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Research paper

Predicting food waste from dynamic inconsistency

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ABSTRACT

Household food waste imposes substantial economic and environmental costs, yet its behavioral determinants remain imperfectly understood. Because food consumption unfolds over multiple stages, it creates scope for dynamically inconsistent choices that may turn good intentions into waste. We investigate this relationship using a nationally representative survey from Germany that combines targeted measures of food purchasing, consumption, and waste with individual present-bias parameters elicited from monetary intertemporal trade-off questions. More present-biased individuals waste significantly more food: a 10% increase in dynamic inconsistency is associated with roughly 2% more waste. This relationship is robust across specifications, replicated using a self-reported procrastination proxy, and stable several weeks later in a second survey wave. We also identify and empirically validate the mechanism linking present bias to food waste: dynamically inconsistent individuals are more likely to deviate from their own consumption intentions, and these deviations are strongly predictive of food waste. Our findings identify present bias as a systematic and previously overlooked driver of avoidable household food waste, suggesting that food policies need to address behavior along the full consumption chain.

1. Introduction

The cost of global food waste and loss is estimated at approximately one trillion USD per year—comparable to the GDP of Turkey, Saudi Arabia or the Netherlands in 2023. Beyond the financial toll, food waste is estimated to account for 8–10 per cent of annual global greenhouse gas emissions and more than one billion discarded meals per day (United Nations Environment Programme, 2024). Reducing food waste is imperative if we are to ease the mounting pressure on food production (FAO, 2019; IPBES, 2019; Mbow et al., 2019) and advance the Sustainable Development Goals more broadly (Willett et al., 2019; Westhoek et al., 2016).

According to the UN Food Waste Report 2024, households are responsible for 60% of all food waste generated. While the issue has risen on the agendas of international institutions and national governments alike, the behavioral drivers of household food waste remain poorly understood. A growing body of literature links household food waste to informational deficits (Aschemann-Witzel et al., 2015; Van Boxstael et al., 2014), failures in planning and provisioning (Stancu et al., 2016; Graham-Rowe et al., 2014), cultural norms (Evans, 2011; Watson and Meah, 2012), and habitual routines around food (Quested et al., 2013). Much of this work, however, assumes that consumers act in accordance with their long-term preferences. Our approach departs from this assumption by drawing on behavioral economic theory and interpreting food waste through the lens of dynamically inconsistent time preferences.

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In this paper, we investigate whether dynamically inconsistent time preferences can predict individual food consumption and waste behavior. Models incorporating self-control problems (Strotz, 1955; Thaler and Shefrin, 1981; Laibson, 1997; O'Donoghue and Rabin, 1999) have been widely applied in economics to explain the difficulties people face when saving money (Meier and Sprenger, 2010), exercising regularly in the gym (Della Vigna and Malmendier, 2006; Royer et al., 2015), and – most pertinent to our setting – maintaining a healthy diet (Danzer and Zeidler, 2024; Read and Van Leeuwen, 1998; Cherchye et al., 2020; Courtemanche et al., 2015; Samek, 2019; Huseynov et al., 2021; Sadoff and Samek, 2019).[1] Like other activities that deliver benefits and incur costs over time, food consumption is an inherently dynamic process encompassing choices across multiple stages, from planning and shopping through preparation to eating (Quested et al., 2013). We propose that food waste arises as an *unintended* consequence of individuals systematically departing from earlier consumption intentions. The mechanism operates as follows. At the grocery shopping stage, individuals purchase fresh food with the intention of eating high quality food in the future. However, when the time comes to act on that intention, dynamically inconsistent individuals revise their earlier plans: the effort required to prepare a fresh meal is weighed against excessively discounted future benefits, rendering the consumption of fresh food unattractive. As a result, the consumption of fresh items is postponed. Because fresh food is highly perishable, these longer-than-intended storage periods translate directly into food waste.

We assess these conceptual implications empirically by leveraging a nationally representative longitudinal dataset from Germany, supplemented by targeted survey items capturing individual food consumption habits, waste behavior, and economic preferences. Specifically, we examine the incidence of food waste at different stages of the food consumption chain: from grocery shopping and food storage through preparation, eating, and leftover management. To estimate a dynamic inconsistency parameter at the individual level, we employ the (β, δ) model formalized by Laibson (1997), O'Donoghue and Rabin (1999), exploiting within-individual variation in payment delay, a measure that is plausibly correlated with a broad range of intertemporal behaviors. We propose three conceptually derived food waste metrics that specifically target lengthy food storage periods and regress these on measures of dynamic inconsistency. Beyond this reduced-form analysis, we pin down the underlying mechanism: dynamically inconsistent individuals revise their fresh food consumption intentions over time, leading to excessive storage durations which, given the predetermined perishability of fresh foods, translate into higher rates of food waste.

The paper first documents substantial heterogeneity in the incidence of food waste across the domestic food consumption chain. The storing stage accounts for the largest share of waste: 58% of respondents report having discovered spoiled food items at home within the previous seven days. Spoiled food is discarded in 94% and fed to animals in 6% of cases. Twenty-four per cent of respondents disposed of food because the best before date had passed, and 20% report having thrown away leftovers that had been stored in the fridge or freezer for later consumption. Food waste at other stages of the food consumption chain is considerably less common—cooking leftovers account for 3% and plate leftovers for 14%.

In Ordinary Least Squares (OLS) regressions, the relationship between dynamically inconsistent time preferences and individual food waste metrics is highly significant. A 10% increase in dynamic inconsistency is associated with a 2.2% increase in food spoilage. More inconsistent individuals also show a significantly stronger tendency to discard food because its best-before date has expired (2.1%) and a higher likelihood to throwing away prepared or stored food intended for later consumption (1.7%). The relationship between dynamic inconsistency and food waste proves highly robust to alternative measures of dynamic inconsistency, and the results remain stable over time: dynamically inconsistent choices are systematically associated with food waste patterns several weeks later. Taken together, our findings suggest that dynamically inconsistent individuals are more prone to wasting food, whereas long-run patience – captured by the exponential discounting parameter δ – bears no association with waste behavior.

We also provide empirical support for the proposed behavioral mechanism. First, dynamically inconsistent individuals do not differ from consistent respondents in their rudimentary consumption planning behavior. Second, dynamic inconsistency is systematically correlated with deviations from individuals' own stated consumption intentions. Third, our comprehensive consumption deviation index is strongly predictive of individual food waste behavior.

This paper makes four main contributions: First, it is the first study to introduce dynamic inconsistency into the food waste literature, both conceptually and empirically. Several economic studies model food waste as a possible consequence of optimal consumer choice (Hamilton and Richards, 2019; Katare et al., 2017; Lusk and Ellison, 2017; Morris and Holthausen, 1994; Ellison and Lusk, 2018).[2] Drawing on a household production framework in which time and labor serve as inputs alongside food purchases, utility is derived from transforming these inputs into consumption (Becker, 1965). These studies treat food waste – with variations in design – as the outcome of rational decision-making, driven by factors such as food prices and income. Our paper adds a behavioral dimension, proposing that individuals may also waste food as an unintended consequence of systematically departing from earlier preferences during the food consumption process.

Second, we collect unique data providing simple yet comprehensive measures of the type and extent of domestic food waste. Measuring food waste is inherently difficult: prior studies rely either on self-reported food waste quantities (Secondi et al., 2015) or infer waste indirectly from comparing biologically predicted food requirements (derived from height, weight, and age) with food purchasing data (Yu and Jaenicke, 2020; Hall et al., 2009). Grounded in our conceptual framework, we collect detailed data on individual consumption and waste habits (emphasizing waste incidences rather than quantities), personal characteristics, lifestyle, food ambience, and economic preferences. Together, these data contribute to a more holistic understanding of food consumption and waste behavior across the entire domestic food consumption chain.

[1] DellaVigna (2009) provides an overview of how self-control problems are conceptualized in the literature.

[2] Psychological or business studies in this space tend to focus on awareness, attitudes, norms, or food consumption environments (Vittuari et al., 2023), and do not engage with behavioral economics in terms of decision making.

