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ABSTRACT

Food Waste and Dynamic Inconsistency: A Behavioral Economics Perspective*

This paper examines the link between dynamically inconsistent time preferences and individual food waste behavior. Food waste is conceptualized as unintentional outcome of choices along the food consumption chain. Capitalizing on a nationally representative longitudinal survey from Germany, we construct targeted metrics of food consumption and waste behaviors. We find that more present-biased individuals waste more food. Our study investigates the behavioral mechanism that involves postponing domestic consumption of healthy food despite good consumption intentions, resulting in food spoilage. Studying inconsistencies between grocery shopping and food preparation is pivotal for understanding the significant, persistent amounts of food waste within households.

JEL Classification: D12, D15, Q53, Q18

Keywords: dynamic inconsistency, food consumption, food waste, healthy eating

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1 Introduction

The cost of global food waste and loss is estimated at around one trillion USD per year. This amount is comparable to the GDP of Turkey, Saudi Arabia or the Netherlands as of the year 2023. Beyond the financial loss, food waste is estimated to account for 8-10 per cent of global carbon emissions. More than one billion meals are wasted every single day, implying that undernutrition and hunger could be eradicated if the challenge of food waste was solved (United Nations Environment Programme, 2024). Ignoring food waste is not an option if we aim to reduce the immense pressure on food production (FAO, 2019; IPBES, 2019; Mbow et al., 2019) or to achieve the Sustainable Development Goals in general (Westhoek et al., 2016; Willett et al., 2019).

According to the UN's Food Waste Report 2024, 60% of waste is generated within households. While the problem has climbed the agenda of international institutions and many national governments, our understanding of why households waste food is still limited. Some explanations address information problems (e.g., about best-before dates), lack of shopping preparation, or excessive shopping due to bargain offers. Yet, while information campaigns have addressed these factors, food waste has not adequately declined.

In this paper, we provide a conceptual framework that links individual food consumption and waste behavior with dynamic inconsistency in time preferences. Models incorporating such self-control problems (Laibson, 1997; O'Donoghue & Rabin, 1999; Strotz, 1955; Thaler & Shefrin, 1981) have been widely applied in economics to explain the difficulties people face when saving money (Meier & Sprenger, 2010), following a healthier diet (Cherchye et al., 2020; Courtemanche et al., 2015; Danzer & Zeidler, 2024; Read & Van Leeuwen, 1998) or exercising more in the gym (Della Vigna & Malmendier, 2006; Royer et al., 2015).[1] In line with activities that deliver future benefits but generate immediate costs, food consumption is a dynamic process requiring choices at different consumption stages, from planning over processing to eating (Quested et al., 2013). In particular, we suggest that individuals waste food as an *unintended* consequence of systematically deviating from earlier preferences in the food consumption process. Initially, individuals purchase healthy food at the grocery shopping stage in an attempt to adopt a healthy lifestyle in the future. But dynamically inconsistent time preferences lead individuals to deviate from their consumption

[1] DellaVigna (2009) provides an overview of conceptualizing self-control problems.

intentions when the advance choice is reconsidered from a present perspective (immediate choice) at home. As consequence, the consumption of healthier food items is postponed and healthy food items are stored longer than intended. Given that most healthy food items are highly perishable, the incidence of food waste increases.

We assess the conceptual implications empirically by leveraging a nationally representative, longitudinal data set from Germany and apply targeted survey items to capture individual food consumption habits, waste behavior, and economic preferences. In particular, we assess the incidence of food waste along the different stages of the food consumption chain: from grocery shopping to food storing, processing, eating, and leftover management. To estimate a dynamic inconsistency parameter at the individual level, we utilize the (β, δ) model formalized by Laibson (1997) and O'Donoghue and Rabin (1999) based on within-individual variation in payment delay, which is plausibly correlated with various intertemporal behaviors. We propose three conceptually derived food waste metrics that target lengthy food storage periods and regress these on measures of dynamic inconsistency. Apart from this reduced from analysis we pin down the mechanism: revising healthy consumption choices over time leads to excessive storage time and, as a consequence of predetermined perishability of healthy foods, more food waste.

The paper first documents substantial heterogeneity in the incidence of food waste along the domestic food consumption chain. The vast majority of food is wasted at the storing stage: 57% of respondents state that they have discovered spoiled food items at home within the last seven days, of which 94% went to waste. Twenty-four per cent of individuals discarded food items because the best before date was expired. And 20% of respondents report having disposed of leftovers that were stored in the fridge or freezer for later consumption. Food waste at other stages of the food consumption chain, like leftovers from cooking (3%) or plate leftovers (14%), are less prevalent.

In Ordinary Least Squares (OLS) regressions, the relation between dynamically inconsistent time preferences (β below 1) and individual food waste metrics are highly significant. An increase in dynamic inconsistency by 10% is associated with an increase in food waste by 2.1%. More inconsistent individuals also show a significantly stronger tendency to through away food because the best before date has expired (2.1%), and they have a higher likelihood to discard prepared and stored food intended for further consumption (1.8%). These results are also stable over time: dynamically inconsistent choices are systematically associated with food waste patterns several months later. Our results suggest that individuals with dynamically inconsistent time preferences have a higher tendency to waste food, while long-run patience (i.e., the exponential discounting parameter δ) is not associated with waste behavior.

We also provide empirical support for our proposed behavioral mechanism. First, dynamically inconsistent individuals do not differ in their consumption planning behavior from consistent respondents. Second, dynamic inconsistency is systematically correlated with deviations from own domestic consumption intentions. Third, our comprehensive consumption deviation index is strongly predictive for individual food waste behavior. In further robustness tests, we show that the negative relation between dynamic inconsistency and food waste is very robust to alternative measures of dynamic inconsistency, and stable over time.

This paper makes three main contributions: This is the first study to pursue a behavioral economics perspective to the literature on food waste, both conceptually and empirically. Several economic studies model food waste as possible consequence of optimal consumer choice (Ellison & Lusk, 2018; Hamilton & Richards, 2019; Katare et al., 2017; Lusk & Ellison, 2017; Morris & Holthausen Jr, 1994).[2] In a household production framework with time and labor as production factors and food purchases as inputs, utility is received from turning inputs into consumption (Becker, 1965). These studies consider (with design variations) food waste as a result of rational decision making, being driven – among other factors – by food prices, and incomes. Our paper adds a behavioral perspective and suggests that individuals waste food as an unintended consequence of systematically deviating from earlier preferences in the food consumption process.

Second, we collect unique data that provide simple and comprehensive measures of type and extent of domestic food waste. Since measuring food waste is difficult, previous studies rely on self-assessed food waste quantities (Secondi et al., 2015) or infer food waste indirectly from comparing biologically predicted food requirements (based on height, weight and age) with food purchasing data (Hall et al., 2009; Yu & Jaenicke, 2020). Backed by our conceptual framework, we collect detailed data on individual consumption and waste habits, personal characteristics, individual lifestyle, food ambience, and economic preferences. The data contribute to a holistic

[2]There are psychological or business studies which focus on awareness problems, attitudes, norms, or food consumption environments (Vittuari et al., 2023). These studies do not relate to behavioral economics in terms of decision making.

understanding of individual food consumption and waste behavior along the entire food consumption chain.

Third, the paper contributes to the literature on dynamic inconsistency in general. Parts thereof focus on real-world applications in the health or food domains, like dynamic inconsistency in actual food consumption choices. Our paper seeks to extend the perspectives taken by Read and Van Leeuwen (1998) and Sadoff et al. (2020) who mainly focus on grocery shopping choices and Danzer and Zeidler (2024) who focus on actual food consumption. Food waste is an economically relevant and costly side-product of dynamically inconsistent consumer choices. The research improves our understanding of why households waste so much food despite the fact that consumers are generally experienced in food choices and have no taste for wasting resources.

The remainder of the paper is structured as follows: Section 2 describes the conceptual framework. Section 3 presents the data set as well as a detailed description of outcome, explanatory and control variables. Section 4 provides reduced form results, explores the mechanism and tests for robustness before Section 5 concludes.

2 Conceptual Framework

Models of dynamically inconsistent preferences provide an explanation for the difficulties that people face when making intertemporal choices: They want to save money, exercise more or eat healthier in the future but when the future becomes present, they stick to their old habits and deviate from their plans. Dynamically inconsistent time preferences were formalized by Laibson (1997) and O'Donoghue and Rabin (1999) in the quasi-hyperbolic discounting model also known as (β, δ) model. An application of how the (β, δ) model operates is sketched out in DellaVigna (2009) and can be applied to the context of food consumption. Dynamic inconsistency in food choices is usually reflected in a trade-off between temptation and food healthiness (Read & Van Leeuwen, 1998; Sadoff et al., 2020).

Assume there are two food items: a less tempting item (e.g., an apple) and a more tempting item (e.g., a chocolate bar). The apple is the healthier good that has investment character: It implies present costs ($c_t < 0$) in comparison to the more tempting food item but delivers future health benefits ($c_{t+k} > 0$). This relative payoff is denoted by c and delivered in period

$t = 1$ (present) and $t = 2$ (future). The chocolate bar is considered the relatively unhealthy good with consumption character. It delivers relatively more pleasure today ($c_t > 0$) but comes at future health costs since $c_{t+k} < 0$. Now let us introduce a third time period, the so-called *advance* perspective $t = 0$, which can be understood as a planning stage. From this perspective, a present-biased individual *plans* to consume according to equation 1:

$$U(c_1, c_2) = \beta\delta c_1 + \beta\delta^2 c_2 \geq 0. \tag{1}$$

The individual consumes if the sum of discounted future payoffs is positive.[3] The parameter δ captures long-run patience and indicates how impatient an individual is with respect to postponing consumption by one period. From an economic rationale, δ falls between 0 and 1: a fully patient individual ($\delta = 1$) is indifferent between consuming today and tomorrow. A lower δ reflects a stronger individual preference for consuming today instead of tomorrow. The parameter β captures dynamic inconsistency. It is added to every future time period. From an *advance* choice perspective, all payments are in the future and β cancels out, simplifying equation 1 to:

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

Equation 2 implies that in an advance choice ($t = 0$), the consumption decision only depends on the relative payoff values c_1 and c_2, and on the level of individual patience δ. For illustration, consider the following example: Assume the payoff from consuming the apple today (in comparison to the chocolate bar) $c_1 = -3$. Because consuming the apple today delivers future health benefits, the relative payoff in the future $c_2 = +5$. The level of patience shall be set at $\delta = 0.9$. From an advance choice perspective in $t = 0$, the individual plans to eat the apple in $t = 1$ since $U = 1.5 > 0$.

For a present-biased individual, the future plan to consume the relatively less tempting apple is not aligned with the actual consumption decision in the present (*immediate choice*). In period $t = 1$, the individual actually consumes according to equation 3:

$$c_1 + \beta\delta c_2 \geq 0. \tag{3}$$

[3] The individual is indifferent between consuming and not consuming if the sum equals zero.

Since the present bias parameter β refers to all payoffs received in the future, the individual is discounting c_2 excessively if $\beta < 1$. A present-biased individual consumes too much of the relatively more tempting food and too little of the less tempting food item because $\beta\delta c_2 < \delta c_2$. For example, assume $\beta = 0.65$. Equation 3 now implies that the utility from consuming the apple today is $U = c_1 + \beta\delta c_2 = -0.075 < 0$. While the present-biased individual planned to eat the apple in $t = 0$, she re-evaluates the choice in period $t = 1$ and switches to consuming the chocolate bar because the future health benefits from consuming the apple are overly discounted. Present bias implies a greater discounting between the present and the future than between any other two equidistant future time periods.

Food consumption is not a one shot decision, but a dynamic process. It involves choices at different stages across time: from meal planning over grocery shopping, storing, food processing and eating to leftover management. Daily food consumption can therefore be modeled as a sequence of decisions made at different points in time along the food consumption chain.[4] Individuals have to make several advance and immediate choices from different time perspectives as they proceed along these stages. At the *planning stage*, individuals make advance choices about which food items to buy in the grocery store. This stage is generally characterized by good intentions. Consumers plan a healthy diet implying that the consumption basket should contain fresh and perishable food (Lappalainen et al., 1998). Yet, at the actual *shopping stage*, the planned choices are reconsidered from an immediate perspective: a present-biased individual might deviate from her plans and include more tempting food items in the food basket. Buying more tempting food in the grocery store is the result of dynamically inconsistent time preferences at the shopping stage. The underlying choice set at this part of the food consumption chain contains all food items available at the grocery store. A result of this dynamic inconsistency is that the choice set for the next stages at home includes more tempting food items than actually intended. Read and Van Leeuwen (1998) and Sadoff et al. (2020) provide evidence for the existence of dynamic inconsistencies at the grocery shopping stage.

In our framework, individuals at the *shopping stage* not only choose a food basket from an immediate choice perspective, they also consider *when* to consume these food items at home. While shoppers might have an intention when to eat healthy food items they can later rearrange

[4]For a visual illustration see Figure B1 in Appendix B.

the order of consumption. During the domestic part of the food consumption process, the initial plans can be reexamined against the background of the choice set which results from the shopping stage. As Cutler et al. (2003) point out such a reexamination can start after few days or even few hours, similar to the typical stock-keeping at home. Present-biased individuals will now deviate from their consumption intentions by preferring relatively more tempting meals in the *processing* and *eating stages*. Danzer and Zeidler (2024) provide evidence for this type of dynamic inconsistency at the eating stage. As a result, the processing of relatively less tempting food items is postponed by at least one time period, and these food items are stored longer than intended. Just consider returning home after a long workday: Most people will prefer immediate gratification (e.g., a frozen pizza) instead of the time-consuming preparation of healthy food (e.g., a salad).

