food waste – Extent, causes and prevention. FAO. Available online at http://www.fao.org/docrep/014/mb060e/mb060e00.pdf

Food and Drugs Administration (FDA). 2019. Confused by date labels on packaged foods? Available online at https://www.fda.gov/consumers/consumer-updates/confused-date-labels-packaged-foods

Fu, Y., C. He and L. Luo. 2021. Does the low-carbon city policy make a difference? Empirical evidence of the pilot scheme in China with DEA and PSM–DID. *Ecological Indicators* 122: 107238.

FUSIONS. 2016. Estimates of European food waste levels. EU. No.311972. Available online at http://www.eu-FUSIONS.org/phocadownload/Publications/Estimates%20of%20European%20food%20waste%20levels.pdf

Gong, Z., L. Su, J.S. Zhang, T. Chen and Y.C. Wang. 2022. Understanding the association between date labels and consumer–level food waste. *Food Quality and Preference* 96: 104373.

Graham, D.J., J.L. Orquin, V.H.M. Visschers. 2012. Eye tracking and nutrition label use: A review of the literature and recommendations for label enhancement. *Food Policy* 37(4): 378–382.

Chang, Q., Y. Yan, X. Li, C. Zhang, M. Zhao. 2021. Why "say one thing and do another"? – A study on the deviation of willingness and behavior of farmers' ecological production. *Journal of Agrotechnical Economics* (04): 85–97.

Chen, L. and H. Wu. 2015. Research Status and Potential Problems of Differences–in–differences Method in China. *The Journal of Quantitative and Technical Economics* 7: 133–148.

Cheng, S., Y. Lu, Y. Ren, Z. Jiang and M. Zhao. 2025. Which food date label brings us the most excellent opportunity to reduce food waste? Evidence from a quasi-natural intervention experiment in urban China. *Agricultural and Food Economics* 13: 14.

Kosa, K.M., S.C. Cates, S. Karns, S.L. Godwin and D. Chambers. 2007. Consumer knowledge and use of open dates: results of a web-based survey. *Journal of Food Protection* 70(5): 1213–1219.

Lin, B. and C. Guan. 2021. Determinants of household food waste reduction intention in China: The role of perceived government control. *Journal of Environmental Management* 299: 113577.
Malek, L., G. Duffy, H. Fowler and L. Katzer. 2020. Use and understanding of labelling information when preparing infant formula: Evidence from interviews and eye tracking. *Food Policy* 93: 101892.
Neubig, C. M. and J. Roosen. 2024. Can I still eat this? Using implicit and explicit measures to explore consumer behavior toward food products with date labels. *Appetite* 200: 107556.
Newsome, R., C.G. Balestrini, M.D. Baum, J. Corby, W. Fisher, K. Goodburn, T.P. Labuza, G. Prince, H.S. Thesmar and F. Yiannas. 2014. Applications and perceptions of date labeling of food. *Comprehensive Reviews in Food Science and Food Safety* 13(4): 745–769.
Nisa, C.F., J.J. Bélanger, B.M. Schumpe. 2022. Assessing the effectiveness of food waste messaging. *Environmental Science and Policy* 132: 224–236.
Reynolds, C., L. Goucher, T. Quested, S. Bromley, S. Gillick, V.K. Wells, D. Evans, L. Koh, A.C. Kanyama, C. Katzeff, Å. Svenfelt, P. Jackson. 2019. Review: Consumption-stage food waste reduction interventions – What works and how to design better interventions. *Food Policy* 83: 7–27.
Schmitt, B. 2024. Consumer information processing and decision-making: origins, findings, applications, and future directions. *Journal of Consumer Research* 51(1): 2–6
Talwar, S., P. Kaur, S. Kumar, J. Salo and A. Dhir. 2022. The balancing act: How do moral norms and anticipated pride drive food waste/reduction behaviour? *Journal of Retailing and Consumer Services* 66: 102901.
Toma, L., M. Costa Font and B. Thompson. 2020. Impact of consumers' understanding of date labelling on food waste behaviour. *Operational Research* 20(2): 543–560.
Turvey, C., M. Moran, J. Sacheck, A. Arashiro, Q. Huang, K. Heley, E. Johnston and R. Neff. 2021. Impact of messaging strategy on consumer understanding of food date labels. *Journal of Nutrition Education and Behavior* 53(5): 389–400.
United Nations Environment Programme (UNEP). 2021. Food waste index report 2021. UNEP, New York, NY. Available online at https://www.unep.org/resources/report/unep-food-waste-index-report-2021
United States Environmental Protection Agency. 2019. Reducing wasted food at home. USEPA, Washington, DC. Available online at https://www.epa.gov/recycle/reducing-wasted-food-home
Verghese, K., H. Lewis, S. Lockrey and H. Williams. 2015. Packaging's role in minimizing food loss and waste across the supply chain: packaging's role in minimizing food waste across the supply chain. *Packaging Technology and Science* 28(7): 603–620.
Visschers, V.H.M., Wickli, N., Siegrist, M. 2016. Sorting out food waste behaviour: a survey on the motivators and barriers of self–reported amounts of food waste in households. *Journal of Environmental Psychology* 45: 66–78.
Waste and Resources Action Programme. 2011. Consumer insight: Date labels and storage guidance.
Wang, S. and S. Zhou. 2025. The effect and mechanism of rural collective property rights system reform in promoting farmers' income increase: Evidence from 2628 farmers based on CFPS data [J/OL]. *Journal of Agrotechnical Economics*: 1–19.
Wilson, N.L.W. and Miao, R. 2025. Food waste, date labels, and risk preferences: An experimental exploration. *Applied Economic Perspectives and Policy*: aepp.13507.
Zamri, G.B., N.K.A. Azizal, S. Nakamura, K. Okada, N.H. Nordin, N. Othman, F. Nadia, A. Sobian, N. Kaida, H. Hara. 2020. Delivery, impact and approach of household food waste reduction campaigns. *Journal of Cleaner Production* 246: 118969.
Zhang, Y., X. Zhao and B. Fu. 2022. Impact of energy saving on the financial performance of industrial enterprises in China: An empirical analysis based on propensity score matching. *Journal of Environmental Management* 317: 115377.