Third, the paper contributes to the broader literature on temptation and dynamic inconsistency, parts of which focus on real-world applications in health and food consumption. Early empirical evidence for time-inconsistent behavior in food consumption comes from Shapiro (2005) and Mastrobuoni and Weinberg (2009). Using field data from low-income U.S. households, Shapiro (2005) documents that consumption patterns vary systematically with payment timing in a manner inconsistent with exponential discounting. Mastrobuoni and Weinberg (2009) extend this line of inquiry, documenting heterogeneity in intra-monthly consumption patterns consistent with self-control problems. More recently, Brownback et al. (2025, 2026) advance both the theoretical and empirical study of time-inconsistent food consumption by linking experimentally elicited time preferences to real-world food choices and evaluating the welfare effects of behavioral food subsidies. We seek to extend the perspectives of Sadoff et al. (2020), Read and Van Leeuwen (1998), Houser et al. (2021), who focus primarily on the trade-off between healthy and unhealthy food in grocery shopping choices, and Samek (2019), Sadoff and Samek (2019), Huseynov et al. (2021), Segovia et al. (2020), who study healthy eating.

We model the intertemporal timing of fresh food consumption and show that present bias delays intended fresh-food consumption, thereby increasing waste. We argue that food waste represents a hitherto overlooked, economically significant, and costly consequence of dynamically inconsistent consumer choices. The research helps explain why households waste so much food despite consumers being generally experienced in food choices and having no intrinsic taste for wasting resources. By combining proxy estimates of (β, δ) time preferences with survey-based measures of patience and procrastination, we further enhance construct validity through methodological triangulation.

Fourth, the paper contributes to the literature on predicting pro-environmental behavior by examining the role of preferences. While Fuhrmann-Riebel et al. (2021), Groh and Ziegler (2022), Fischbacher et al. (2021) investigate time preferences in relation to energy and electricity savings, we extend this line of research by linking dynamically inconsistent time preferences to individual food waste behavior.

The remainder of the paper is structured as follows: Section 2 develops the conceptual framework. Section 3 presents the dataset and provides detailed descriptions of the outcome, explanatory, and control variables. Section 4 presents the reduced-form results, explores the proposed mechanism, and conducts robustness checks. Section 5 concludes.

2. Conceptual framework

A growing literature outside economics explains household food waste through information deficits as well as structural and behavioral drivers. Explanations include a lack of knowledge, suboptimal storage practices, and confusion around "best-before" labels (Aschemann-Witzel et al., 2015); failures in planning and provisioning, such as overbuying due to promotional incentives, poor meal planning, or inaccurate assessments of household needs (Stancu et al., 2016; Graham-Rowe et al., 2014); and cultural and social norms surrounding aesthetic standards and hospitality (Watson and Meah, 2012). More recent research emphasizes behavioral factors – including cognitive biases, over-optimism, habitual shopping routines, and moral disengagement – that can generate food waste even when consumers are aware of the problem (Quested et al., 2013). Another explanation is experiential learning: households experimenting with new foods or recipes may discard items they find unappealing or difficult to prepare (Neff et al., 2015).

Together, these explanations offer valuable insights, but typically rest on the assumption that consumers behave consistently with their long-term preferences. Our behavioral economic approach departs from this assumption by foregrounding the *temporal* dimension of food consumption: because purchasing, preparation, and eating occur at distinct points in time, consumers face a series of intertemporal choices at each stage of the food consumption process. We argue that present-biased individuals systematically postpone the consumption of fresh food at the preparation stage, and model food waste as an unintended consequence of this dynamically inconsistent behavior.

2.1. Theoretical background

Dynamically inconsistent time preferences were formalized by Laibson (1997) and O'Donoghue and Rabin (1999) using the quasi-hyperbolic discounting model—commonly referred to as the (β, δ) model. Our application of the (β, δ) model follows DellaVigna (2009) closely, adapting his framework to the timing of food consumption. Importantly, our model captures the intertemporal timing of fresh food consumption, abstracting from the alternative meal option; in practice, delayed consumption will often be accompanied by substitution toward convenience food.

Consider a good with an immediate payoff and a delayed payoff. Let c_1 be the immediate payoff in $t = 1$ and c_2 be the delayed, future payoff in time $t = 2$. A good with investment character has the features $c_1 < 0$ and $c_2 > 0$: the good requires effort in $t = 1$ but delivers benefits in $t = 2$. Conversely, a leisure good has the features $c_1 > 0$ and $c_2 < 0$: it provides benefits in $t = 1$ at costs in $t = 2$.

From a planning perspective (*advance choice*), $t = 0$, a present-biased individual with $\beta < 1$ *plans* to consume the good in $t = 1$ if the relative payoffs are larger or equal zero:

$$\beta\delta c_1 + \beta\delta^2 c_2 \geq 0 \quad \text{or} \quad c_1 + \delta c_2 \geq 0 \tag{1}$$

The parameter δ captures the degree of long-run discounting: $\delta = 1$ for a fully patient individual, whereas different degrees of impatience toward future benefits are captured with $\delta < 1$. The parameter β captures present-biased behavior. If $\beta = 1$, the individual behaves consistently over time. For values of $\beta < 1$, the individual shows a certain degree of present bias, with smaller values of

β implying more dynamically inconsistent behavior. Because the present bias parameter β is time-invariant, it cancels out from an advance choice perspective in $t = 0$.

Yet, how much does the individual *actually* consume in $t = 1$? From an *immediate choice* perspective, the individual consumes if:

$$c_1 + \beta\delta c_2 \geq 0. \tag{2}$$

Since the parameter β refers to all payoffs received in the future, the individual is discounting the future payoff c_2 excessively with $\beta < 1$. Present bias implies a greater discounting between the present and the future than between any other two equidistant future time periods because $\beta\delta c_2 < \delta c_2$.

What are the implications of the (β, δ) model for the consumption of fresh food? Fresh food is a good with investment character: it entails present costs ($c_1 < 0$) but yields future benefits ($c_2 > 0$). The costs are reflecting the effort involved in washing, chopping and cooking fresh ingredients, which increases preparation time and reduces cooking ease (Sen et al., 2021).[3] The benefits arise from the superior nutritional quality: while fresh food is broadly comparable to convenience foods in its energy content, it typically contains fewer additives and is richer in vitamins, minerals and fiber (Pollard et al., 2002; Bucher et al., 2015).[4]

Consider an individual planning to consume a fresh meal in $t = 0$. Following Eq. (1), from an advance perspective the individual *wants* to consume the fresh meal, since the anticipated utility is positive.[5] However, since the benefits from consuming fresh food are excessively discounted from an immediate perspective ($\beta\delta c_2 < \delta c_2$), following Eq. (2), the individual does *not* actually consume the fresh meal because the discounted utility is negative in $t = 1$.[6] As a result of not consuming the fresh meal at $t = 1$, fresh food is stored longer than intended. Given predetermined perishability, a longer storage duration directly increases the likelihood of spoilage and, ultimately, food waste.

A related but distinct pathway operates through taste and temptation: even holding preparation effort fixed, the immediate hedonic appeal of convenience food may compete with the longer-term nutritional aspirations that motivated the original purchase of fresh ingredients. Both pathways are consistent with our framework and may interact in practice.

2.2. Food consumption: Process over time

Daily food consumption is not a single decision but a dynamic process, involving choices at successive stages over time: from meal planning and grocery shopping through storing, food preparation, and eating to leftover management. As individuals move through these stages, they face a series of advance and immediate choices made from shifting time perspectives. We illustrate this framework in Figure A1 in Appendix A.

While the model in Section 2.1 isolates the intertemporal decision to consume fresh food at the intended time, in practice food consumption unfolds in a broader choice environment in which fresh food competes with convenience alternatives. Postponing the preparation of a fresh meal will therefore often coincide with substituting toward a ready-made option—a pattern consistent with evidence from food-choice studies showing that immediate choices systematically shift toward less effortful alternatives (Read and Van Leeuwen, 1998; Sadoff et al., 2020). The key observable consequence is that fresh food remains in storage longer than intended, increasing its exposure to spoilage.

More specifically, at the *planning stage*, individuals make advance choices about which food items to purchase, a stage typically characterized by good intentions, with consumers planning a high quality diet and envisioning a consumption basket rich in fresh food (Lappalainen et al., 1998). Importantly, individuals are aware of the substantial preparation effort required for fresh food. At the *shopping stage*, however, these plans are reconsidered from an immediate perspective. A present-biased individual may deviate from her prior intentions and include fewer fresh food items in the shopping basket, substituting convenience food instead—a direct consequence of dynamically inconsistent time preferences.[7] The choice set available for subsequent decision stages at home therefore contains more convenience food than originally intended. Sadoff et al. (2020), Read and Van Leeuwen (1998) provide evidence for dynamic inconsistency at the grocery shopping stage.