What does a longer storage time imply? Healthy food is normally plant-based, has fewer additives and is unprocessed. As a consequence, the healthy option is more perishable (Bucher et al., 2015) and requires more time and effort to prepare or process (Cutler et al., 2003). Time costs of food preparation are especially relevant for domestic food consumption in the household production framework by Becker (1965): Individuals do not derive utility from purchasing food inputs in the grocery store, but from eating prepared meals.[5] We assume that consumers have roughly correct beliefs about the predetermined perishability and required effort when making food purchases at the grocery store.[6]

To sum up, present-biased behavior leads to postponing the consumption of healthy food at home. Since healthy food is perishable, a longer storage time directly increases the likelihood of food decay and, as a consequence, food waste.

3 Empirical Strategy

In the following, we describe the data set, the food waste and time inconsistency metrics, as well as the econometric approach.

[5]Some people might derive utility from food preparation activities. We ignore this here.

[6]For simplification, we also abstract from potentially incorrect storage behavior that might further reduce storage life at home.

3.1 Data Set

3.1.1 Data Overview We collect unique nationally representative survey data 'Grocery Shopping and Consumption in Germany' (ELKiD) funded through Catholic University Eichstaett-Ingolstadt, Germany. The goal of the project was the in-depth study of food purchasing and consumption behavior among households in Germany. The data comprise two interviews 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 with a representative pool of respondents in Germany, applying stratified random sampling by gender, age and state of residency. Each wave of the online survey lasted about 20 minutes.

Our analysis focuses on survey items about food planning, food purchasing, food processing and eating behavior but also economic preferences as well as socio-demographic characteristics and personal lifestyle. We collect information about food waste behavior in both waves. Economic preferences and measures of dynamic inconsistency are only collected in wave 1; hence, we link them to food waste measures collected in wave 2 to investigate the stability of the relation between dynamic inconsistency and food waste behavior over time.

After carefully cleaning the data, we have information on 1,266 individuals across Germany in wave 1 and 861 individuals in wave 2.[7] This implies a dropout rate of around 30%. An attrition analysis reveals that younger, less educated and less risk averse individuals drop out.[8] Since we include age, education and risk preference as control variables in our regressions, we are able to capture these compositional differences. We also observe that dynamically more inconsistent individuals are less likely to respond to wave 2. While this pattern is consistent with the (β,δ)-model[9], it suggests that the wave 2 sample becomes somewhat more dynamically consistent. However, we do not anticipate problems for two reasons: First, a comparison of means reveals only a small and weakly significant between-sample difference. The average beta (β) is 0.89 in wave 1 and 0.90 in wave 2 ($p < 0.010$). Second, it is more challenging to detect a significant

[7]We exclude observations with implausible values on household composition and age. We further exclude observations with implausibly large values (above the 97.5% quantile) of long-run patience δ (for details see Section 3.3). Excluding these observations neither changes the results nor affects the conclusions drawn from the analysis. Results are available upon request.

[8]Results are summarized in Table B2 in Appendix B.

[9]All respondents were upfront informed, that they take part in a panel survey.

relationship between dynamic inconsistency and food waste in a more dynamically consistent sample, resulting in rather conservative estimates.

Over the last two days preceding the survey, respondents have prepared an average of 3.3 dishes and eaten an average of 3.5 dishes at home. Only 3.6% of respondents state to have not prepared a single dish. These numbers suggest that survey participants are able to make informed statements about their food consumption and waste habits at home.

3.1.2 Summary Statistics Table 1 reports summary statistics for outcome and control variables in waves 1 and 2. A detailed variable description can be found in Table B1 in Appendix B. As control variables, we include individual risk preference since the future is inherently risky while the present is not (Andreoni & Sprenger, 2012b). We follow the work of Falk et al. (2018) and assess risk preferences by the 'Willingness to take risks' variable as a self-reported variable measured on an 11-point Likert scale ranging from 0 to 10. Among the personal characteristics are age, gender, education and employment status. In wave 1 (wave 2), half of survey participants are female (48%) and the mean age is 44.6 years (47 years). Modeling food waste as consequence of optimal consumer choice, Lusk and Ellison (2017, 2020) and Morris and Holthausen Jr (1994) predict human capital to affect the amount of food waste in households. Similarly, labor market activity can serve as an indicator for time constraints that might affect the incidence and amount of food waste in a household. Hence, we include dummies for tertiary education (51% in wave 1, 52% in wave 2) and employment (71% in wave 1, 70% in wave 2) in the regression framework.

[insert Table 1 here]

We further include the following household controls: a single household dummy equaling 1 if an individual is not living together with partners, children or other relatives like parents, siblings etc. In the survey, 48% (51%) of respondents indicate to live in a single household. Like Ellison and Lusk (2018), we also include a dummy variable equaling 1 if a child below the age of 12 lives in the household (13% in wave 1, 15% in wave 2). Since Lusk and Ellison (2017) and Morris and Holthausen Jr (1994) emphasize the role of income in modeling food waste, we control for the natural log of total household income in all regression specifications. The self-reported disposable monthly household income is around €2,664 in wave 1 and €2,688 in wave 2. We also control for place of residence (urban vs. rural) and the walking distance to the next grocery store, measured in minutes, as proxies for the availability of food. The average walking distance is around 13 minutes.

A final category of control variables includes food behavior and lifestyle characteristics. First, we include a veggy dummy as measure for a vegetarian or vegan diet. Individuals following a vegetarian diet seem to be more concerned about pro-environmental behavior (Lades et al., 2021). This attitude might also affect food waste. Around 18% of respondents indicate to follow a predominantly vegetarian or vegan diet. Ellison and Lusk (2018) emphasize that food prices matter for food waste decisions. To proxy food prices, we include the share of organic food, which measures the average share of organic food items bought during a grocery shopping trip within the last four weeks (the most prevalent category being 11-20%). We also calculate a discounter index between 0 and 1, which indicates the ratio of discounters among all grocery stores regularly used by respondents (47%). Further control variables include the number of individual grocery purchases per week (both on-site and online), the Covid-19 stringency index and the number of days working from home. The last two variables proxy for the pandemic situation in 2021 and will be discussed in the robustness section.

In all regressions, the following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. The preference measures and variables for gender, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Education is measured in both waves. When investigating wave 2 food waste, we apply wave 1 values as controls for these plausibly time-invariant variables.

3.2 Food Waste Metrics

To capture household food waste we focus on behavior at the storing stage and use the following 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 clear and easy to answer, as they do not rely on subjective estimates of quantities or frequencies. Their strength is in assessing food waste at the extensive margin; they are, however, limited in assessing the intensive margin of food waste.

The food spoilage indicator FSI is composed of the sum of four food categories[10] in which food spoilage was detected within the last seven days: fruits and vegetables, dairy products, meat or fish products, bread and bakery products. More specifically, respondents state whether they detected food items in storage which they no longer wanted to eat due to their deteriorated texture or condition. Individual answers are coded as binary outcomes and summarized across food categories, so that the FSI can take values between 0 and 4. A value of four implies that food from all four categories has spoiled in the last seven days, and so on. The average index value for wave 1 (wave 2) is 1.2 (1.1), according to Table 1. Most prevalent in wave 1 is food waste of fruits and vegetables (42%), followed by bread (33%) and meat or fish and diary products (24% and 23%). In wave 2, numbers look similar.[11]

The best-before waste dummy BBW is assigned a value of one if an individual reports having discarded food within the past seven days due to the best-before date. Although many foods are still edible after the elapse of the best before date, consumers might dump it for safety concerns or lack of knowledge (Neff et al., 2015; Quested et al., 2011). Experimental evidence by Ellison and Lusk (2018) suggest that the expiration date affects disposal decisions. Since the conceptual framework is based on repeated postponement of consumption of less tempting food, more food will exceed the best before date. In wave 1 (wave 2) 24% (21%) of individuals report some best-before waste (see Table 1).

The waste of leftovers dummy WL equals one if an individual states to have thrown away leftovers from cooking or eating, including those stored in the fridge or freezer for further consumption. We include this behavior because consuming leftovers might be less tempting if the portion size is small or additional food preparation efforts are required. In line with this, Ellison and Lusk (2018) observe that individuals are less likely to discard leftovers if they can form a complete new meal. In wave 1 (wave 2) 20% (22%) of individuals report to waste leftovers (see Table 1).

Our measurement approach departs from earlier studies (Secondi et al., 2015) that try to col-

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

[11]Most prevalent is food waste of fruits and vegetables (34%), followed by bread (31%) and meat or fish and diary products (22% and 19%).

lect subjective estimates of the amount of food waste. We rely on dummy variables as consumers tend to remember instances of food waste, but seriously underestimate the amount of food they waste (Neff et al., 2015; Quested et al., 2011). We prefer accuracy regarding different food types at the expense of insights into food waste quantities. Alternative methods, like food waste diaries (Koivupuro et al., 2012) are known to influence behavior through attention effects. Waste composition analyses in municipalities (Lebersorger & Schneider, 2011; Schneider & Obersteiner, 2007) are inaccurate and hard to link to individual behavior. Macroeconomic food purchasing-consumption comparisons (Hall et al., 2009; Landry & Smith, 2019; Yu & Jaenicke, 2020) are based on purchasing surveys and individual biological information (height, weight, gender and age) to estimate calorie requirements, but remain highly inaccurate.

Our approach, instead, circumvents under-reporting by framing food waste with precise contextual information and over a short period of time (seven days). The waste questions are embedded into the survey that also asks detailed information about food purchasing, processing and eating behavior. By these means, we generate accurate waste information that can be linked to the economic preference framework. This approach is most comparable to the study of Ellison and Lusk (2018) who use a vignette approach.

3.3 Dynamic Inconsistency Measure

To embed our empirical approach into the (β, δ) model for dynamic inconsistency introduced in Section 2, we need to derive β and δ parameters for all respondents. The literature provides different approaches to elicit time preference parameters: The method proposed by Andreoni and Sprenger (2012a) uses Convex Time Budget (CTB) sets to structurally identify time and risk preference parameters. While increasingly popular, its relative complexity makes it suitable for experimental settings rather than surveys.[12] We therefore follow Courtemanche et al. (2015) who take hypothetical intertemporal monetary trade-offs from the 2006 NLSY (National Longitudinal Survey of Youth), a panel administered by the US Bureau of Labor Statistics. Based on two questions, a patience parameter δ and an inconsistency parameter β are calculated. Both questions are identical, but refer to different delay periods. Let us denote the delay period by k

[12] An alternative but also lengthy approach is the 'staircase' method developed by Cornsweet (1962) and popularized by Falk et al. (2018).

with $k \in \{1, 12\}$. Hence, $k = 1$ stands for one month delay and $k = 12$ represents 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 ($k = 12$) is an intertemporal discounting question over an annual time interval, the *month* question ($k = 1$) refers to a monthly time interval. While differences in time frames may seem subtle, the decisive information is underlined in the survey and both questions are in consecutive order and framed in order to highlight the change in reference period. The two different questions yield an $amount_k$ which we can use to compute the following *annualized discount factors* DF_k for one month ($k = 1$) and one year ($k = 12$):

$$DF_k = \left[\frac{1,000}{(1,000 + amount_k)} \right]^{\frac{12}{k}} . \tag{4}$$

For measuring dynamic inconsistencies, we exploit the different time references across both questions: A dynamically consistent individual should display the same *annualized discount factor* over the monthly and the annual interval. By contrast, a present-biased respondent will show decreasing impatience over time resulting in a larger discount factor for the annual compared to the monthly delay.

According to the quasi-hyperbolic discounting framework of Laibson (1997) and O'Donoghue and Rabin (1999), an individual discounts future outcomes in τ periods at a rate $\beta\delta^{\tau}$. For $\beta = 1$, the quasi-hyperbolic discounting mode reduces to standard exponential discounting with a constant discounting factor over time. For $\beta < 1$, individuals exhibit present-bias: they deviate from their own future-looking plans in favor of actions involving immediate gratification. Because future costs are overly discounted, planned actions that are more beneficial from an advance perspective are postponed and eventually never realized. Assuming annual reference periods, individual responses to the two questions imply the following relation:

$$\beta\delta^{\frac{k}{12}} = \frac{1,000}{(1,000 + amount_k)}. \tag{5}$$

Solving for β and δ yields

$$\beta = \frac{1,000}{[\delta(1,000 + amount_{12})]} \tag{6}$$

and

$$\delta = \left[\frac{(1,000 + amount_1)}{(1,000 + amount_{12})}\right]^{\frac{12}{11}}. \tag{7}$$

The average discount factors for the annual (monthly) delay questions are 0.74 (0.43); these numbers correspond to annual interest rates of 35% (one year) and 132% (one month), respectively. The greater patience over longer delays is in line with diminishing impatience over time as predicted by quasi-hyperbolic discounting. Although both interest rates are high, they are in line with preferences being sticky towards the status quo option (Loewenstein, 1988; McAlvanah, 2010; Shelley, 1993). Since both elicitation questions involve immediate payoffs (i.e., today) as intertemporal reference point, one can expect smaller discount factors (and greater interest rates) compared to methods without one single intertemporal reference point. Interestingly, interest rates in our sample are significantly smaller compared to Courtemanche et al. (2015) who use the same elicitation technique.