Importantly, individuals at the *shopping stage* do not only choose what to buy, but also form intentions *when* to consume food items at home. Individuals often purchase food in advance – typically days before consumption – because grocery shopping is a time-consuming activity that is not repeated for every single product a consumer wishes to buy. This temporal separation between purchase and consumption creates an intertemporal choice problem: at the time of shopping, the consumer must decide how much fresh food to buy for future preparation, knowing that the associated effort will only be incurred at a later stage. These intentions, however, are subject to revision, sometimes within hours of returning home (Cutler et al., 2003). At the *preparation* and *eating stages*, present-biased individuals deviate from their earlier consumption plans by opting for more convenient alternatives that require less

[3] Effort costs of food preparation are particularly relevant for domestic food consumption in the household production framework by Becker (1965), since individuals derive utility not from purchasing ingredients, but from consuming prepared meals. While some people might derive utility from food preparation activities, we ignore this here.

[4] Even when objective differences in nutritional quality are small, evidence from consumer psychology and food economics suggests that consumers exhibit a preference for fresh products, largely driven by perceived quality advantages (Connell et al., 2018; Dudley et al., 2025).

[5] We assume that consumers hold roughly accurate beliefs about the predetermined perishability and preparation effort of fresh food at the time of purchase. For simplification, we also abstract from potentially incorrect storage behavior that may further reduce shelf life at home.

[6] For further details, we direct the interested reader to Appendix A.

[7] Shopping for fresh meal ingredients is generally more time-consuming than purchasing convenience food.

preparation effort. As a result, the consumption of fresh food items is postponed by at least one time period, and these food items remain in storage longer than intended. Since fresh foods are neither processed nor preserved with additives, prolonged storage renders them increasingly susceptible to spoilage and, ultimately, to being wasted.

Together, these two frictions – the structural time gap between shopping and consumption, and the investment character of fresh food with earlier effort costs and later nutritional benefits – explain why delay of fresh food arises systematically among present-biased individuals, making it more vulnerable to waste than convenience food. Overall, the fresh–convenience trade-off reflects a tension between quality-oriented perceptions and effort-reducing considerations.

2.3. Institutional context

We test the predictive power of time inconsistency for food waste behavior using data from Germany. Average household waste per capita amounts to 78 kg per year, which is broadly representative of the global average (United Nations Environment Programme, 2024). That said, some country-specific features warrant clarification: Food labeling in Germany – and in the European Union more broadly – is governed by clear legal regulations (Regulation (EU) No 1169/2011), in contrast to the United States, where labeling practices are largely voluntary and vary widely. In the US, manufacturers may use different and sometimes overlapping terms – such as "best-before", "use-by, " or "sell-by" dates – often without standardized definitions. In Germany, by contrast, highly perishable products such as fresh meat or fish are required to carry a use-by date (*Verbrauchsdatum*), after which they may no longer legally be sold. All other food products must display a best-before date (*Mindesthaltbarkeitsdatum*), indicating the minimum period during which a product retains its expected quality. Although products may legally be sold after the best-before date, retailers generally avoid doing so, as they remain liable for the product's condition and must guarantee its quality.

The consumption context also differs between Europe and the US. Consumers in Germany and Europe typically exhibit strong store loyalty and stable purchasing routines (Krumme et al., 2013), unlike in the US, where food experimentation and a desire for novelty are more prevalent (Lusk, 2019). Consequently, alternative explanations of food waste – such as experiential learning – appear less applicable in our setting.

3. Empirical strategy

In what follows, we describe the dataset, the measures of food waste and time inconsistency, and the econometric approach.

3.1. Dataset

3.1.1. Data overview

We use unique, nationally representative survey data on grocery shopping and consumption behavior, collected under the project 'Grocery Shopping and Consumption in Germany' (ELKiD), funded by the Catholic University Eichstaett-Ingolstadt, Germany. The project was designed for an in-depth study of food purchasing and consumption behavior among households in Germany. The data comprise two online survey waves per respondent: wave 1 was conducted in February–March 2021, followed by wave 2 in June–early July 2021. The survey was implemented by Respondi, an established market research company, using stratified random sampling by gender, age, and state of residence, yielding a sample representative of the German population. For a detailed data description and documentation, see Appendix B.

Our analysis draws on survey items covering food planning, purchasing, processing and consumption behavior, as well as economic preferences, socio-demographic characteristics, and personal lifestyle. Food waste behavior is elicited in both waves. After careful data cleaning, the final sample comprises 1281 individuals in wave 1 and 874 individuals in wave 2.[8] The main analysis relies on the wave 1 sample, while wave 2 is used in the robustness checks.

Our survey participants are well positioned to make informed statements about their food consumption and waste behavior at home. In the two days preceding the survey, respondents prepared an average of 3.3 dishes and consumed an average of 3.5 dishes at home. Only 2.7% of respondents report not having prepared a single dish.

3.1.2. Summary statistics

Table 1 reports summary statistics for outcome and control variables in wave 1, with detailed variable descriptions provided in Table B1 in Appendix B. We include individual risk preferences as a control variable, given that the future is inherently uncertain

[8] We exclude observations with implausible age values, as well as observations with economically implausibly values of long-run patience δ (above the 97.5th percentile, for details see Section 3.3). These exclusions neither affect the main results nor alter the conclusions. Results are reported in Table C3 of Appendix C.

Table 1
Summary statistics.

Statistic	N	Mean	SD	Min	Max
Outcomes:					
Food Spoilage Indicator (FSI)	1281	1.237	1.375	0	4
Best Before Waste dummy (BBW)	1281	0.244	0.429	0	1
Waste Leftovers dummy (WL)	1281	0.202	0.402	0	1
Main regressors:					
Beta (β)	1281	0.887	0.150	0.005	1.121
Delta (δ)	1281	0.832	0.185	0.081	1.110
Procrastination	1281	4.294	2.706	0	10
Patience	1281	5.945	2.145	0	10
Controls:					
Risk seeking	1281	4.498	2.347	0	10
Age	1281	44.540	14.337	18	69
Female	1281	0.498	0.500	0	1
Tertiary education dummy	1281	0.514	0.500	0	1
Employment dummy	1281	0.707	0.455	0	1
Single household dummy	1281	0.477	0.500	0	1
Net household income	1281	2655.634	1647.878	250	10,001
Child under 12 dummy	1281	0.134	0.341	0	1
City dummy	1281	0.380	0.486	0	1
Distance grocery store	1281	12.859	10.620	1	36
Vegetarian dummy	1281	0.176	0.381	0	1
Share organic food	1281	2.186	1.702	0	7
Discounter index	1281	0.468	0.291	0	1
No. grocery purchases	1281	2.326	1.932	0	10
Working from home (days)	1281	1.443	2.043	0	5
Covid-19 stringency index	1281	71.841	4.497	66.667	80.093
Mechanism Analysis					
Domestic Deviation Index (DDI)	1281	1.032	1.108	0	4
Fridge Checking Dummy	1281	0.784	0.412	0	1
Shopping List Dummy	1281	0.790	0.407	0	1
Planning horizon (days)	1260	3.924	1.915	0	8

Note: Table reports summary statistics for outcome and control variables measured in wave 1. Reported are the number of observations (N), the mean (Mean) and standard deviation (SD) as well as the minimum (Min) and maximum (Max) values for each variable. In the last line (Planning horizon (days)), 21 respondents indicate to not have bought fresh fruits and vegetables at all. This reduces the sample size for the variable to 1260. Data source: ELKiD 2021.

while the present is not (Andreoni and Sprenger, 2012b).[9] Following Falk et al. (2018), we measure risk preferences using the self-reported 'Willingness to take risks' variable, recorded on an 11-point Likert scale from 0 to 10. Personal characteristics include age, gender, education, and employment status. In wave 1, half of respondents are female and the mean age is 45 years. Drawing on models of food waste as a consequence of optimal consumer choice, Lusk and Ellison (2017), Morris and Holthausen (1994), Lusk and Ellison (2020) predict that human capital shapes household food waste levels. Labor market activity proxies for time constraints that may influence both the incidence and magnitude of food waste (Secondi et al., 2015). We therefore include binary indicators for tertiary education (51%) and employment (71%) in the regression framework.

Household-level controls include a dummy for single-person households, equal to 1 if the respondent lives alone (48%), and a dummy for the presence of a child under 12 in the household (13%), following Ellison and Lusk (2018). Consistent with Morris and Holthausen (1994), Lusk and Ellison (2017), who emphasize the role of income in food waste modeling, we control for the natural log of total household income. Mean self-reported disposable monthly household income is €2656. We further include place of residence (urban vs. rural) and walking distance to the next grocery store (in minutes) as proxies for food availability, with an average walking distance of approximately 13 min.

A final set of controls captures food behavior and lifestyle characteristics. We include a dummy for vegetarian or vegan diet (18%), as individuals following plant-based diets tend to exhibit stronger pro-environmental orientations (Lades et al., 2021). Following Ellison and Lusk (2018), who highlight the role of food prices in waste decisions, we proxy prices through the shares of organic and discounter food purchases (Herrmann et al., 2009). Between 11 and 20% of items purchased during a grocery trip in the past four weeks were organic, and 47% of stores regularly visited by respondents are discounters. Additional controls include the number of grocery shopping trips per week (in-store and online), the Covid-19 stringency index, and the number of days worked from home. The latter two variables proxy for pandemic conditions in 2021 and are discussed further in the robustness section.

[9] The relationship between risk preferences and food waste is theoretically ambiguous: while more risk-averse consumers may waste less food by purchasing items with greater remaining shelf life (Tsiros and Heilman, 2005), they may alternatively waste more by overpurchasing as a precaution against stock-outs (Li et al., 2024) or by discarding items at a lower spoilage threshold out of health concerns (Wilson and Miao, 2025).

3.2. Food waste metrics

To measure household food waste, we focus on behavior at the storage stage and employ three outcome variables: a food spoilage indicator (FSI), a best-before waste dummy (BBW) and a waste of leftovers dummy (WL). All three indicators are conceptually straightforward and easy to respond to, as they require no subjective estimates of quantities or frequencies. Their key strength lies in capturing food waste at the extensive margin – that is, the incidence of waste – though they are limited in their ability to assess the intensive margin.

The FSI is constructed as the sum of four binary indicators of food spoilage detected within the past seven days, spanning the following product categories: fruits and vegetables, dairy products, meat or fish products, and bread and bakery products.[10] Specifically, respondents indicate whether they discovered food items in storage that they no longer wished to consume due to deteriorated texture or condition.[11] Summing the four binary outcomes, the FSI ranges from 0 to 4, where a value of 4 indicates spoilage across all categories within the past week. The mean index value in wave 1 is 1.3 (Table 1). Spoilage is most prevalent for fruits and vegetables (42%), followed by bread and bakery products (33%), meat or fish (25%), and dairy products (23%). It is worth noting that food spoilage does not necessarily equal food waste. The FSI captures food removed from its intended use for human consumption; however, when asked how they handle spoiled food in general, 94% of respondents report discarding it (at least in part), while 6% report feeding it to animals. We therefore consider the FSI a strong proxy for food waste, while acknowledging that it may to a limited extent reflect an aversion to consuming spoiled food.[12] Importantly, however, reluctantly consuming spoiled food is itself an undesirable outcome that is fully consistent with our proposed mechanism: in both cases, food has been stored beyond its intended consumption date, resulting in deterioration. The FSI therefore captures the full range of adverse consequences of excessive storage duration – whether the spoiled food is ultimately discarded or consumed despite its condition – and its validity as a proxy for the consequences of time-inconsistent behavior is if anything strengthened by this observation.

The best-before waste dummy BBW takes a value of one if an individual reports having discarded food in the past seven days due to exceeding its best-before or use-by date. While many foods remain edible beyond these dates, consumers may discard them out of safety concerns or lack of awareness (Neff et al., 2015; Quested et al., 2011). Experimental evidence by Ellison and Lusk (2018) confirms that expiration dates meaningfully influence disposal decisions. Within our conceptual framework, the repeated postponement of fresh food naturally increases the likelihood that items will surpass their best-before or use-by date. In wave 1, 24% of respondents report best-before food waste (see Table 1).

The leftover waste dummy WL takes a value of one if an individual reports having discarded leftovers from cooking or eating that were stored in the fridge or freezer for later consumption. This behavior is relevant within our framework, as consuming leftovers may require additional preparation effort when leftover portion sizes are small. Consistent with this, Ellison and Lusk (2018) find that individuals are less likely to discard leftovers when they can be combined into a complete new meal. In wave 1, 20% of respondents report discarding leftovers (see Table 1).

Our measurement approach departs from earlier studies (Secondi et al., 2015) that elicit subjective estimates of food waste quantities. We instead rely on dummy variables, as consumers tend to recall specific instances of food waste but systematically underestimate the amounts discarded (Quested et al., 2011; Neff et al., 2015). This trades off insights into waste quantities for greater accuracy across distinct food waste types. Alternative methods carry well-documented limitations: food waste diaries (Koivupuro et al., 2012) are prone to attention effects that alter the very behavior being measured; municipal waste composition analyses (Schneider and Obersteiner, 2007; Lebersorger and Schneider, 2011) lack precision and cannot be linked to individual-level behavior; and macroeconomic food purchasing-consumption comparisons (Yu and Jaenicke, 2020; Landry and Smith, 2019; Hall et al., 2009), which infer caloric surplus from purchasing surveys and individual biological characteristics (height, weight, gender and age), remain highly imprecise.

Our approach mitigates under-reporting by framing waste questions with precise contextual detail and restricting recall to a short reference period of seven days. The waste items are embedded within a broader survey covering food purchasing, preparation, and eating behavior, enabling us to generate accurate waste measures that can be directly linked to the economic preference framework. This design is most comparable to the vignette-based approach employed by Ellison and Lusk (2018).

3.3. Dynamic inconsistency measure

A growing empirical literature suggests that present bias reflects a relatively stable behavioral tendency that generalizes across domains. For example, Cheung et al. (2022) elicit time preferences using convex time budgets across monetary, healthy food, and unhealthy food domains and find that present bias arises in all three domains, that time-inconsistency measures are positively correlated across domains, and that both monetary and food present bias predict real-world unhealthy behaviors. Complementing this evidence, a comprehensive psychological review concludes that delay-discounting measures are positively correlated across monetary and food domains, pointing to substantial cross-domain stability in intertemporal preferences (Odum et al., 2020). Taken

[10] These categories have been documented as primary sources of household food waste (Buzby et al., 2011; Quested et al., 2011).

[11] The original question asks: *Please think about the last 7 days (not including today). During this time, have you discovered any food at home from the following categories that, due to its condition or quality, you no longer wanted to (fully) eat?*.

[12] In a robustness check we replicate our main analysis, first, by restricting the sample to respondents who generally discard spoiled food (Table C4 in Appendix C). Second, we create a Waste of Spoiled Food Indicator as product of the Food Spoilage Indicator (FSI) and a disposal dummy equaling 1 if respondents report to waste spoiled food (or parts thereof) (Table C5 in Appendix C). In both specifications, all results are preserved.

together, these findings support the use of monetary present-bias measures as proxies for intertemporal inconsistency in food-related behaviors.

To embed our empirical approach into the (β, δ) model of dynamic inconsistency, we need to recover β and δ for all respondents. The literature offers several strategies for eliciting time preference parameters. The method proposed by Andreoni and Sprenger (2012a) uses Convex Time Budgets (CTB) to structurally identify time and risk preference parameters simultaneously. While increasingly popular, its relative complexity makes it better suited to experimental settings than large-scale surveys.[13]

We therefore draw on the literature employing hypothetical intertemporal monetary trade-off questions, which combine ease of implementation with a strong track record in measuring time preferences in large-scale surveys (Courtemanche et al., 2015; Nuscheler and Roeder, 2016). This approach suits our empirical framework well, as it yields approximations of (β, δ) parameters for all respondents while keeping the survey design tractable. We adopt two questions from the 2006 wave of the National Longitudinal Survey of Youth (NLSY), a panel administered by the US Bureau of Labor Statistics. A patience parameter δ and an inconsistency parameter β are then derived from these two questions, which are identical in wording but differ in their delay periods. Denoting the delay period by k with $k \in \{1, 12\}$, $k = 1$ corresponds to a one-month delay and $k = 12$ to a one-year delay. The question reads:

> Suppose you have won a prize of €1000, which you can claim immediately. However, you can also wait for k month(s) to claim the prize. If you wait, you will receive more than €1000. What is the smallest amount of money you would need to receive in addition to the €1000 in k month(s) to convince you to wait instead of claiming the prize now? Enter this additional $amount_k$ of money in the text box.