Summary statistics for time preference parameters are displayed in Table 1. The sample mean of the estimated present bias parameter β is 0.89, which is slightly higher compared to estimates in Courtemanche et al. (2015).[13] Ninety-six per cent of individuals exhibit a β value at or below 1; the remaining 4% show future bias. The estimate for the long-run patience parameter δ is 0.83. Ninety-eight per cent of individuals have a δ value at or below 1. These numbers imply discounting of the immediate future period with $\beta\delta = 0.74$ while any other future period is discounted with 0.83 or 20.48% per year (see Figure A1 in the Appendix for parameter distributions).

[13]Courtemanche et al. (2015) calculate an annual interest rate of 66% (one year) and 257% (one month), implying a β and δ of 0.8 and 0.75, respectively.

3.4 Econometric Specification

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

$$y_{i,t} = \alpha_0 + \alpha_1 \beta_i + \mathbf{X}_{i,t} \alpha_2 + \epsilon_{i,t}, \tag{8}$$

with i indexing the individual, t being wave 1 or 2 and α_0 being the constant. The parameter β is the regressor of interest. We consider three different food waste measures y as outlined in Subsection 3.2: The FSI measures the incidence of spoilage across four different food categories, the BBW dummy indicates whether an individual discarded food because of the best before date, and the WL dummy equals 1 if stored leftovers were wasted. Our regressions rely on cross-sectional information from waves 1 and 2 since all three outcome variables are observed in both waves. The error term ϵ is iid. We apply robust standard errors.

The vector $\mathbf{X}$ includes three sets of control variables. First, the behavioral parameters long-run patience δ and risk preference. Second, socio-demographic and household characteristics: age, gender, dummies for tertiary education, employment, single-person household, or the presence of a child below age 12, as well as the walking distance to the next grocery store (in mins). The third category contains food behavior and individual lifestyle controls: a dummy for vegetarian diet, share of organic food purchases, discounter index, and the number of grocery purchases per week.

We first assess unconditional correlations between the dynamic inconsistency measure β, the long-run patience parameter δ as well as the discount factors DF_1 and DF_{12} with economic variables that have an intertemporal component (Table A1 in Appendix A). There is a strong correlation between DF_{12} and long-run patience δ ($\rho = 0.59$) while DF_1 covaries strongly with the present bias parameter β ($\rho = 0.84$). The parameters β and δ are not systematically correlated, but both discount factors are ($\rho = 0.83$).

For economic variables all correlation coefficients go in the expected direction suggesting that the time measures truly capture intertemporal preferences. More present-biased individuals ($\beta \downarrow$) have a significantly lower likelihood of holding a tertiary education degree, are significantly more likely to smoke and have a higher body mass index (BMI). They also report an unhealthier diet compared to less present-biased individuals. Although correlation coefficients are relatively small they are comparable to those reported in Courtemanche et al. (2015). The long-run patience parameter δ is not systematically associated with education, smoking, BMI or healthy diet while the discount factors DF show the expected correlations.

4 Results

We now test the proposed framework empirically. In Section 4.1, we first provide descriptive insights into the food planning and consumption process and show how much food respondents waste along the different consumption stages. We then provide results of reduced-form regressions before investigating potential mechanisms behind the relationship between dynamic inconsistency and food waste in Section 4.2.

4.1 Dynamic Inconsistency and Food Waste

4.1.1 Food Consumption Process and Waste Figure 1 depicts the food consumption process and summarizes descriptive statistics for the different food waste measures. Accordingly, 57% (51%) of respondents state in the first (second) survey wave that they detected at least one spoiled food item (FSI); and almost all respondents (94%) discard at least parts of these spoiled food items (the rest feeds them to animals etc.). The incidence of best-before waste (BBW) is 24% (21%) of individuals in the first (second) survey wave, reflecting waste because the best-before date has elapsed (Table 1). The latter numbers are comparable to the incidence of wasting leftovers (WL), 20% (22%) in wave 1 (2).

[insert Figure 1 here]

Figure 1 also displays the incidence of food waste at other stages of the consumption process. Regarding the *processing stage*, 72% of individuals who prepared too large portions did so on purpose. Only 3% of individuals report to waste food after processing; 87% of respondents store processing leftovers in the fridge or freezer. At the *eating stage*, plate leftovers are reported by 11% for the last meal. Fourteen per cent of individuals indicate to throw away plate leftovers in general; 51% of individuals store plate leftovers in the fridge or freezer for later consumption. These numbers suggest that the majority of food is indeed wasted at the *storing stage*.

Figure 1 further shows statistics for deviating from own intentions to consume a healthier food basket along the consumption chain. Referring to the grocery store level, 58% of individuals in the sample agree (rather or strongly) to have made unintended impulse purchases of sweets or snacks.Among the statements referring to domestic consumption, 26% ordered more food from delivery services than intended, 17% of respondents indicate to have omitted planned fresh meals, 17% report to have eaten more convenience food than intended, and 43% have stored fruits and vegetables longer than intended.

The descriptive statistics summarized in Figure 1 are in line with our proposed framework suggesting that food waste is most often an (unintended) outcome of postponing the consumption of healthier food items over time, rather than a consequence of leftover management. As healthier food items are stored longer, the likelihood of waste increases.

4.1.2 Reduced-Form Regressions In the first step, we regress the FSI on the present bias parameter β (col. 1 of Table 2) and control variables, which are added gradually (col. 2-5). The coefficient of interest, β, decreases slightly as more control variables are added, but remains highly significantly different from zero throughout all specifications.

[insert Table 2 here]

According to Table 2 the FSI decreases as β increases (present bias decreases) suggesting that present-biased individual waste more food. In terms of effect sizes, an increase of β by 10% is associated with a decrease in the FSI by 0.1 units or 2.1% (column 4).[14] The long-run patience parameter δ does not carry a significant coefficient. In line with the theoretical considerations in section 2, these results suggest that dynamic inconsistency is more relevant for food waste behavior than long-run patience.

Summarizing coefficients for control variables, respondents indicating to be more risk seeking and to be employed (in line with Grainger et al. (2018) and Secondi et al. (2015)) experience

[14] If β increases by 1.11 units from 0.01 (minimum) to 1.12 (maximum), the FSI decreases by 1.06 units or $(1.06/5) * 100 = 21\%$. If β increases by 0.11 units or 10% (roughly from the mean estimate of $\beta = 0.888$ to time consistency with $\beta = 1$), the index value decreases by 0.106 units or $(0.11/5) * 100 = 2.1\%$.

systematically more food waste, as do respondents indicating a higher number of grocery purchases per week. Living in a city is associated with less food waste, in line with Secondi et al. (2015) but contrary to Landry and Smith (2019). Older people waste less food, a relation that is robust across the literature (Jörissen et al., 2015; Koivupuro et al., 2012; Piras et al., 2021; Quested et al., 2013; Secondi et al., 2015). In line with Buzby et al. (2002) and Secondi et al. (2015), women have a slightly higher likelihood of wasting food; as have respondents with at least one child below the age of 12 (in line with Ellison and Lusk (2018), Grainger et al. (2018), and Piras et al. (2021) but in contrast to Landry and Smith (2019)). Education, income, diet (vegetarian), distance to the grocery store, or shopping behavior (organic, discounter) are not significantly related to food waste behavior.

Table 3 summarizes results for all three outcome variables. All regressions replicate the full specification with complete controls.[15] While the first three columns apply to wave 1 food waste measures, columns 4-6 are based on second wave outcomes. Each column shows results for one of the three outcome variables FSI, BBW, or WL. Time-variant control variables are taken from the respective wave. Preference measures, gender and tertiary education are measured in wave 1 and assumed constant over time.

[insert Table 3 here]

Wave 1 coefficients for β are significant for all outcome variables (columns 1-3). In column 2, the coefficient indicates that an increase in β by 10% is associated with a decreased likelihood of food waste because the best before date has elapsed by 2.1%.[16] A similar increase in β correlates with a decrease in the likelihood of wasting stored leftovers by 1.8%. Turning to wave 2 outcomes, coefficients stay significant: An increase in β from 0.89 to 1 correlates with a decrease in the FSI index by 1.3%, followed by a decrease in food waste because of the best before date by 3.1%. The change for waste of stored leftovers is -1.9%. To account for multiple hypothesis testing we also report sharpened false discovery rate q-values (Anderson, 2008). Still, significant coefficient estimates prevail for FSI and BBW regressions. Table A3 in Appendix A provides an overview of all coefficient estimates.

[15] Detailed results for control variables are displayed in Table A3 in Appendix A.

[16] The effect size is calculated as follows: An increase in β by 1.11 units (from min to max value) leads to a decrease in the dummy by 0.193 ($1.11 \times -0.193 = 0.214$) or 21.4 points. A 10% increase in β is equivalent to a 0.11 unit change. The effect therefore is $0.214 \times 0.1 = 0.0214$ or 2.1%.

The fact that β is significantly related to outcomes collected many weeks later suggests that dynamic inconsistency is a roughly stable behavioral parameter. Although coefficient estimates for β vary slightly between wave 1 and 2, this difference is only significant for the FSI: Results from a joint regression of the FSI on β, a wave dummy, a β-wave interaction term and control variables reveal a systematic difference for the β estimate in column 1 vs. 4 ($p = 0.007$). For the other two comparisons (columns 2 vs. 5 and 3 vs. 6), the difference in estimates for β is statistically not significant ($p = 0.817$ and $p = 0.823$). Long-run patience measured by δ is not related to any food waste measure in wave 1 or 2; more risk seeking individuals tend to waste more food. The reduced-form evidence suggests a systematic link between individual dynamic inconsistency and food waste behavior. Next, we test the mechanism developed in Section 2.

4.2 Mechanism

Present bias implies a deviation between initial consumption intentions (at the shopping stage: advance choice) and actual consumption (immediate choice at home). As a consequence, the consumption of healthy food items is postponed and these food items are stored longer than intended, increasing the likelihood of food waste. We investigate this proposed mechanism in three steps. First, we provide evidence that dynamically inconsistent individuals plan their domestic food consumption at the shopping stage like consistent individuals. Second, we show that dynamically inconsistent individuals deviate from their intentions and postpone domestic consumption of healthy food items. Third, we link deviations from consumption intentions to individual food waste behavior.

4.2.1 Meal planning Planning future domestic consumption (advance choice) implies preparation of the shopping trip (e.g., stocktaking and preparation of a shopping list) and deciding on the planning horizon (i.e., for how many days to purchase fruits and vegetables in advance). Asked for planning habits with respect to the last grocery shopping trip, 78% of respondents indicate to have checked their inventory before the shopping trip. And 79% of individuals indicate to have compiled a grocery checklist. Two-thirds of respondents did both. In terms of planning horizon, respondents indicate to buy fruits and vegetables for an average of four days in advance. We take the three variables "inventory checking" (dummy), "shopping list" (dummy) and "planning horizon" (in days) as measures of the planning process and regress them on two different measures for dynamic inconsistency: one is the parameter β as before, the other is a present bias dummy like in Ashraf et al. (2006) and Meier and Sprenger (2010). To create the dummy, we use a threshold at $\beta < 0.95$. At this cut-off, 49% of individuals are classified as present-biased.[17]

Table 4 provides evidence that dynamically inconsistent individuals do not systematically differ from consistent respondents in their planning behavior. Focusing on the first outcome variable (fridge inventory check), dynamically more inconsistent individuals do not show a systematic tendency to engage less in consumption planning. No matter whether we use β or the present bias dummy, both coefficients are not distinguishable from zero. Results for the second (shopping list) and third (advance purchase period for fruits and vegetables) outcome variables are similar.[18] Table A4 in Appendix A provides an overview of all coefficient estimates.

[insert Table 4 here]

4.2.2 Measuring deviations from intentions Dynamic inconsistency leads to deviations from intentions to consume healthy food at home. We test this proposition utilizing five survey questions that focus on 'deviating from intentions' in the following food domains: impulse snack purchases, impulse food deliveries, omitted fresh meal preparations, convenience food consumption, or unused fresh food. Respondents can indicate their agreement to five separate statements on a 4-point Likert scale from "Agree not at all" to "Strongly agree":

> Please indicate your agreement to the following statements.
>
> **On average over the past four weeks, I have...**
>
> [1]... also bought sweets or snacks that I had not intended to buy before entering the supermarket.
>
> [2]... spontaneously had food delivered by restaurants or delivery services or picked up food myself instead of preparing something myself.
>
> [3]... personally cooked or prepared fresh meals less often at home than intended.

[17] Results summarized in Table 4 are not sensitive to threshold specifications.

[18] Regressions for the advance purchase outcome are based on 1,246 observations since 20 respondents indicate to have not bought fruits and vegetables in advance during the last four weeks.

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

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

While the first statement refers to deviations at the grocery stage, statements 2-5 apply to domestic food consumption behavior. These statements capture consumption behavior involving more tempting – and, hence, less healthy – food. For each of the five questions, we code dummies taking the value of one for responses that rather or strongly agree, zero otherwise. Mean values of all five items are summarized in Figure 1 and discussed in Section 4.1.