The *year* question ($k = 12$) elicits intertemporal discounting over an annual horizon, while the *month* question ($k = 1$) does so over a monthly horizon. Although the difference in time frames may appear subtle, the relevant information is underlined in the survey instrument, and the two questions appear consecutively in a framing designed to highlight the change in reference period. A growing body of literature relies on comparable hypothetical survey items to measure time preferences and time inconsistency. Courtemanche et al. (2015) use the identical two questions from the 2006 NLSY in their study of obesity and, drawing on experimental evidence (Johnson and Bickel, 2002; Madden et al., 2003), argue that hypothetical choices can capture time preferences reliably. Similar hypothetical approaches are employed in labor market research (van Huizen and Plantenga, 2014). More recently, Brownback et al. (2026) develop an incentivized two-question module with the explicit aim of creating a short, transferable survey instrument that does not require complex price lists. Other contributions proxy time inconsistency through observed behaviors using factor analysis (DellaVigna and Paserman, 2005). In our data, the survey-based β measure is strongly correlated with such behavioral indicators (see Table C1 in Appendix C), further supporting the validity of the hypothetical items.

Each question yields an $amount_k$ from which we compute the following *annualized discount factors* DF_k for the one-month ($k = 1$) and one-year ($k = 12$) horizons:

$$DF_k = \left[\frac{1,000}{(1000 + amount_k)}\right]^{\frac{12}{k}}. \tag{3}$$

To measure dynamic inconsistency, we exploit the difference in time horizons across the two questions. A dynamically consistent individual should display the same *annualized discount factor* over both the monthly and the annual intervals. A present-biased respondent, by contrast, will exhibit declining impatience over time, resulting in a larger discount factor for the annual than for the monthly delay. It bears noting that our survey questions vary only the back-end delay (1 vs. 12 months) while holding the front-end delay fixed at zero. As a result, this design does not yield the canonical, structurally identified present-bias parameter β in the strict quasi-hyperbolic sense; in principle, the setup may be more closely comparable to hyperbolic discounting. For empirical tractability, intuitive interpretation, and comparability, we nonetheless employ the quasi-hyperbolic discounting model and interpret β as a meaningful reduced-form proxy for time inconsistency that captures declining impatience over time.[14]

Within the quasi-hyperbolic discounting framework of Laibson (1997), O'Donoghue and Rabin (1999), an individual discounts future outcomes τ periods ahead at a rate $\beta\delta^{\tau}$. When $\beta = 1$, the model reduces to standard exponential discounting with a constant discounting factor across horizons. For $\beta < 1$, individuals are present-biased: they systematically deviate from their own forward-looking plans in favor of immediate gratification. Because future benefits are excessively discounted, actions that appear more beneficial from an advance perspective are postponed and may ultimately never be carried out.

Assuming annual reference periods, individual responses to the two questions imply the following relationship:

$$\beta\delta^{\frac{k}{12}} = \frac{1,000}{(1000 + amount_k)}. \tag{4}$$

Solving for β and δ yields

$$\beta = \frac{1,000}{[\delta(1000 + amount_{12})]} \tag{5}$$

[13] An alternative, though equally lengthy, approach is the staircase method developed by Cornsweet (1962) and popularized by Falk et al. (2018).

[14] Tables C6 and C7 of Appendix C present robustness checks using a general hyperbolic discounting parameter derived from the same intertemporal choices. The results are qualitatively unchanged, confirming that our findings are not sensitive to the specific parametrization of time preferences.

and

$$\delta = \left[\frac{(1000 + amount_1)}{(1000 + amount_{12})}\right]^{\frac{12}{11}}. \quad (6)$$

The average discount factors for the annual and monthly delay questions are 0.74 and 0.43, respectively, corresponding to implied annual interest rates of 35% (one year) and 132% (one month). The greater patience observed over longer delays is consistent with diminishing impatience over time, as predicted by quasi-hyperbolic discounting. Although both interest rates are high, they are in line with preferences exhibiting stickiness towards the status quo (Shelley, 1993; Loewenstein, 1988; McAlvanah, 2010). Since both elicitation questions use an immediate payoffs – that is, today – as the intertemporal reference point, smaller discount factors (and correspondingly higher interest rates) are to be expected relative to methods without a single shared reference point. Notably, the interest rates in our sample are substantially lower than those reported by Courtemanche et al. (2015), who employ the same elicitation technique.

Summary statistics for the time preference parameters are displayed in Table 1. The sample mean of the present bias parameter β is 0.89, slightly above estimates in Courtemanche et al. (2015).[15] Ninety-six per cent of individuals have a β value at or below 1; the remaining 4% exhibit future bias. The long-run patience parameter δ has a sample mean of 0.83, with 97% of individuals displaying a δ value at or below 1.[16] Together, these estimates imply that the immediate future period is discounted at $\beta\delta = 0.74$, while all other future periods are discounted at 0.83, or approximately 20.5% per year (see Figure C1 in Appendix C for the full parameter distributions).

To assess the construct validity of our measures, we examine unconditional correlations between the dynamic inconsistency parameter β and the long-run patience parameter δ with economic outcomes that have an intertemporal component. According to Table C1 in Appendix C, β and δ are not systematically correlated with one another. Correlations between β and economic outcomes run in the expected directions, supporting the interpretation that our monetary trade-off measures capture stable intertemporal preferences: more present-biased individuals ($\beta \downarrow$) are less likely to hold a tertiary education degree, more likely to smoke, have a higher Body Mass Index, and report a less healthy diet. Although modest in magnitude, these correlations are consistent with – and of comparable size to – those reported by Courtemanche et al. (2015). The long-run patience parameter δ is not systematically associated with education, smoking, BMI or diet quality. Overall, the pattern in Table C1 closely mirrors the findings of Courtemanche et al. (2015).

3.4. Econometric specification

To estimate the relationship between food waste y and individual-level dynamic inconsistency DI (i.e., the parameter β), we specify the following cross-sectional OLS regression:

$$y_{i,t} = \alpha_0 + \alpha_1 DI_i + \mathbf{X}_{i,t}\alpha_2 + \epsilon_{i,t}, \quad (7)$$

where i indexes the individual, t denotes wave 1 or 2, and α_0 is the constant. We consider three different food waste measures y as outlined in Section 3.2: The FSI measures the incidence of spoilage across four food categories; the BBW dummy indicates whether an individual discarded food due to an expired best-before or use-by date; and the WL dummy equals 1 if stored leftovers were wasted. The parameter α_1 is the coefficient of interest. The error term ϵ is assumed iid, and we apply heteroskedasticity-robust standard errors throughout.

The vector $\mathbf{X}$ comprises three sets of control variables. The first is the behavioral parameter long-run patience δ. The second encompasses risk preferences and socio-demographic and household characteristics: age, gender, and dummies for tertiary education, employment status, single-person household, and the presence of a child under age 12, as well as the walking distance to the nearest grocery store (in mins). The third set contains food behavior and lifestyle controls: a dummy for vegetarian diet, the share of organic food purchases, a discounter index, and the number of grocery shopping trips per week.

4. Results

Section 4.1 presents descriptive evidence on the food planning and consumption process, documents the incidence of food waste across the different stages of the consumption chain, and reports the reduced-form regression results. Section 4.2 examines the construct validity of the dynamic inconsistency measure, and Section 4.3 investigates the mechanisms underlying the relationship between dynamic inconsistency and food waste.

[15] Courtemanche et al. (2015) report annual interest rates of 66% (one year) and 257% (one month), implying $\beta = 0.8$ and $\delta = 0.75$.

[16] All statements refer to our analysis sample with $N = 1281$ respondents.



Fig. 1. Food waste incidence along the food consumption stages.
Note: The figure depicts the food consumption chain. It summarizes food waste incidences at the different stages and provides information on how many respondents deviate from their intentions in the food consumption process. Data source: ELKiD dataset.

4.1. Dynamic inconsistency and food waste

4.1.1. Food consumption process and waste

Fig. 1 summarizes descriptive evidence on two aspects of the food consumption process: the extent to which respondents deviate from their intended behavior, and the stages at which food waste occurs. On the first dimension, we document a consistent pattern of deviation from intentions to consume fresh food. While 58% of respondents report unintentionally purchasing sweets and snacks when grocery shopping, 17% report unintentionally eating more convenience food than planned. In addition, 17% report unintentionally skipping fresh meals, and 26% order more food from delivery services than intended.[17]

On the second dimension, Fig. 1 shows that the largest share of food wasted occurs at the storage stage. While only 3% (11%) of respondents report having cooked (served) too much, 43% report having stored food longer than intended.[18] With respect to food waste outcomes, 58% of respondents discovered at least one spoiled food item within the previous seven days[19] compared to just 3% and 14% who report generally discarding leftovers from cooking or serving, respectively.

Taken together, the descriptive picture in Fig. 1 is consistent with food waste arising primarily from postponed consumption and excessively long storage rather than from poor leftover management: as fresh food items are stored longer than intended, the likelihood of spoilage and waste increases.

4.1.2. Reduced-form regressions

In a first step, we regress the FSI on the standardized present-bias parameter β (column 1 of Table 2), adding control variables gradually across subsequent specifications (columns 2 and 3). The coefficient on dynamic inconsistency, DI, decreases slightly as controls are introduced but remains highly statistically significant across all specifications.

Table 2 shows that the FSI decreases as β increases (i.e., as present bias diminishes), suggesting that more present-biased individuals waste more food. A one standard deviation increase in time inconsistency is associated with a decline in the FSI of 0.162. In terms of absolute effect sizes, a 10% increase of β is associated with a decrease in the FSI of 0.1 units or 2.2% (column 3).[20] Table 2 also reports results for the remaining two outcome variables: BBW in column 4 and WL in column 5, both estimated with the full set of controls. In column 4, a 10% increase in β is significantly associated with a 2.1% reduction in the likelihood of discarding food due to an expired best-before date.[21] A similar increase in β is associated with a 1.7% reduction in the likelihood of wasting stored leftovers. To account for multiple hypothesis testing, we additionally report sharpened false discovery rate q-values (Anderson, 2008; Storey, 2002); significant estimates persist for the FSI and BBW regressions. The long-run patience parameter δ

[17] We discuss the underlying survey questions in more detail in Section 4.3. Secondi et al. (2015) find that consumers regard freezer use as the most effective strategy for reducing food waste, a pattern consistent with time-inconsistent consumption behavior.

[18] More specifically, this question pertains to the storage of fruits and vegetables.

[19] Of these, 94% report generally discarding at least parts of spoiled food.

[20] If β increases by 1.11 units from 0.01 (minimum) to 1.12 (maximum), the FSI decreases by 1.08 units or $(1.08/5) * 100 = 22\%$. If β increases by 0.11 units or 10% (roughly from the sample mean of $\beta = 0.888$ to time consistency at $\beta = 1$), the index value decreases by 0.11 units or $(0.11/5) * 100 = 2.2\%$.

[21] The effect size is calculated as follows: a 1.11-unit increase in β (from minimum to maximum) implies a decrease in the dummy of $1.11 \times -0.193 = -0.214$, or 21.4 percentage points. A 10% increase in β corresponds to a 0.11-unit change, implying an effect of $0.211 \times 0.1 = 0.021$, or 2.1%.

Table 2
Dynamic inconsistency and food waste behavior.

	Food Spoilage Indicator (FSI)			Best Before Waste Dummy (BBW)	Waste Leftovers Dummy (WL)
	(1)	(2)	(3)	(4)	(5)
Beta (β) (z-score)	−0.204***	−0.172***	−0.162***	−0.029**	−0.023*
	(0.041)	(0.040)	(0.041)	(0.013)	(0.012)
Delta (δ) (z-score)	−0.010	0.039	0.037	−0.0005	0.006
	(0.041)	(0.040)	(0.040)	(0.013)	(0.012)
Risk seeking		0.060***	0.054***	0.015***	0.007
		(0.017)	(0.017)	(0.005)	(0.005)
Age		−0.012***	−0.012***	−0.004***	−0.004***
		(0.003)	(0.003)	(0.001)	(0.001)
Female		0.013	0.017	−0.019	0.018
		(0.076)	(0.079)	(0.025)	(0.023)
Tertiary education dummy		−0.080	−0.065	−0.013	0.006
		(0.078)	(0.079)	(0.025)	(0.023)
Employment dummy		0.287***	0.276***	0.033	0.037
		(0.082)	(0.081)	(0.027)	(0.024)
Single household dummy		−0.032	−0.057	0.029	−0.021
		(0.093)	(0.094)	(0.029)	(0.026)
Log household income		0.050	0.048	0.040**	0.020
		(0.058)	(0.058)	(0.018)	(0.017)
Child under 12 dummy		0.228*	0.225*	0.068*	0.085**
		(0.119)	(0.119)	(0.041)	(0.041)
City dummy		−0.197**	−0.183**	−0.006	−0.009
		(0.080)	(0.080)	(0.025)	(0.024)
Distance grocery store		−0.002	−0.001	−0.001	0.0004
		(0.004)	(0.004)	(0.001)	(0.001)
Vegetarian dummy			−0.137	−0.050	−0.033
			(0.102)	(0.031)	(0.031)
Share organic food			0.009	−0.012	−0.006
			(0.024)	(0.007)	(0.007)
Discounter index			0.067	−0.026	0.042
			(0.137)	(0.042)	(0.039)
No. grocery purchases			0.071***	0.013*	0.022***
			(0.023)	(0.007)	(0.006)
Sample mean waste index	1.237			0.244	0.202
p-value β	0.000	0.000	0.000	0.025	0.058
q-value β	0.000	0.000	0.000	0.068	0.252
N	1,281	1,281	1,281	1,281	1,281
Adjusted R^2	0.021	0.079	0.087	0.046	0.054

Note: The table summarizes results from Ordinary Least Squares (OLS) regressions with robust standard errors. The food waste outcome variables Food Spoilage Indicator (col. 1–3), Best Before Waste Dummy (col. 4) and Waste Leftovers Dummy (col. 5) are regressed on β, δ and control variables. In columns 1–3, control variables are gradually added. Column 3 shows the fully specified model for the Food Spoilage Indicator. Columns 4 and 5 show the fully specified model for the Best Before Waste Dummy and the Waste Leftovers Dummy. The following control variables are included: (1) risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child under 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number of grocery purchases per week. The dynamic inconsistency measure β and long-run patience parameter δ are standardized with mean 0 and standard deviation 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021.

(in columns 1–3) is never statistically significant. Consistent with the theoretical framework developed in Section 2, these results suggest that dynamic inconsistency is more relevant than long-run patience for explaining food waste behavior.

Turning to the control variables, respondents who are more risk-seeking and those who are employed (consistent with Secondi et al. (2015)) systematically waste more food, as do those indicating a higher number of grocery shopping trips per week. Living in a city is associated with less food spoilage—consistent with Secondi et al. (2015) but contrary to Landry and Smith (2019). Older people waste less food, a finding that is robust across the literature (Secondi et al., 2015; Piras et al., 2021; Quested et al., 2013; Koivupuro et al., 2012). Contrary to Buzby et al. (2002), Secondi et al. (2015), women in our sample do not differ significantly from men in their likelihood of wasting food. Consistent with Piras et al. (2021), Ellison and Lusk (2018) but contrary to Landry and Smith (2019), the presence of at least one child under age 12 in the household is associated with a slightly higher tendency to waste food. Education, income, dietary choice (vegetarian), distance to the grocery store, and shopping behavior (organic purchases, discounter use) are not significantly related to food waste behavior.

Table 3
Procrastination and food waste behavior.

	Food Spoilage Indicator (FSI)			Best Before Waste Dummy (BBW)	Waste Leftovers Dummy (WL)
Procrastination (z-score)	0.172***	0.148***	0.143***	0.047***	0.050***
	(0.039)	(0.038)	(0.038)	(0.012)	(0.011)
Patience (z-score)	0.036	−0.072*	−0.071*	−0.010	0.005
	(0.041)	(0.042)	(0.043)	(0.013)	(0.012)
Risk seeking		0.065***	0.059***	0.014***	0.003
		(0.018)	(0.018)	(0.005)	(0.005)
Sample mean waste index	1.237			0.244	0.202
Further controls					
Household characteristics	No	Yes	Yes	Yes	Yes
Food behavior & lifestyle	No	No	Yes	Yes	Yes
p-value Procrastination	0.000	0.000	0.000	0.000	0.000
q-value Procrastination	0.000	0.001	0.001	0.001	0.000
N	1,281	1,281	1,281	1,281	1,281
Adjusted R^2	0.015	0.076	0.085	0.054	0.065

Note: The table summarizes results from Ordinary Least Squares (OLS) regressions with robust standard errors. The food waste outcome variables Food Spoilage Indicator (col. 1–3), Best Before Waste Dummy (col. 4) and Waste Leftovers Dummy (col. 5) are regressed on self-reported measures of procrastination and patience, and control variables. In columns 1–3, control variables are gradually added. Column 3 shows the fully specified model for the Food Spoilage Indicator. Columns 4 and 5 show the fully specified model for the Best Before Waste Dummy and the Waste Leftovers Dummy. The following control variables are included: (1) risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child under 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number of grocery purchases per week. The procrastination and patience variables are standardized with mean 0 and standard deviation 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021.