Combining statements 2-5, we construct a 'domestic deviation index' (DDI), by summing up the four dummy variables.[19] The resultant index ranges from 0 to 4. Greater index values indicate more deviations from consumption intentions. The mean index value is 1.03, with a standard deviation of 1.1. The DDI is negatively correlated with following a healthy diet: $\rho = -0.21$ ($p = 0.00$).

In Table 5, we regress the DDI on β, gradually adding control variables from columns 1 to 4. Across specifications, dynamically inconsistent behavior is significantly correlated with deviating more from own consumption intentions at home. In line with expectations, more patient individuals (with higher δ) deviate less from their consumption plans, but this correlation becomes indistinguishable from zero after controlling for personal characteristics. Table A5 in Appendix A provides an overview of all coefficient estimates.

[insert Table 5 here]

4.2.3 Deviations from intentions and food waste Finally, we regress all three food waste measures from both waves on the DDI (measured in wave 1) to link the postponement of domestic consumption of perishable food items to individual food waste behavior (Table 6). In all regression specifications, the DDI coefficient is highly significant. In column 1, an increase in the DDI by one unit is associated with an increase in the FSI by 0.403 units or 8.1%. For comparison: an increase in the DDI by 10% is associated with an increase in the FSI by 4.0%. Further, a 10% increase in deviation behavior is associated with a 4.8% increase in the likelihood of food

[19] For robustness, we also construct a DDI+ index which combines statements 1-5. While statement 1 refers to impulse purchases in the supermarket, one could argue that deviating from intentions *at home* is enabled by the availability of sweets and snacks that are captured in the first statement. The results are robust to using DDI+ instead of DDI as dependent variable. Results are available upon request.

waste owing to the best before date (BBW) (col. 2). The likelihood to waste stored leftovers (WL) increases by 3.5% (col. 3). Columns 4-6 refer to food waste measures from wave 2 and are collected several weeks after the DDI measure. The results for a rise in the deviation at home index of 10% are similar and suggest a stable relationship: the FSI increases by 3.2%, the BBW by 4.8%, and the WL by 3.9%. Again, all results are robust to multiple hypothesis testing, as reported by sharpened q-values. As before, there is no systematic relationship between long-run patience δ and food waste measures; risk seeking individuals waste more food. Table A6 in Appendix A provides an overview of all coefficient estimates. Summarizing the evidence from all three steps, we find empirical support for the theoretical idea that postponing consumption of perishable food drives food waste.

[insert Table 6 here]

4.3 Robustness Tests

Next, we consider factors that might potentially bias coefficient estimates like respondents' inattention or measurement error. Thereafter, we provide evidence for the stability of the link between dynamic inconsistency and food waste over time and in the face of the Covid-19 pandemic.

4.3.1 Limited Attention and Measurement Error Attention in everyday life is a limited resource. According to DellaVigna (2009), a reduced salience or competing stimuli might systematically distract attention from the incidence of domestic food waste. If inattention led respondents to answer the two survey questions about monetary delays *not* according to individual preferences, our calculations of β would be inaccurate. Inattentive respondents might possibly underestimate food waste and answer both delay questions identically, yielding an underestimation of β. This would bias coefficients upwards.[20]

Even in the absence of inattention, measurement error in β might prevail, since the parameter identification relies on only two survey questions. If the regressor of interest β was plagued by

[20] After excluding individuals with identical responses in both monetary delay questions (19% of the sample) we still observe highly significant coefficients for the FSI and the BBW. The coefficients in the WL regressions turn marginally insignificant but were already estimated with lower precision in the main analysis in Table 3. What makes a limited attention explanation less plausible is the fact that none out of six coefficients for the two survey waves significantly change in size after excluding potentially inattentive respondents.

measurement error, the estimated coefficients would suffer from attenuation bias, producing conservative estimates.

As a robustness check for both problems we suggest an alternative measure for dynamic inconsistency: The survey includes two items measuring the level of *procrastination* and *patience*, which are both taken from the German Socio-Economic Panel (GSOEP).[21] The procrastination variable asks how much individuals agree with the statement 'I tend to put off tasks even when I know it would be better to do them right away'. Procrastination is used as proxy for dynamic inconsistency because this measure captures the aspect of postponing unpleasant tasks and deviating from own plans made for the future. The patience variable asks how strongly an individual would be willing to give up something that benefits her today in order to benefit more in the future. The patience variable is used as proxy for long-run discounting. Both variables are measured on an 11-point Likert scale ranging from zero (no agreement/willingness at all) to ten (total agreement/willingness).

We re-run our analysis from Table 3 applying the procrastination variable as proxy for dynamic inconsistency. The results are summarized in Table 7. Table 7 shows that the procrastination coefficient is highly significant across all specifications (col. 1-3 (4-6) again refer to the three food waste measures from wave 1 (wave 2)). A 10% increase in procrastination is associated with an increase in the wave 1 FSI by 0.055 units or 1.1% (col. 1). A similar increase in procrastination correlates with an increase in the likelihood of food wasted because of the best before date by 1.7% (col. 2), and with a 1.9% higher likelihood of stored leftover waste (col. 3). Wave 2 results are similar with changes of 1.2%, 1.4% and 2.0%, respectively. These elasticities are in similar ranges as those using the original β metric. These results do not change when accounting for multiple hypothesis testing using sharpened q-values. Table A7 in Appendix A provides an overview of all coefficient estimates.

[insert Table 7 here]

The test suggest that the findings and overall conclusions are robust to alternative model specifications: Estimates from a regression of individual food waste behavior on dynamic inconsistency are statistically significantly different from zero.

[21] The influential study by Falk et al. (2018) empirically validates the GSOEP self-assessment items.

4.3.2 Stability of Dynamic Inconsistency

An important aspect of economically relevant behavior is its stability over time. While we can calculate the two parameters β and δ only for wave 1, the procrastination measure is observable in both waves. The intertemporal correlation coefficient between wave 1 and wave 2 procrastination is large and highly significant: $\rho = 0.65$ ($p < 0.00$).

We now repeat the regression analysis from Table 7 with the wave-specific measures of procrastination to assess significant differences between estimates over time (Table A2 in Appendix A). A comparison of column 1 vs. 4, 2 vs. 5 and 3 vs. 6 reveals no systematic difference between estimates: the interaction term of procrastination and wave is statistically insignificant with $p = 0.427$, $p = 0.952$ and $p = 0.403$. This finding suggests that the correlation between dynamically inconsistent preferences and food waste behavior is stable over time.

4.3.3 Covid-19 Pandemic

Since both survey waves took place during the first half of 2021, we test for robustness of our results to the Covid-19 pandemic.[22] To approach this, we account for the stringency of pandemic control: the German government implemented a number of containment measures that restricted the economic and social lives of citizens in almost all areas.[23] In Germany, political agreements on the handling of the Covid-19 pandemic between the federal government and the 16 state governments were formulated in the Infection Protection Act (IfSG, 2000) enabling federal states to enact Covid-19 restrictions. Based on this act, the design of disaster control and public health regulation was in the responsibility of state governments (IfSG, §32 & §54). As a consequence, the exact implementation of Covid-19 containment policies differed across states and induced variation in the policy stringency that we can exploit to control for the local pandemic situation. We therefore utilize data on the policy stringency index at the federal state level in Germany, that were manually collected and computed by Danzer et al. (2023) following the method described in Hale et al. (2020), and merge these data with the survey respondents based on their zip code. During data collection in the first survey wave, the stringency index varied between 80.1 in Saxony and Brandenburg and 66.7 in North Rhine-

[22] We point the reader to Appendix C for a discussion on how the Covid-19 pandemic might affect our empirical strategy.

[23] Daycare facilities and schools were closed, and remote work was encouraged or enforced whenever possible. Private gatherings were restricted to small numbers of people and public events were canceled. An international travel ban was introduced and internal movements were limited.

Westphalia and Hesse (see Figure C1 in Appendix C). Since food waste measures refer to the last seven days before taking the survey, we consider the state policy stringency index 10 days prior to the respective survey dates in both waves.[24]

As a second variable capturing the individual pandemic situation, we propose the number of days worked remotely from home. This measure is included in the survey in both waves and can take values between 0 (no working from home) to 5 (full working week remotely). In survey wave 1 employed respondents worked on average 1.5 days remotely from home (Table 1). In wave 2, the mean is 1.2 days.

All our results are very robust to controlling for the pandemic policy stringency and the extent of working from home. Results are summarized in Tables C1,C2,C3,C4, and C5 in Appendix C. It suggests that the relationship between dynamic inconsistency and food waste is not biased by the pandemic situation.

5 Conclusion

This paper adds a new behavioral economics perspective on household food waste and contributes to an understanding of the role of dynamic inconsistency in time preferences. Conceptualizing food waste as unintended consequence of deviating from own intentions to consume healthy food at home, we show that more present-biased individuals waste more food in a representative sample for Germany. This result is robust to different model specifications including different sets of controls and using alternative measures for present-biased behavior. Testing the conceptually derived mechanisms, we find that more present-biased individuals do make plans for domestic food consumption, but deviate from these plans when the future becomes present. These individuals are more likely to postpone the consumption of perishable food at home, implying longer storage durations and more food spoilage. Individuals who deviate more from consumption intentions also waste more food at home. While those results speak for Germany alone, they likely have external validity: Food waste is a global phenomenon, with the average household waste per capita per year amounting to 79 kg, even marginally higher than in Germany (United Nations Environment Programme, 2024).

[24]The results are very robust to considering policy stringency indices two or four weeks prior to survey dates. These results are available upon request.

This study provides new insights necessary for a holistic understanding of food policies and unintended consequences of small design changes. As an example, the US Department of Agriculture (USDA) allows online pre-orderings of grocery purchases in the Supplemental Nutrition Assistance Program (SNAP) that is targeted at low-income communities in the US.[25] From a behavioral economics perspective, ordering groceries online instead of purchasing them in the grocery store works as a commitment device (Sadoff et al., 2020) that ties individuals to their advance grocery choices made at home. Hence, present-biased individuals can no longer be tempted by unhealthy food choices in the supermarket. Without considering actual consumption, such small policy design changes might look promising to foster healthier nutrition in a population at risk. Contrary to this argumentation, our results suggest that dynamically inconsistent time preferences not only affect grocery shopping but also food consumption behavior at home. In effect, choosing healthy groceries online does not necessarily imply to also consume healthily at home. Instead, healthy food items might spoil and end up as food waste. Consequently, a well-intended policy might not alter food consumption habits but produce food waste instead, with its negative environmental and societal consequences. Our paper points to the importance of understanding detailed behavioral mechanisms along the full consumption process to design effective food policies and mitigate adverse policy effects.

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

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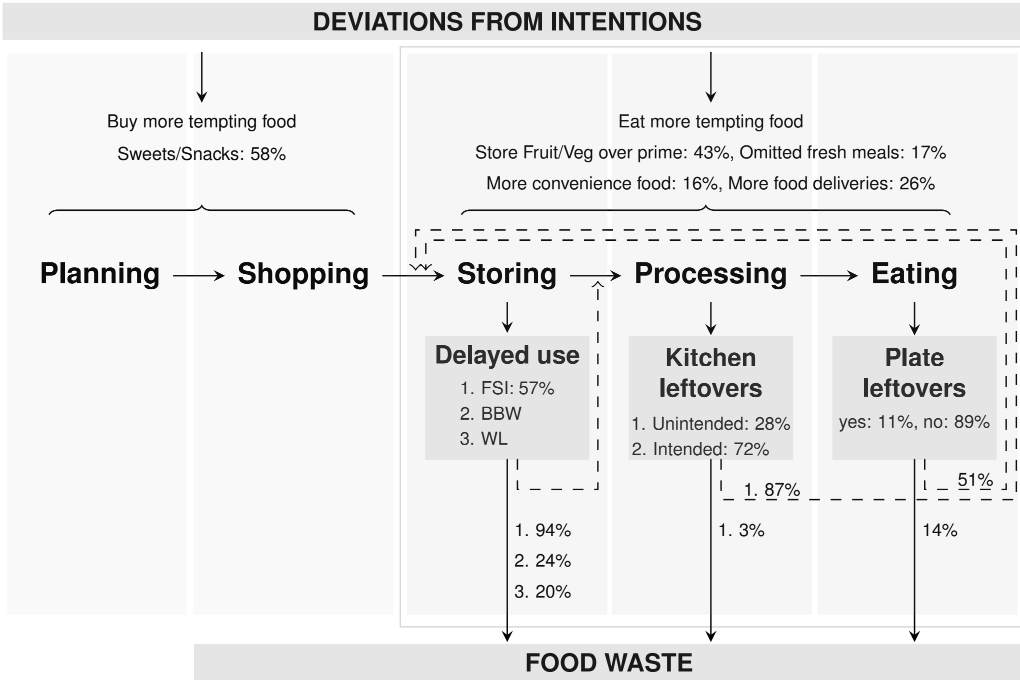
Figure 1: *Dynamic inconsistency and food waste*



Note: The figure depicts the food consumption chain and summarizes incidences based on the survey data with respect to two areas. In the upper part of the figure, present-biased individuals deviate from their intentions to consume healthier food in the future. In the lower part of the figure, present-biased individuals postpone the consumption of healthier food items which increases the likelihood of food waste. The reported numbers reflect the incidence of food waste behavior for the different consumption stages .