4.2. Concept validity of dynamic inconsistency

So far, dynamic inconsistency has been measured using two monetary trade-off questions. We complement this approach with alternative measures drawn from self-reported indicators in the German Socio-Economic Panel (GSOEP), specifically survey items on *procrastination* and *patience* (SOEP-IS Group, 2024). These variables have been validated as proxies for time-inconsistent behavior in prior economic research (Falk et al., 2018), and including them allows us to address known limitations of the (β, δ) framework, such as sensitivity to task framing, response noise, or potential inattention.[22] Survey-based proxies, while less granular, may better capture trait-level self-control and goal-setting tendencies.

Our survey therefore includes two items measuring *procrastination* and *patience*. The procrastination item asks respondents how much they agree with the statement 'I tend to put off tasks even when I know it would be better to do them right away'. It serves as a proxy for dynamic inconsistency, capturing the tendency to postpone unpleasant tasks and deviate from one's own future plans. The patience item asks how willing an individual would be to forgo a current benefit in order to gain a larger benefit in the future, and serves as a proxy for long-run discounting. Both items are measured on an 11-point Likert scale ranging from zero (no agreement or willingness at all) to ten (complete agreement or willingness).

We re-estimate the specifications from Table 2 using these alternative measures. Columns 1 to 3 of Table 3 report results for the standardized survey-based *procrastination* measure against the FSI, while columns 4 and 5 report results for BBW and WL. The estimates are similar in magnitude and significance to those based on β. The coefficients on *patience* are not consistently distinguishable from zero, mirroring the earlier null results for δ. Taken together, the self-reported measures corroborate the monetary trade-off approach: food waste is well predicted by dynamic inconsistency, but not by long-run discounting.

4.3. Mechanism

Present bias implies a wedge between initial consumption intentions – formed at the shopping stage as an advance choice – and actual consumption, which reflects an immediate choice at home. As a consequence, the consumption of fresh food items is postponed and these food items are stored longer than intended, increasing the likelihood of waste. We investigate this proposed mechanism in three steps. First, we examine whether present-biased individuals differ in advance meal planning and find no systematic differences. Second, we show that they nonetheless deviate from their consumption intentions by postponing the consumption of fresh food items. Third, we link deviations from consumption intentions to individual food waste behavior.

[22] As an additional test for inattention, we exclude all respondents who provide identical answers to both NLSY questions underlying our calculations of β and δ; results are preserved (Table C2).

Table 4
Consumption planning behavior and deviating from intentions.

	Inventory Checking Dummy (1)	Shopping List Dummy (2)	Planning Horizon (days) (3)	Domestic Deviation Index (DDI) (4)	(5)	(6)
Beta (β) (z-score)	−0.001	0.013	−0.084	−0.137***	−0.089***	−0.076**
	(0.012)	(0.012)	(0.056)	(0.033)	(0.032)	(0.031)
Delta (δ) (z-score)	−0.004	0.004	0.006	−0.097***	−0.036	−0.036
	(0.012)	(0.012)	(0.054)	(0.031)	(0.031)	(0.031)
Risk seeking	0.002	−0.000	−0.055**		0.030**	0.025*
	(0.005)	(0.005)	(0.023)		(0.013)	(0.013)
Sample mean behaviors	0.784	0.790	3.924	1.032		
Further controls						
Household characteristics	Yes	Yes	Yes	No	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	No	No	Yes
p-value β	0.909	0.303	0.134	0.000	0.005	0.016
q-value β	0.954	0.405	0.212	0.008	0.013	0.046
N	1,281	1,281	1,260	1,281	1,281	1,281
Adjusted R^2	0.017	0.042	0.136	0.022	0.109	0.123

Note: The table summarizes results from Ordinary Least Squares (OLS) regressions with robust standard errors. Columns 1–3 refer to the first step of the mechanism: meal planning. The outcome variables 'Inventory Checking Dummy' (col. 1), 'Shopping List Dummy' (col. 2) and 'Planning horizon (days)' (col.3) are regressed on β, δ and control variables. The following control variables are included: (1) risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child under 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number of grocery purchases per week. Regressions for col. (3) are based on 1260 observations, as 21 respondents report not having purchased fruits and vegetables in advance during the past four weeks. Columns 4–6 refer to the second step of the mechanism: measuring deviations from intentions. The domestic deviation index is regressed on β, δ, and control variables that are gradually added. Column 6 reports regression results from the fully specified model. In all columns, the dynamic inconsistency measure β and long-run patience parameter δ are standardized with mean 0 and standard deviation 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021.

4.3.1. Meal planning

Failing to plan meals in advance is one channel through which present-biased consumers may end up purchasing food they do not cook. However, planning is itself a costly activity with delayed benefits. Since we do not observe these costs and benefits, the model yields no clear prediction for how planning should vary with present bias, making it an empirical question. To assess whether planning behavior differs systematically across respondents with different degrees of present bias, we examine three measures of how consumers typically prepare for grocery trips: checking existing inventory, compiling a shopping list, and deciding on a planning horizon (i.e., how many days ahead to purchase fresh produce). Among our respondents, 78% report having checked their fridge inventory before their most recent grocery trip and 79% report having compiled a shopping list; two-thirds did both. Respondents purchase fruits and vegetables an average of four days in advance.

Regressing each planning measure on the parameter β, we find that dynamically inconsistent individuals do not systematically differ from their consistent counterparts in any of the three planning dimensions (Table 4). Coefficients across all outcomes are statistically indistinguishable from zero. This null result is consistent with models of naïve present bias (O'Donoghue and Rabin, 1999): naïve consumers form plans at similar rates as time-consistent individuals because they systematically overestimate their future self-control. It is important to note, however, that our measures capture only whether some form of advance planning takes place—not the precision or content of that plan. Time-inconsistent consumers may still differ along these unobserved dimensions, but our data do not allow us to disentangle them. The theoretically more relevant test – whether present-biased individuals deviate more from their stated consumption intentions – is examined in the following section.

4.3.2. Measuring deviations from intentions

Dynamic inconsistency predicts deviations from intentions to consume fresh food at home. We test this proposition using five survey questions that capture such deviations across the following food-related domains: impulse snack purchases, unplanned food deliveries, omitted fresh meal preparations, unintended convenience food consumption, or unused fresh produce. Respondents indicate their agreement with each of five statements on a 4-point Likert scale from "Do not agree at all" to "Strongly agree":

> Please indicate your agreement with the following statements.
>
> **On average over the past four weeks, I have...**
>
> [1]... bought sweets or snacks that I had not intended to buy before entering the supermarket.
>
> [2]... spontaneously had food delivered by a restaurant or delivery service, or picked up food, instead of preparing a meal myself.

[3]... cooked or prepared fresh meals at home less often than intended.

[4]... eaten more convenience food than intended.

[5]... unintentionally stored fruits and vegetables past their prime.

Statement [1] captures deviations at the grocery shopping stage, while statements [2]–[5] pertain to domestic food consumption behavior, covering both convenience and fresh food choices. For each statement, we construct a dummy variable equal to one if the respondent rather agrees or strongly agrees, and zero otherwise. Fig. 1 reports the share of respondents agreeing with each statement. At the grocery stage, 58% of report having made unintended impulse purchases of sweets or snacks. Among the domestic consumption statements, 26% ordered more food from delivery services, 17% omitted planned fresh meals, 17% ate more convenience food and 43% have stored fruits and vegetables longer than intended.

Combining statements [2]–[5], we construct a Domestic Deviation Index (DDI) by summing the four dummy variables.[23] The index ranges from 0 to 4, with higher values indicating greater deviation from consumption intentions. The sample mean is 1.03 (standard deviation: 1.1), and the DDI is negatively correlated with self-reported diet quality ($\rho = -0.21$, $p = 0.000$).

Columns 4 to 6 of Table 4, report regressions of the DDI on β, with control variables added gradually. Across all specifications, dynamic inconsistency is significantly associated with greater deviation from domestic consumption intentions. More patient individuals (higher δ) deviate less from their consumption plans, though this association becomes statistically indistinguishable from zero once personal characteristics are controlled for.

4.3.3. Deviations from intentions and food waste

Finally, we regress all three food waste measures on the DDI to link the postponement of fresh food consumption to individual food waste behavior (Table 5). The DDI coefficient is highly significant across all specifications. In column 1, a one-unit increase in the DDI (corresponding to 20%) is associated with a 0.470-unit increase in the FSI, or 9.4%. For comparison, a 10% increase in deviation behavior is associated with a 4.7% increase in the FSI. A 10% increase in the DDI is further associated with a 4.8% higher likelihood of discarding food due to an expired best-before date (BBW, column 4) and a 3.5% higher likelihood of wasting stored leftovers (WL, column 5). All results remain robust to multiple hypothesis testing, as confirmed by sharpened q-values. As before, there is no systematic relationship between long-run patience δ and any of the food waste measures, while risk-seeking individuals continue to waste more food. Taken together, the evidence across all three steps supports the view that postponing fresh food consumption is a key driver of food waste.