Table 1: *Summary statistics*

Statistic	N	Mean	SD	Min	Max
Outcomes Wave 1:					
Food Spoilage Indicator (FSI)	1,266	1.221	1.366	0	4
Best Before Waste dummy (BBW)	1,266	0.239	0.427	0	1
Waste Leftovers dummy (WL)	1,266	0.200	0.400	0	1
Outcomes Wave 2:					
Food Spoilage Indicator (FSI)	861	1.062	1.338	0	4
Best Before Waste dummy (BBW)	861	0.213	0.409	0	1
Waste Leftovers dummy (WL)	861	0.217	0.413	0	1
Main regressors:					
Beta (β)	1,266	0.888	0.151	0.005	1.121
Delta (δ)	1,266	0.832	0.183	0.081	1.110
Regressors robustness:					
Procrastination Wave 1	1,266	4.305	2.705	0	10
Procrastination Wave 2	861	4.283	2.838	0	10
Patience	1,266	5.953	2.142	0	10
Controls Wave 1:					
Risk seeking	1,266	4.496	2.346	0	10
Age	1,266	44.568	14.300	18	69
Female	1,266	0.501	0.500	0	1
Tertiary education dummy	1,266	0.514	0.500	0	1
Employment dummy	1,266	0.709	0.455	0	1
Single household dummy	1,266	0.479	0.500	0	1
Net household income	1,266	2,663.989	1,651.898	250.000	10,001.000
Child below 12 dummy	1,266	0.134	0.341	0	1
City dummy	1,266	0.378	0.485	0	1
Distance grocery store	1,266	12.887	10.663	1	36
Vegetarian dummy	1,266	0.176	0.381	0	1
Share organic food	1,266	2.187	1.702	0	7
Discounter index	1,266	0.468	0.290	0.000	1.000
No. grocery purchases	1,266	2.306	1.906	0	10
Working from home (days)	1,266	1.445	2.049	0	5
Covid-19 stringency index	1,266	71.813	4.497	66.667	80.093
Controls Wave 2:					
Age	861	47.319	13.656	18	69
Female	861	0.482	0.500	0	1
Tertiary education dummy	861	0.517	0.500	0	1
Employment dummy	861	0.703	0.457	0	1
Single household dummy	861	0.509	0.500	0	1
Net household income	861	2,688.341	1,627.193	250.000	10,001.000
Child below 12 dummy	861	0.154	0.362	0	1
City dummy	861	0.377	0.485	0	1
Share organic food	861	2.348	1.858	0	7
No. grocery purchases	861	3.001	2.612	0	20
Working from home (days)	861	1.194	1.884	0	5
Covid-19 stringency index	861	62.214	2.374	59.259	69.907
Mechanism Analysis					
Domestic Deviation Index (DDI)	1,266	1.024	1.106	0	4
Fridge Checking Dummy	1,266	0.784	0.411	0	1
Shopping List Dummy	1,266	0.791	0.407	0	1
Purchase Fruits & Vegs in Advance	1,246	3.931	1.910	0	8

Note: Table reports summary statistics for outcome variables measured in wave 1 and wave 2, and control variables measured in wave 1 and 2. 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. The number of observations in the first wave is 1,266, in wave 2, it is 861. In the last line, 20 respondents indicate to not have bought fresh fruits and vegetables. This reduces the sample size for the variable to 1,246. Data source: ELKiD 2021

Table 2: *Food spoilage and dynamic inconsistency*

	Food Spoilage Indicator (FSI)			
	(1)	(2)	(3)	(4)
Beta (β)	-1.322^{***}	-1.307^{***}	-1.125^{***}	-1.059^{***}
	(0.273)	(0.271)	(0.265)	(0.271)
Delta (δ)		0.030	0.174	0.159
		(0.223)	(0.223)	(0.223)
Risk seeking		0.086^{***}	0.062^{***}	0.057^{***}
		(0.017)	(0.017)	(0.017)
Age			-0.012^{***}	-0.013^{***}
			(0.003)	(0.003)
Female			1.375^{*}	1.467^{*}
			(0.806)	(0.823)
Diverse			0.007	0.013
			(0.076)	(0.079)
Tertiary education dummy			-0.069	-0.056
			(0.078)	(0.079)
Employment dummy			0.277^{***}	0.269^{***}
			(0.082)	(0.081)
Single household dummy			-0.015	-0.041
			(0.093)	(0.094)
Log household income			0.070	0.066
			(0.058)	(0.058)
Child below 12 dummy			0.213^{*}	0.213^{*}
			(0.120)	(0.120)
City dummy			-0.200^{**}	-0.185^{**}
			(0.080)	(0.080)
Distance grocery store			-0.001	-0.0002
			(0.004)	(0.004)
Vegetarian dummy				-0.141
				(0.103)
Share organic food				0.007
				(0.024)
Discounter index				0.029
				(0.138)
No. grocery purchases				0.068^{***}
				(0.023)
Constant	2.394^{***}	1.968^{***}	1.707^{***}	1.571^{***}
	(0.250)	(0.306)	(0.499)	(0.510)
Sample mean FSI		1.221		
N	1,266	1,266	1,266	1,266
Adjusted R^2	0.020	0.041	0.075	0.082

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The Food Spoilage Indicator (FSI) measured in wave 1 is regressed on β and all control variables that are gradually added. The following control variables are included: (2) preference measures: long-run patience measure, risk seeking behavior, (3) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (4) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table 3: *Food waste behavior and dynamic inconsistency*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β)	-1.059^{***}	-0.193^{**}	-0.160^{**}	-0.649^{**}	-0.278^{***}	-0.169^{*}
	(0.271)	(0.086)	(0.080)	(0.317)	(0.104)	(0.097)
Delta (δ)	0.159	0.005	0.023	-0.208	-0.070	0.014
	(0.223)	(0.069)	(0.064)	(0.274)	(0.085)	(0.080)
Risk seeking	0.057^{***}	0.016^{***}	0.007	0.064^{***}	0.023^{***}	0.015^{**}
	(0.017)	(0.005)	(0.005)	(0.021)	(0.006)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.025	0.046	0.039	0.008	0.084
q-value β	0.000	0.054	0.192	0.074	0.010	0.246
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.082	0.042	0.050	0.127	0.085	0.078

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on β and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table 4: *Consumption planning behavior*

	Inventory Checking Dummy		Shopping List Dummy		Planning Horizon (in days)	
	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic inconsistency measure	-0.005	-0.018	0.088	-0.024	-0.600	-0.035
	(0.079)	(0.024)	(0.081)	(0.023)	(0.374)	(0.103)
Delta (δ)	0.003	-0.002	0.043	0.035	0.039	0.044
	(0.067)	(0.067)	(0.068)	(0.069)	(0.295)	(0.298)
Risk seeking	0.002	0.002	-0.001	-0.001	-0.059^{**}	-0.059^{**}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)
Sample mean behaviors	0.784	0.784	0.791	0.791	3.931	3.931
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.952	0.449	0.282	0.286	0.109	0.738
q-value β	0.969	0.796	0.493	0.561	0.178	0.907
N	1,266	1,266	1,266	1,266	1,246	1,246
Adjusted R^2	0.017	0.017	0.043	0.043	0.136	0.134

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The variables 'Fridge Checking Dummy', 'Shopping List Dummy' and 'Purchase Fruits & Vegs in Advance' measured in wave 1 are regressed on β (columns 1, 3, 5) or a present bias dummy taking the value 1 if $\beta < 0.95$ (columns 2, 4, 6), and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table 5: *Deviating from intentions at home*

	Domestic Deviation Index (DDI)			
	(1)	(2)	(3)	(4)
Beta (β)	-0.913^{***}	-0.890^{***}	-0.593^{***}	-0.505^{**}
	(0.221)	(0.218)	(0.210)	(0.209)
Delta (δ)		-0.499^{***}	-0.235	-0.241
		(0.170)	(0.172)	(0.169)
Risk seeking		0.054^{***}	0.032^{**}	0.028^{**}
		(0.014)	(0.014)	(0.013)
Sample mean DDI			1.025	
Further controls				
Preference controls	No	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes
Food behavior & lifestyle	No	No	No	Yes
p-value β	0.000	0.000	0.005	0.016
N	1,266	1,266	1,266	1,266
Adjusted R^2	0.015	0.034	0.108	0.122

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The deviate at home index measured in wave 1 is regressed on β and all control variables that are gradually added. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table 6: *Deviating from intentions and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Deviation Index (DDI)	0.403***	0.096***	0.069***	0.318***	0.095***	0.078***
	(0.037)	(0.012)	(0.012)	(0.047)	(0.014)	(0.015)
Delta (δ)	0.276	0.031	0.042	−0.096	−0.032	0.042
	(0.207)	(0.065)	(0.062)	(0.268)	(0.085)	(0.079)
Risk seeking	0.046***	0.013***	0.006	0.056***	0.020***	0.013**
	(0.016)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Sample mean waste index	1.219	0.238	0.198	1.067	0.212	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.000	0.000	0.000
q-value β	0.000	0.000	0.000	0.000	0.000	0.000
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.163	0.092	0.079	0.179	0.130	0.111

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the deviate at home index and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

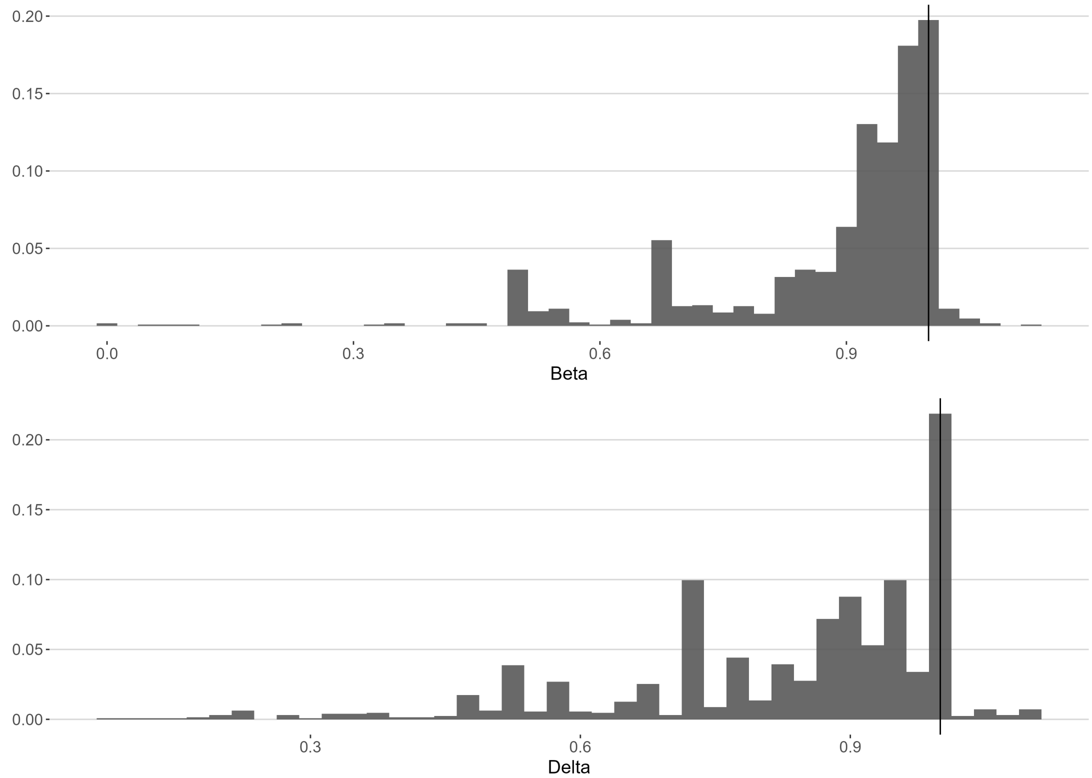
Table 7: *Procrastination and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.055***	0.017***	0.019***	0.058***	0.014***	0.020***
	(0.014)	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)
Patience	−0.029	−0.005	0.002	−0.024	−0.001	−0.005
	(0.020)	(0.006)	(0.006)	(0.024)	(0.007)	(0.007)
Risk seeking	0.060***	0.016***	0.004	0.064***	0.021***	0.013**
	(0.018)	(0.005)	(0.005)	(0.022)	(0.007)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.001	0.008	0.000
q-value β	0.001	0.001	0.000	0.001	0.033	0.001
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.081	0.049	0.062	0.135	0.084	0.091

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the level of procrastination and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Appendix A

Figure A1: *Distribution of beta and delta*



Note: The figure depicts the distribution of the two time preference parameters. The distribution of the present bias parameter β is depicted in the upper panel while the lower panel shows the distribution of the long-run patience parameter δ. In both panels, the vertical line marks the value 1 which implies dynamically consistent preferences when β is considered and no impatience when δ is considered.

Table A1: *Correlation of time preference measures with intertemporal variables*

	$DF12$	$DF1$	Beta (β)	Delta (δ)
$DF12$	–	–	–	–
$DF1$	$0.83***$	–	–	–
Beta (β)	$0.54***$	$0.84***$	–	–
Delta (δ)	$0.59***$	$0.17***$	-0.02	–
Tertiary education dummy	$0.06**$	$0.11***$	$0.11***$	-0.02
Smoker dummy	$-0.05*$	$-0.06**$	$-0.07***$	0.00
Body mass index	-0.04	$-0.05*$	$-0.06**$	-0.02
Healthy diet	$0.06**$	$0.09***$	$0.10***$	0.00

Note: The table provides pairwise Spearman correlation coefficients of the time preference measures $DF12$, $DF1$, beta (β) and delta (δ) with the intertemporal variables: tertiary education dummy, smoking dummy, body mass index and healthy diet. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A2: *Procrastination and food waste behavior over time*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.055***	0.017***	0.019***	0.079***	0.015***	0.021***
wave 1/ wave 2	(0.014)	(0.004)	(0.004)	(0.015)	(0.005)	(0.005)
Patience	−0.029	−0.005	0.002	−0.019	−0.0005	−0.004
	(0.020)	(0.006)	(0.006)	(0.023)	(0.007)	(0.007)
Risk seeking	0.060***	0.016***	0.004	0.062***	0.021***	0.013**
	(0.018)	(0.005)	(0.005)	(0.021)	(0.007)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.000	0.002	0.000
q-value β	0.001	0.001	0.000	0.000	0.009	0.000
N	1,270	1,270	1,270	866	866	866
Adjusted R^2	0.081	0.049	0.062	0.150	0.086	0.096

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the level of procrastination measured in wave 1 and 2, and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A3: *Food waste behavior and dynamic inconsistency*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β)	-1.059^{***}	-0.193^{**}	-0.160^{**}	-0.649^{**}	-0.278^{***}	-0.169^{*}
	(0.271)	(0.086)	(0.080)	(0.317)	(0.104)	(0.097)
Delta (δ)	0.159	0.005	0.023	−0.208	−0.070	0.014
	(0.223)	(0.069)	(0.064)	(0.274)	(0.085)	(0.080)
Risk seeking	0.057^{***}	0.016^{***}	0.007	0.064^{***}	0.023^{***}	0.015^{**}
	(0.017)	(0.005)	(0.005)	(0.021)	(0.006)	(0.006)
Age	-0.013^{***}	-0.004^{***}	-0.004^{***}	-0.014^{***}	-0.004^{***}	-0.003^{***}
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	0.013	−0.013	0.022	0.115	−0.034	0.026
	(0.079)	(0.025)	(0.023)	(0.092)	(0.028)	(0.029)
Tertiary education dummy	−0.056	−0.012	0.011	−0.117	-0.048^{*}	0.005
	(0.079)	(0.025)	(0.023)	(0.091)	(0.028)	(0.028)
Employment dummy	0.269^{***}	0.032	0.039	0.101	−0.025	0.028
	(0.081)	(0.027)	(0.024)	(0.100)	(0.030)	(0.030)
Single household dummy	−0.041	0.041	−0.012	-0.466^{***}	-0.075^{**}	-0.101^{***}
	(0.094)	(0.029)	(0.026)	(0.096)	(0.031)	(0.031)
Log household income	0.066	0.045^{**}	0.024	−0.090	0.002	−0.023
	(0.058)	(0.018)	(0.017)	(0.071)	(0.021)	(0.022)
Child below 12 dummy	0.213^{*}	0.064	0.089^{**}	0.225^{*}	0.118^{***}	0.137^{***}
	(0.120)	(0.041)	(0.041)	(0.135)	(0.046)	(0.046)
City dummy	-0.185^{**}	−0.012	−0.007	−0.068	−0.040	0.004
	(0.080)	(0.026)	(0.024)	(0.093)	(0.029)	(0.030)
Distance grocery store	−0.0002	−0.001	0.001	−0.003	−0.002	0.001
	(0.004)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	−0.141	−0.048	−0.035	−0.145	−0.033	−0.026
	(0.103)	(0.031)	(0.031)	(0.107)	(0.034)	(0.037)
Share organic food	0.007	-0.013^{*}	−0.008	−0.029	−0.007	−0.002
	(0.024)	(0.007)	(0.007)	(0.024)	(0.008)	(0.008)
Discounter index	0.029	−0.027	0.032	0.021	−0.068	−0.021
	(0.138)	(0.042)	(0.039)	(0.150)	(0.046)	(0.046)
No. grocery purchases	0.068^{***}	0.010	0.021^{***}	0.115^{***}	0.015^{**}	0.025^{***}
	(0.023)	(0.007)	(0.006)	(0.020)	(0.006)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
p-value β	0.000	0.025	0.046	0.039	0.008	0.084
q-value β	0.000	0.054	0.192	0.074	0.010	0.246
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.082	0.042	0.050	0.127	0.085	0.078

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on β and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A4: *Consumption planning behavior*

	Inventory Checking Dummy		Shopping List Dummy		Planning Horizon (in days)	
	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic inconsistency measure	−0.005	−0.018	0.088	−0.024	−0.600	−0.035
	(0.079)	(0.024)	(0.081)	(0.023)	(0.374)	(0.103)
Delta (δ)	0.003	−0.002	0.043	0.035	0.039	0.044
	(0.067)	(0.067)	(0.068)	(0.069)	(0.295)	(0.298)
Risk seeking	0.002	0.002	−0.001	−0.001	−0.059**	−0.059**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)
Age	0.001	0.0004	0.0004	0.0005	0.008*	0.007*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Female	−0.731***	−0.729***	−0.254	−0.255	−0.644	−0.619
	(0.033)	(0.033)	(0.415)	(0.415)	(2.711)	(2.646)
Tertiary education dummy	0.049*	0.047*	−0.025	−0.024	0.275**	0.260**
	(0.025)	(0.025)	(0.024)	(0.024)	(0.108)	(0.108)
Employment dummy	−0.003	−0.002	−0.040	−0.040	−0.162	−0.159
	(0.026)	(0.026)	(0.025)	(0.025)	(0.123)	(0.124)
Single household dummy	−0.063**	−0.064**	−0.108***	−0.107***	0.123	0.117
	(0.027)	(0.027)	(0.026)	(0.026)	(0.125)	(0.125)
Log household income	0.016	0.015	−0.019	−0.019	−0.010	−0.025
	(0.018)	(0.018)	(0.018)	(0.018)	(0.084)	(0.085)
Child below 12 dummy	−0.007	−0.005	−0.036	−0.037	0.046	0.066
	(0.035)	(0.035)	(0.036)	(0.036)	(0.156)	(0.155)
City dummy	0.045*	0.045*	0.002	0.003	0.010	0.002
	(0.025)	(0.025)	(0.025)	(0.025)	(0.112)	(0.112)
Distance grocery store	0.0004	0.0004	0.003**	0.003**	0.022***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
Vegetarian dummy	−0.018	−0.019	−0.030	−0.030	−0.130	−0.139
	(0.032)	(0.032)	(0.031)	(0.031)	(0.135)	(0.135)
Share organic food	0.012	0.011	0.017**	0.017**	0.011	0.005
	(0.008)	(0.008)	(0.007)	(0.007)	(0.033)	(0.033)
Discounter index	0.013	0.014	−0.025	−0.025	−0.397**	−0.395**
	(0.043)	(0.043)	(0.043)	(0.042)	(0.186)	(0.186)
No. grocery purchases	−0.010	−0.010	−0.015**	−0.015**	−0.310***	−0.307***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.028)	(0.029)
Sample mean behaviors	0.784	0.784	0.791	0.791	3.931	3.931
p-value β	0.952	0.449	0.282	0.286	0.109	0.738
q-value β	0.969	0.796	0.493	0.561	0.178	0.907
N	1,266	1,266	1,266	1,266	1,246	1,246
Adjusted R^2	0.017	0.017	0.043	0.043	0.136	0.134

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The variables 'Fridge Checking Dummy', 'Shopping List Dummy' and 'Purchase Fruits & Vegs in Advance' measured in wave 1 are regressed on β (columns 1, 3, 5) or a present bias dummy taking the value 1 if $\beta < 0.95$ (columns 2, 4, 6), and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A5: *Deviating from intentions at home*

	Domestic Deviation Index (DDI)			
	(1)	(2)	(3)	(4)
Beta (β)	-0.913^{***}	-0.890^{***}	-0.593^{***}	-0.505^{**}
	(0.221)	(0.218)	(0.210)	(0.209)
Delta (δ)		-0.499^{***}	-0.235	-0.241
		(0.170)	(0.172)	(0.169)
Risk seeking		0.054^{***}	0.032^{**}	0.028^{**}
		(0.014)	(0.014)	(0.013)
Age			-0.021^{***}	-0.021^{***}
			(0.002)	(0.002)
Female			-0.263	-0.180
			(0.303)	(0.305)
Tertiary education dummy			-0.177^{***}	-0.163^{***}
			(0.061)	(0.061)
Employment dummy			0.064	0.050
			(0.069)	(0.069)
Single household dummy			0.134^{*}	0.105
			(0.071)	(0.071)
Log household income			0.096^{**}	0.109^{**}
			(0.047)	(0.048)
Child below 12 dummy			0.223^{**}	0.227^{**}
			(0.102)	(0.101)
City dummy			-0.013	-0.003
			(0.063)	(0.063)
Distance grocery store			0.004	0.006^{**}
			(0.003)	(0.003)
Vegetarian dummy				0.015
				(0.090)
Share organic food				-0.020
				(0.018)
Discounter index				0.122
				(0.106)
No. grocery purchases				0.072^{***}
				(0.017)
Sample mean DDI			1.025	
p-value β	0.000	0.000	0.005	0.016
N	1,266	1,266	1,266	1,266
Adjusted R^2	0.015	0.034	0.108	0.122

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The deviate at home index measured in wave 1 is regressed on β and all control variables that are gradually added. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A6: *Deviating from intentions and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Deviation Index (DDI)	0.403***	0.096***	0.069***	0.318***	0.095***	0.078***
	(0.037)	(0.012)	(0.012)	(0.047)	(0.014)	(0.015)
Delta (δ)	0.276	0.031	0.042	−0.096	−0.032	0.042
	(0.207)	(0.065)	(0.062)	(0.268)	(0.085)	(0.079)
Risk seeking	0.046***	0.013***	0.006	0.056***	0.020***	0.013**
	(0.016)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Age	−0.005*	−0.002**	−0.003***	−0.007*	−0.002	−0.001
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	−0.002	−0.018	0.019	0.067	−0.047*	0.014
	(0.075)	(0.024)	(0.022)	(0.090)	(0.027)	(0.028)
Tertiary education dummy	−0.008	0.001	0.019	−0.066	−0.035	0.017
	(0.076)	(0.024)	(0.023)	(0.089)	(0.028)	(0.028)
Employment dummy	0.252***	0.027	0.036	0.101	−0.024	0.028
	(0.078)	(0.026)	(0.024)	(0.096)	(0.030)	(0.030)
Single household dummy	−0.090	0.030	−0.020	−0.509***	−0.088***	−0.111***
	(0.090)	(0.028)	(0.026)	(0.094)	(0.030)	(0.031)
Log household income	0.004	0.031*	0.014	−0.149**	−0.018	−0.038*
	(0.056)	(0.018)	(0.016)	(0.071)	(0.021)	(0.022)
Child below 12 dummy	0.147	0.046	0.077*	0.202	0.114**	0.131***
	(0.117)	(0.040)	(0.040)	(0.129)	(0.044)	(0.045)
City dummy	−0.195**	−0.014	−0.008	−0.057	−0.037	0.007
	(0.077)	(0.025)	(0.024)	(0.090)	(0.029)	(0.029)
Distance grocery store	−0.002	−0.001	0.0003	−0.004	−0.002	0.001
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	−0.158*	−0.052*	−0.037	−0.160	−0.039	−0.030
	(0.092)	(0.030)	(0.030)	(0.105)	(0.034)	(0.037)
Share organic food	0.008	−0.012*	−0.007	−0.027	−0.007	−0.001
	(0.023)	(0.007)	(0.007)	(0.023)	(0.007)	(0.007)
Discounter index	−0.014	−0.038	0.024	−0.036	−0.084*	−0.035
	(0.130)	(0.042)	(0.039)	(0.146)	(0.045)	(0.046)
No. grocery purchases	0.043*	0.004	0.017***	0.095***	0.009	0.020***
	(0.022)	(0.006)	(0.006)	(0.021)	(0.005)	(0.006)
Sample mean waste index	1.219	0.238	0.198	1.067	0.212	0.217
p-value β	0.000	0.000	0.000	0.000	0.000	0.000
q-value β	0.000	0.000	0.000	0.000	0.000	0.000
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.163	0.092	0.079	0.179	0.130	0.111