4.4. Robustness tests

We next establish the stability of the relationship between dynamic inconsistency and food waste over time, and demonstrate robustness to the Covid-19 pandemic.

4.4.1. Stability of the dynamic inconsistency relationship

An important property of economically relevant behavior is its stability over time. We exploit our second wave of data collection, conducted several weeks after the initial survey, to test whether dynamic inconsistency predicts food waste behavior in the medium run. Specifically, we regress food waste from wave 2 on time preferences from wave 1 (β, δ, *procrastination* and *patience*). Control variables are drawn from wave 2 for time-varying characteristics (age, employment status, single-person household, household income, presence of a child under 12, city dummy, share of organic food purchases, and weekly grocery shopping frequency) and from wave 1 for factors assumed to be time-invariant (gender, education, risk preference, distance to grocery store, vegetarian diet, and discounter index). Descriptive statistics for wave 2 variables are reported in Table D1 in Appendix D.

Despite a substantially smaller and more dynamically consistent sample in wave 2, dynamic inconsistency remains a significant predictor of all three food waste metrics, regardless of whether we use β (columns 1–3 of Table D2) or *procrastination* (columns 4–6).[24]

The fact that β significantly predicts outcomes collected several weeks later suggests that dynamic inconsistency is a reasonably stable behavioral trait. Although coefficient estimates for β differ slightly between the two waves, these differences are not statistically significant: joint regressions of each food waste measure on β, a wave dummy, a β-wave interaction term, and control variables reveal no systematic variation in the β estimate across waves. Long-run patience δ is unrelated to all food waste measures in both waves. Overall, the reduced-form evidence points to a systematic and stable link between individual dynamic inconsistency and food waste behavior.

[23] For robustness, we also construct a DDI+ index combining all five statements [1]–[5]. Although statement [1] refers to impulse purchases at the supermarket, one could argue that the availability of unintended snacks at home enables subsequent deviations in domestic consumption. Results are robust to using DDI+ in place of DDI and are available upon request.

[24] Attrition between wave 1 and 2 is discussed in Appendix D.

Table 5
Deviating from intentions and food waste behavior.

	Food Spoilage Indicator (FSI)			Best Before Waste Dummy (BBW)	Waste Leftovers Dummy (WL)
	(1)	(2)	(3)	(4)	(5)
Domestic Deviation Index (DDI)	0.470***	0.426***	0.415***	0.096***	0.070***
	(0.034)	(0.036)	(0.037)	(0.012)	(0.012)
Delta (δ) (z-score)	0.032	0.056	0.055	0.003	0.009
	(0.037)	(0.037)	(0.037)	(0.012)	(0.011)
Risk seeking		0.048***	0.045***	0.012**	0.005
		(0.016)	(0.016)	(0.005)	(0.005)
Sample mean waste index	1.237			0.244	0.202
Further controls					
Household characteristics	No	Yes	Yes	Yes	Yes
Food behavior & lifestyle	No	No	Yes	Yes	Yes
p-value DDI	0.000	0.000	0.000	0.000	0.000
q-value DDI	0.000	0.000	0.000	0.000	0.000
N	1,281	1,281	1,281	1,281	1,281
Adjusted R^2	0.141	0.170	0.173	0.096	0.083

Note: The table summarizes results from Ordinary Least Squares (OLS) regressions with robust standard errors. The food waste outcome variables Food Spoilage Indicator (col. 1–3), Best Before Waste Dummy (col. 4) and Waste Leftovers Dummy (col. 5) are regressed on the Domestic Deviation Index (DDI). In columns 1–3, control variables are gradually added. Column 3 shows the fully specified model for the Food Spoilage Indicator. Columns 4 and 5 show the fully specified model for the Best Before Waste Dummy and the Waste Leftovers Dummy. The following control variables are included: (1) risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child under 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number of grocery purchases per week. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021.

4.4.2. Robustness to the Covid-19 pandemic

Since both survey waves were conducted during the first half of 2021, we test whether our results are robust to the Covid-19 pandemic context.[25] To do so, we account for variation in the stringency of pandemic containment measures. The German federal government and the 16 state governments implemented a broad range of restrictions affecting economic and social life across many domains.[26] Under the Infection Protection Act (IfSG, 2000), responsibility for designing and implementing disaster control and public health regulation rested with individual state governments (IfSG, §32 & §54), meaning that the precise implementation of containment policies – and therefore their stringency – varied across federal states. We exploit this cross-state variation by merging survey respondents with state-level policy stringency index data, manually collected and computed by Danzer et al. (2023) based on respondents' zip codes. During the first survey wave, the stringency index ranged from 80.1 in Saxony and Brandenburg to 66.7 in North Rhine-Westphalia and Hesse (see Figure E1 in Appendix E). Since our food waste measures refer to the seven days preceding the survey, we assign each respondent the state-level stringency index recorded ten days prior to their survey dates in both waves.[27] As a second measure of individual pandemic exposure, we include the number of days worked remotely from home, which was collected in both waves and ranges from 0 (no remote work) to 5 (full remote working week). In wave 1, employed respondents worked an average of 1.4 days remotely; in wave 2, the mean was 1.2 days (Table 1).

All results are robust to controlling for pandemic policy stringency and the extent of remote work. As reported in Tables E1 and E2 in Appendix E, the relationship between dynamic inconsistency and food waste is not materially affected by the pandemic environment.

5. Conclusion

This paper introduces a behavioral economics perspective on household food waste and contributes to our understanding of the role of dynamic inconsistency in intertemporal decision-making. Conceptualizing food waste as an unintended consequence of deviating from one's own intentions to consume fresh food at home, we show that more present-biased individuals waste more food in a nationally representative sample for Germany. This result is robust across model specifications, alternative sets of controls, and alternative measures of present-biased behavior. Testing the conceptually derived mechanism, we find that more present-biased individuals do form plans for domestic food consumption, but systematically deviate from those plans once the future becomes

[25] Appendix E discusses how the Covid-19 pandemic may affect our empirical strategy.

[26] These included closures of daycare facilities and schools, encouragement or enforcement of remote work, restrictions on private gatherings, cancellation of public events, an international travel ban, and limitations on internal movement.

[27] Results are robust to using stringency indices measured two or four weeks prior to the survey date; these results are available upon request.

present. These – possibly naïve – individuals are more likely to postpone the consumption of fresh food at home, resulting in longer storage durations and greater food spoilage. Individuals who deviate more from their consumption intentions also waste more food.

These findings carry important implications for the design of food policies and for anticipating their unintended consequences. Consider, for example, the US Department of Agriculture's (USDA) Supplemental Nutrition Assistance Program (SNAP), which allows online pre-ordering of groceries and is targeted at low-income communities.[28] From a behavioral economics perspective, online grocery ordering functions as a commitment device (Sadoff et al., 2020) that ties individuals to the advance choices they made at home, removing the temptation of convenience food at the point of in-store purchase. Such design changes can appear promising for improving nutritional quality in vulnerable populations. Yet our results suggest that dynamically inconsistent time preferences affect not only grocery shopping but also food consumption behavior at home. Choosing fresh groceries online does not necessarily translate into preparing and eating fresh meals: without a corresponding change in domestic consumption behavior, fresh items may go uncooked, spoil, and end up as waste. A well-intended policy aimed at improving diet quality may thus produce food waste instead, with attendant environmental and societal costs.

Our paper underscores the importance of understanding behavioral mechanisms across the full consumption chain when designing effective food policies and mitigating adverse unintended effects. Interventions shown to promote higher-quality diets – such as decision delay techniques (DeJarnette, 2020) – may also help curb the impulsive deviations from consumption intentions that drive food waste.

Declaration of Generative AI and AI-assisted technologies in the writing process

While preparing this manuscript, the authors used OpenAI, Claude, and DeepL Writing to improve readability and language. After using these tools, the authors reviewed and edited the content as needed. We take full responsibility for the content of the publication.

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Declaration of competing interest

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

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jebo.2026.107810.

Data availability

Data will be made available on request.

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[28] https://www.ers.usda.gov/amber-waves/2021/july/online-supplemental-nutrition-assistance-program-snap-purchasing-grew-substantially-in-2020/

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