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the deviate at home index and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table A7: *Procrastination and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.055***	0.017***	0.019***	0.058***	0.014***	0.020***
	(0.014)	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)
Patience	−0.029	−0.005	0.002	−0.024	−0.001	−0.005
	(0.020)	(0.006)	(0.006)	(0.024)	(0.007)	(0.007)
Risk seeking	0.060***	0.016***	0.004	0.064***	0.021***	0.013**
	(0.018)	(0.005)	(0.005)	(0.022)	(0.007)	(0.006)
Age	−0.013***	−0.004***	−0.003***	−0.014***	−0.004***	−0.003**
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	0.048	−0.004	0.031	0.144	−0.024	0.032
	(0.079)	(0.025)	(0.023)	(0.091)	(0.028)	(0.028)
Tertiary education dummy	−0.087	−0.020	0.002	−0.134	−0.056*	−0.001
	(0.080)	(0.025)	(0.023)	(0.090)	(0.029)	(0.028)
Employment dummy	0.278***	0.035	0.044*	0.121	−0.018	0.035
	(0.081)	(0.027)	(0.024)	(0.099)	(0.031)	(0.030)
Single household dummy	−0.036	0.043	−0.011	−0.476***	−0.078**	−0.104***
	(0.094)	(0.029)	(0.026)	(0.095)	(0.031)	(0.031)
Log household income	0.068	0.046***	0.026	−0.101	−0.005	−0.024
	(0.058)	(0.018)	(0.016)	(0.070)	(0.021)	(0.022)
Child below 12 dummy	0.271**	0.077*	0.098**	0.281**	0.134***	0.153***
	(0.121)	(0.041)	(0.041)	(0.134)	(0.046)	(0.046)
City dummy	−0.205**	−0.018	−0.011	−0.086	−0.045	0.001
	(0.080)	(0.026)	(0.024)	(0.093)	(0.029)	(0.029)
Distance grocery store	−0.001	−0.001	0.0004	−0.003	−0.002	0.001
	(0.004)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	−0.138	−0.047	−0.035	−0.132	−0.034	−0.022
	(0.102)	(0.031)	(0.031)	(0.107)	(0.035)	(0.036)
Share organic food	0.005	−0.013*	−0.009	−0.031	−0.009	−0.002
	(0.025)	(0.007)	(0.007)	(0.024)	(0.008)	(0.008)
Discounter index	0.061	−0.020	0.039	0.045	−0.062	−0.012
	(0.138)	(0.042)	(0.039)	(0.150)	(0.046)	(0.045)
No. grocery purchases	0.071***	0.010	0.021***	0.114***	0.015**	0.024***
	(0.023)	(0.007)	(0.006)	(0.020)	(0.006)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
p-value β	0.000	0.000	0.000	0.001	0.008	0.000
q-value β	0.001	0.001	0.000	0.001	0.033	0.001
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.081	0.049	0.062	0.135	0.084	0.091

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the level of procrastination and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food and number grocery shopping. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Appendix B

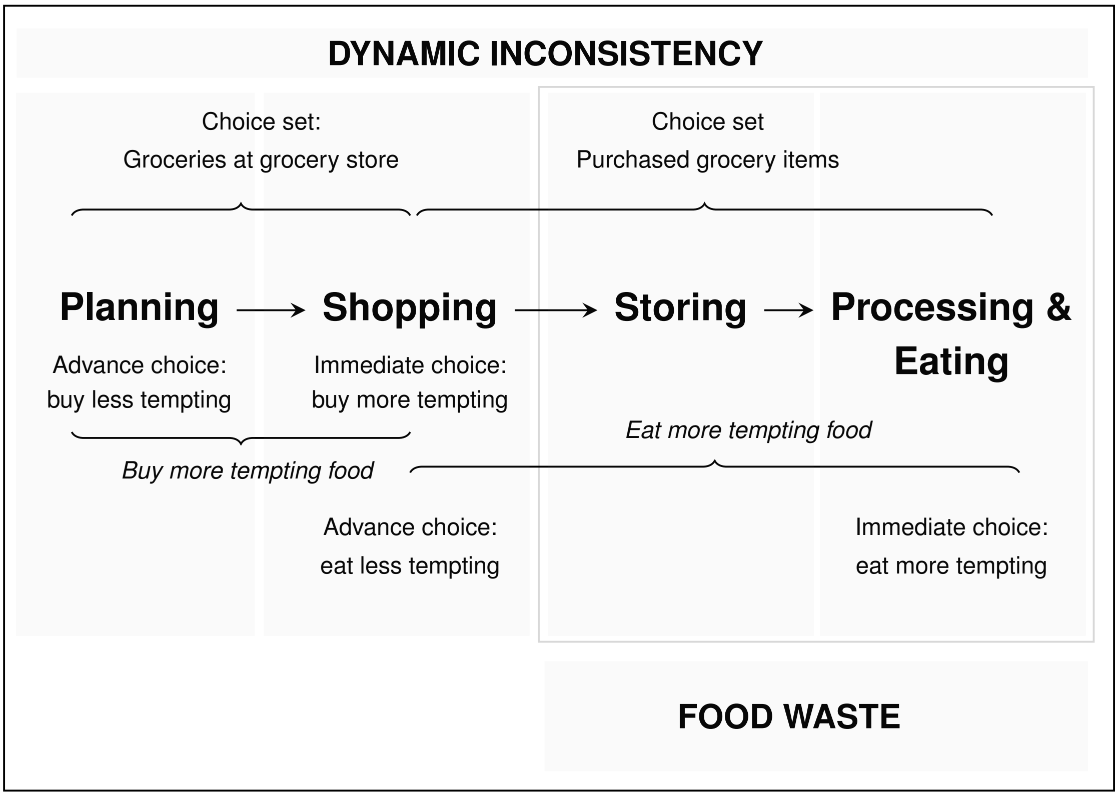
Table B1: *Description of variables*

Variable name	Definition
Outcomes:	
Food Spoilage Indicator (W1/W2)	Index ranging from 0 to 4 indicating whether food from the four categories fruits and vegetables, dairy products, meat and fish products, bakery products went bad within the last seven days (dummy variables equaling 1 or 0). A value of 0 indicates that no groceries of the four categories were found that went bad; a value of 4 indicates that groceries from all four categories were found at home that could not be (fully) eaten anymore. Measured in both waves 1 and 2.
Best Before Waste Dummy (W1/W2)	Dummy equaling 1 if groceries were thrown away because best before date was exceeded (within the last seven days). Measured in both waves 1 and 2.
Waste Leftovers Dummy (W1/W2)	Dummy equaling 1 if already prepared food that was stored for later intake was thrown away (within the last seven days). Measured in both waves 1 and 2.
Regressors:	
Beta (β)	Present bias parameter; beta < 1 indicates dynamically inconsistent behavior, beta equaling 1 indicates time consistent behavior; derived from two hypothetical questions used in the NLSY 2006 wave asking for an amount of money required to be willing to delay a payment of 1,000 Euros by one year/ one month.
Delta (δ)	Long-run discounting parameter reflecting the level of patience an individual has towards utility from future payments; derived from two hypothetical questions used in the NLSY 2006 wave asking for an amount of money required to be willing to delay a payment of 1,000 Euros by one year/ one month; the smaller delta, the more impatient an individual is; delta equaling 1 implies full patience.

Deviate at home index:	Index ranging from 0 to 4 capturing actual consumption behavior (immediate choice) deviating from intended consumption behavior (advance choice); based on food-specific consumption behavior at home: more food deliveries than intended, less fresh cooking than intended, more convenience food than intended, leave fruits and vegetables out longer than intended.
Procrastination	Tendency to postpone tasks that knowingly could be performed already; measured on 11-point Likert scale ranging from 0 to 10; 0 indicates "does not describe me at all" and 10 indicates "describes me perfectly"; taken from the German Socio-Economic Panel.
Patience	Willingness to forgo an activity delivering utility today to profit more in the future; measured on 11-point Likert scale ranging from 0 to 10; 0 indicates "not at all willing to forgo activity" and 10 indicates "very willing to forgo activity"; taken from the German Socio-Economic Panel.
Controls:	
Risk seeking	Self-assessed level of general risk aversion; measured on 11-point Likert scale ranging from 0 to 10; 0 indicates "not at all willing to take risks" and 10 indicates "very willing to take risks"; taken from the German Socio-Economic Panel.
Age	Individual age in years.
Female	Variable indicating the sex of a respondent (female/male/diverse). Male is the reference category, the category diverse is omitted in results.
Tertiary education dummy	Dummy equaling 1 if individual has a tertiary education degree.
Employment dummy	Dummy equaling 1 if individual is employed (or self-employed) in a part-time or full-time job (also including different forms of voluntary social or ecological purpose jobs).
Single household dummy	Dummy equaling 1 if individual is not living together with a partner, children or other relatives.
Log household income	Logarithmized monthly net household income (in Euros); income categories transformed to numeric information by calculating the category means.
Child below 12 dummy	Dummy equaling 1 if at least one child below the age of 12 lives in the household.

City dummy	Dummy equaling 1 if individual lives in a city (0 for living in rural area).
Distance grocery store	Walking distance to reach the next supermarket; 1: 0-2 minutes, 3: 3-5 min., 8: 6-10 min., 13: 11-15 min., 18: 16-20 min., 23: 21-25 min., 28: 26-30 min., 33: 31-35 min., 36: more than 35 min. (categories transformed to numeric information by calculating the category means).
Vegetarian dummy	Dummy equaling 1 if individual has followed a predominantly vegetarian or vegan diet.
Share organic food	Average share of organic groceries in shopping basket (within the last four weeks); 0: 0%, 1: 1-10%, 2: 11-20%, 3: 21-30%, 4: 31-40%, 5: 41-60%, 6: 61-80%, 7: 81-100%; categories are assigned a numeric value between 0 and 7.
Discounter index	Index ranging from 0 to 1 indicating the weight discount supermarkets have in the household supermarket portfolio (only considering supermarkets that were regularly visited within the last four weeks); a value of 0 implies the household never shops groceries in discount supermarkets; a value of 1 implies the household only shops groceries in discount supermarkets; a value of 0.5 indicates one out of total two grocery stores that are regularly visited is a discounter.
No. grocery purchases	Number of own total grocery purchases (online and on-sight) per week (average over last four weeks).
Working from home (days)	Number of days an individual indicated to be working remotely from home; ranges from 0 to 5 working days.
Covid-19 stringency index	Index indicating the stringency of political containment measures due to the Covid-19 virus; computed at the state level for all sixteen German federal states; ranges between 0 and 100.

Figure B1: *Food consumption process and dynamic inconsistency*



Note: The figure depicts the food consumption process. Daily food consumption decisions are modelled as a sequence of single consumption choices that are made at different points in time: from purchase planning, grocery shopping and storing to food processing and eating. Individuals have to make several advance and immediate choices from different time perspectives as they go along these stages. At the planning stage, individuals make an advance choice about which food items to buy in the grocery store. Reconsidering this choice at the actual shopping stage from an immediate perspective, a present-biased individual might deviate from her plans and include relatively more tempting food items in the food basket. Considering the second part of the consumption process, present-biased individuals make an advance choice to eat a relatively less tempting meal at home in the future. By purchasing the food basket, carrying it home and storing the food items, some time passes and the future consumption intention made at the grocery store has to be reconsidered in the present at home. A present-biased individual now deviates from her consumption intention by preferring a relatively more tempting meal.

Table B2: Attrition analysis

	Attrition Dummy		
	(1)	(2)	(3)
Age	-0.009^{***}	-0.009^{***}	-0.008^{***}
	(0.001)	(0.001)	(0.001)
Female	0.023	0.020	0.028
	(0.025)	(0.025)	(0.025)
Tertiary Education dummy	-0.151^{***}	-0.152^{***}	-0.143^{***}
	(0.025)	(0.026)	(0.026)
Employment dummy		-0.028	-0.034
		(0.029)	(0.029)
Single household dummy		0.003	0.005
		(0.030)	(0.030)
Child below 12 dummy		0.083^{*}	0.076^{*}
		(0.043)	(0.043)
Log household income		0.003	0.006
		(0.020)	(0.021)
City dummy		0.013	0.019
		(0.026)	(0.026)
Beta (β)			-0.176^{***}
			(0.068)
Delta (δ)			-0.123
			(0.078)
Risk seeking			0.017^{***}
			(0.005)
Constant	0.803^{***}	0.775^{***}	0.867^{***}
	(0.050)	(0.160)	(0.175)
N	1,266	1,266	1,266
Adjusted R^2	0.088	0.089	0.101

Note: Ordinary Least Squares (OLS) regressions with robust standard errors. Table reports results from regressing an attrition dummy equaling 1 if an individual responds in wave 1 but not in wave 2 on socio-economic and household characteristics. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Appendix C

Figure C1 depicts the development of the Covid-19 pandemic situation and stringency of governmental regulations between May 2020 and September 2021. Part a) shows the development of the Covid-19 incidence rate that is an official measure of the number of individuals diagnosed with Covid-19 per 100,000 inhabitants within the last seven days.[26] Part b) depicts the Oxford Policy Stringency Index developed by Hale et al. (2020). The index constitutes a composite measure based on nine different indicators including school closures, workplace closures, cancellation of public events, restrictions on public political gatherings, public transport closure, stay at home requirements, restrictions on internal movement, international travel controls and public information campaigns.[27] It can take values between 0 (no measures) and 100 (strictest measures) with higher values indicating stricter containment policies.

The gray shaded areas highlight the data collection periods of the survey. Despite both survey waves being conducted during low incidence periods[28], policy stringency is high during survey wave 1 with index values ranging between 77 and 83. Until wave 2, stringency decreases to a level of 67 but remains relatively high thereafter. Figure C1 illustrates that life in Germany during the data collection was substantially restricted.

This raises the question how the Covid-19 pandemic affected food consumption and waste behavior and dynamic inconsistency measures? First, the pandemic could affect the levels of food wasted at home. Roe et al. (2021) register some initial panic purchases early during the pandemic which, however, disappeared until 2021. Also, individuals spent more time at home, changing food purchases behavior. Although all these changes started in 2020 and citizens should have adapted by the time of the survey, we explicitly ask participants about changes in their consumption behavior before and after the pandemic.[29] Only 5% of respondents state that they would now waste more food compared to pre-pandemic levels, while 20% indicate to waste less

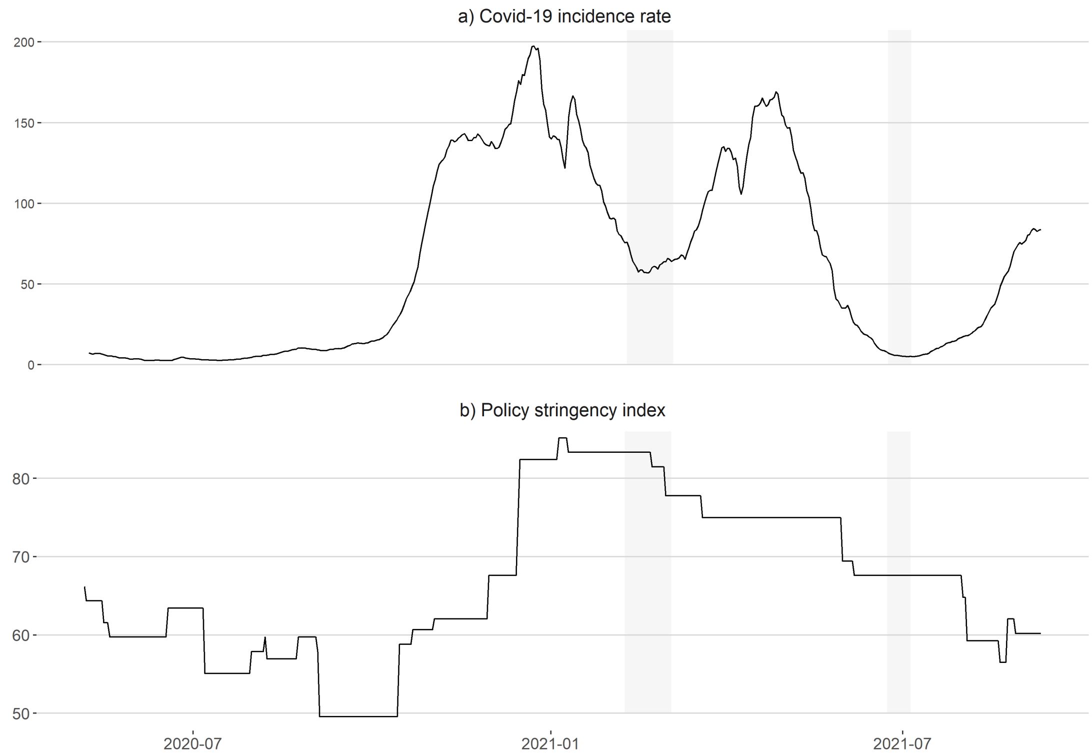
[26]The data on incidence rates are taken from the Robert Koch Institute, the government's central scientific institution in the field of biomedicine with the mission to safeguard public health in Germany.

[27]Oxford Covid-19 Government Response Tracker: https://covidtracker.bsg.ox.ac.uk/.

[28]During the implementation of wave 1, the average incidence rate for Germany ranges between 50 and 70. During wave 2, the incidence rate falls below 30.

[29]The exact wording of the question is: Looking back to the past four weeks, how has your personal consumption behavior changed compared to before the Corona pandemic? Please rate the following statement: "The amount of food that I throw away has...".

Figure C1: *Covid-19 incidence rates and policy strigency index*



Note: The figure depicts the pandemic situation and stringency of policy response between May 2020 and September 2021 in Germany. Panel a) plots the development of the Covid-19 incidence rate while panel b) shows the Oxford Policy Stringency Index created by Hale et al. (2020). The index constitutes a composite measure based on nine different indicators including school closures, workplace closures, cancellation of public events, restrictions on public political gatherings, public transport closure, stay at home requirements, restrictions on internal movement, international travel controls and public information campaigns. It can take values between 0 (no measures) and 100 (strictest measures) with higher values indicating stricter containment policies. The two gray shaded areas indicate the times of data collection. Wave 1 was implemented in February-March 2021, followed by wave 2 in June-early July 2021. Data sources: Robert Koch Institute (panel a) and Global Change Data Lab (Oxford Coronavirus Government Response Tracker) (pabel b) food. This is in line with results by Masotti et al. (2022) for the Corona pandemic. Changes may also occur with respect to the number of grocery shopping trips (Roe et al., 2021) to obey with social distancing rules, potentially impacting food waste levels. Asked for changes in the number of on-site and online grocery shopping instances, around two thirds indicate no changes, while the remainder equally increases or decreases the number of trips.In the econometric specification, we control for the number of online and on-site grocery purchases. Overall, we expect to measure – if anything – a lower bound of food waste levels in the survey.

Second, the pandemic situation could have altered behavioral patterns especially for rather inconsistent individuals since due to political containment measures, daily life during Covid-19 was forced to become less spontaneous and to follow more routines (at least for the majority of individuals). This effect might be especially strong for inconsistency related to food consumption if - compared to the pre-pandemic counterfactual situation - otherwise rather inconsistent individuals might indicate and experience less deviations of actual from planned food consumption behavior. If dynamically inconsistent individuals become more similar to dynamically consistent individuals with respect to their waste behavior, the detection of an effect in the survey data would become more difficult. As a consequence, the Covid-19 pandemic situation works against finding an effect of dynamic inconsistencies on food waste behavior.

If actually rather inconsistent individuals show more consistent behavior, and if individuals also waste less food due to the pandemic, not controlling for the pandemic situation would cause an omitted variable bias resulting in an overestimation of the true effect of dynamic inconsistency on food waste. Since we will apply two questions about the willingness to wait to receive a monetary amount over two different time intervals in the future to identify present-biased behavior, this concern would be alleviated under the assumption that behavior in the money domain is not sensitive to behavior in the food consumption domain. The question is whether Covid-19 related behavioral changes affect the present bias measure over money? This might for example be the case if the current pandemic situation influences the sense of time. During a period with high incidence rates, a month might feel like a year because social and economic life is more restricted. As a consequence, an individual might only be willing to postpone receiving a payment by one month if she receives more additional money compared to a period with low incidence rates. Becoming relatively more impatient about the monthly delay of a payment would increase the present bias ($\beta \downarrow$). Following this reasoning, a changing pandemic situation might indeed lead to an upward bias of β coefficient estimates.

Table C1: *Food waste behavior and dynamic inconsistency*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β)	-1.054^{***}	-0.191^{**}	-0.161^{**}	-0.675^{**}	-0.280^{***}	-0.173^{*}
	(0.271)	(0.086)	(0.081)	(0.314)	(0.103)	(0.095)
Delta (δ)	0.158	0.004	0.022	-0.244	-0.074	0.006
	(0.223)	(0.069)	(0.064)	(0.275)	(0.085)	(0.080)
Risk seeking	0.057^{***}	0.016^{***}	0.007	0.060^{***}	0.022^{***}	0.014^{**}
	(0.017)	(0.005)	(0.005)	(0.021)	(0.006)	(0.006)
Working from home (days)	-0.010	-0.002	0.007	0.068^{***}	0.009	0.016^{*}
	(0.022)	(0.007)	(0.006)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index (10 days)	-0.004	-0.002	-0.002	-0.001	-0.005	-0.008
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
p-value β	0.000	0.026	0.047	0.030	0.007	0.071
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.081	0.041	0.050	0.132	0.086	0.084

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on β and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases and (4) Covid controls: working from home measured in days and Covid-19 stringency index 10 days back. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, working from home, policy stringency. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table C2: *Consumption planning behavior*

	Inventory Checking Dummy		Shopping List Dummy		Planning Horizon (in days)	
	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy	Beta (β)	Present Bias Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic inconsistency measure	-0.010	-0.016	0.084	-0.023	-0.603	-0.034
	(0.078)	(0.024)	(0.081)	(0.023)	(0.374)	(0.104)
Delta (δ)	0.002	-0.001	0.043	0.036	0.037	0.042
	(0.066)	(0.067)	(0.068)	(0.068)	(0.295)	(0.297)
Risk seeking	0.001	0.001	-0.001	-0.001	-0.059^{**}	-0.059^{**}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)
Working from home (days)	0.017^{***}	0.017^{***}	0.011^{*}	0.011^{*}	0.020	0.018
	(0.006)	(0.006)	(0.006)	(0.006)	(0.028)	(0.028)
Covid-19 stringency index (10 days)	0.002	0.001	0.001	0.001	-0.004	-0.004
	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.011)
Sample mean behaviors	0.784	0.784	0.791	0.791	3.931	3.931
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.901	0.514	0.302	0.322	0.107	0.745
N	1,266	1,266	1,266	1,266	1,246	1,246
Adjusted R^2	0.021	0.021	0.044	0.044	0.135	0.133

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The variables 'Fridge Checking Dummy', 'Shopping List Dummy' and 'Purchase Fruits & Vegs in Advance' measured in wave 1 are regressed on β (columns 1, 3, 5) or a present bias dummy taking the value 1 if $\beta < 0.95$ (columns 2, 4, 6), and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases and (4) Covid controls: working from home measured in days and Covid-19 stringency index 10 days back. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, working from home, policy stringency. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table C3: *Deviating from intentions at home*

	Domestic Deviation Index (DDI)				
	(1)	(2)	(3)	(4)	(5)
Beta (β)	-0.913^{***}	-0.890^{***}	-0.593^{***}	-0.505^{**}	-0.514^{**}
	(0.221)	(0.218)	(0.210)	(0.209)	(0.210)
Delta (δ)		-0.499^{***}	-0.235	-0.241	-0.238
		(0.170)	(0.172)	(0.169)	(0.169)
Risk seeking		0.054^{***}	0.032^{**}	0.028^{**}	0.027^{**}
		(0.014)	(0.014)	(0.013)	(0.013)
Working from home (days)					0.006
					(0.016)
Covid-19 stringency index (10 days)					0.009
					(0.007)
Sample mean DDI		1.025			
Further controls					
Preference controls	No	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes
Food behavior & lifestyle	No	No	No	Yes	Yes
p-value β	0.000	0.000	0.003	0.012	0.010
N	1,266	1,266	1,266	1,266	1,266
Adjusted R^2	0.015	0.034	0.108	0.122	0.122

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The deviate at home index measured in wave 1 is regressed on β and all control variables that are gradually added. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases and (4) Covid controls: working from home measured in days and Covid-19 stringency index 10 days back. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, working from home, policy stringency. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table C4: *Deviating from intentions and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Domestic Deviation Index (DDI)	0.405***	0.096***	0.069***	0.315***	0.095***	0.077***
	(0.037)	(0.012)	(0.012)	(0.047)	(0.014)	(0.015)
Delta (δ)	0.272	0.030	0.041	−0.129	−0.035	0.034
	(0.208)	(0.065)	(0.061)	(0.269)	(0.085)	(0.079)
Risk seeking	0.047***	0.014***	0.006	0.053***	0.020***	0.012**
	(0.017)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Working from home (days)	−0.014	−0.003	0.006	0.061**	0.006	0.014*
	(0.021)	(0.007)	(0.006)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index (10 days)	−0.009	−0.003	−0.002	−0.001	−0.005	−0.008
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Sample mean waste index	1.219	0.238	0.198	1.067	0.212	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.000	0.000	0.000
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.163	0.092	0.079	0.183	0.130	0.115

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the deviate at home index and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases and (4) Covid controls: working from home measured in days and Covid-19 stringency index 10 days back. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, working from home, policy stringency. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021

Table C5: *Procrastination and food waste behavior*

	Food Spoilage Indicator (FSI) wave 1	Best Before Waste Dummy (BBW) wave 1	Waste Leftovers Dummy (WL) wave 1	Food Spoilage Indicator (FSI) wave 2	Best Before Waste Dummy (BBW) wave 2	Waste Leftovers Dummy (WL) wave 2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.055***	0.017***	0.018***	0.057***	0.013**	0.019***
	(0.014)	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)
Patience	−0.029	−0.005	0.002	−0.026	−0.002	−0.006
	(0.020)	(0.006)	(0.006)	(0.024)	(0.007)	(0.007)
Risk seeking	0.061***	0.016***	0.005	0.061***	0.021***	0.013**
	(0.018)	(0.005)	(0.005)	(0.022)	(0.007)	(0.006)
Working from home (days)	−0.016	−0.004	0.005	0.064**	0.007	0.015*
	(0.022)	(0.007)	(0.007)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index (10 days)	−0.005	−0.002	−0.001	0.002	−0.005	−0.007
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Sample mean waste index	1.221	0.239	0.20	1.062	0.213	0.217
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.001	0.010	0.000
N	1,266	1,266	1,266	861	861	861
Adjusted R^2	0.080	0.048	0.061	0.140	0.083	0.095

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. All three food waste outcome variables measured in wave 1 and 2 are regressed on the level of procrastination and all control variables. The following control variables are included: (1) preference measures: long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, distance grocery store, (3) food behavior and lifestyle characteristics: vegetarian dummy, share of organic food, discounter index and number grocery purchases and (4) Covid controls: working from home measured in days and Covid-19 stringency index 10 days back. The following control variables are measured in wave 1 *and* 2: age, employment dummy, single household dummy, log net household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, working from home, policy stringency. Preference measures and variables on gender, tertiary education, distance to next grocery store, vegetarian dummy and discounter index are only measured in wave 1. Levels of significance: *0.10, **0.05, ***0.01. Data source: ELKiD 2021