Dynamic Inconsistencies and Food Waste: Assessing Food Waste from a Behavioral Economics Perspective.

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Abstract

This paper investigates the link between dynamically inconsistent time preferences and individual food waste behavior. Food waste is conceptualized as unintended consequence of inconsistent consumption choices along the food consumption chain: Because present-biased individuals postpone the consumption of healthier food, storage time is prolonged and food more likely to be wasted. Capitalizing on a rich data set from a nationally representative survey, the paper constructs targeted measures of time-related food consumption and waste behaviors. In line with the theory, I find that more present-biased individuals waste more food. This finding is robust to different variable specifications. The paper points to the importance of considering dynamic inconsistencies at different stages of the food consumption process to foster the intended effects of food policy changes (increase healthy nutrition) and diminish unintended behavioral consequences (food waste).

Keywords: Dynamic inconsistency, food consumption, food waste, food policy
JEL Codes: D11, D12, D15, Q18, Q53

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1 Introduction

A main challenge of our time is global food security. An ever growing world population, increasing occurrences of extreme weather events due to climate change combined with a non-sustainable management of limited resources put immense pressure on food production (FAO, 2019; IPBES, 2019; Mbow et al., 2019; Westhoek et al., 2016). Besides a more sustainable use of resources and a transformation to a more plant-based diet, one option to increase global food security is to reduce food waste (Toensmeier et al., 2020; Westhoek et al., 2016; Willett et al., 2019). Estimates of Gustavsson et al. (2011) suggest that around 30% of the global food production for human consumption is lost or wasted along the food chain. In developed countries, the majority of waste is generated by consumers (Delgado et al., 2021; Griffin et al., 2009). Households in the European Union are responsible for over 50% of total waste along the food value chain (Scherhaufer et al., 2012; Stenmarck et al., 2016). In absolute terms, consumers in Europe and North-America waste 95-115 kg of food per capita and year (Gustavsson et al., 2011). At household level, estimates for UK suggest that 1 out of 5 groceries go to waste (Quested & Johnson, 2009).

This paper investigates the question why do consumers waste food? I will shed light on this topic by examining the role of dynamically inconsistent time preferences as driver for household food waste. Models incorporating self-control problems (Laibson, 1997; O'Donoghue & Rabin, 1999; Strotz, 1955; Thaler & Shefrin, 1981) are widely applied in economics. The dynamic inconsistency predicted by these models provide an explanation for the difficulties people face to save more money or exercise more in the future; all activities that deliver future benefits but generate costs today. Also food consumption is a process over time and requires choices at different stages, from food planning to food processing and eating (Quested et al., 2013). In this paper, I first provide a conceptual framework to link food consumption and waste behavior with dynamic inconsistencies. In a second step, I assess the conceptual implications empirically by applying novel and rich survey data on individual food consumption and waste behavior and economic preferences.

This paper seeks to make three main contributions. First, to the best of my knowledge this study is the first to add a behavioral economics dimension to the rational decision making notion of the literature on food waste. 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). Given 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). Although design variations exist, these studies consider food waste as possible result of rational decision making, being driven -among other factors- by food prices, income and wages. This paper adds a behavioral perspective suggesting that individuals throw away food as an *unintended* consequence of systematically deviating from own preferences along the food consumption process. Summarizing the conceptual framework that links dynamic inconsistency and food waste, I suggest that dynamically inconsistent individuals have intentions about when to consume healthier food items at home. This advance choice is made at the grocery shopping stage and results from the always present desire to adapt a healthier lifestyle (in the future). Dynamic inconsistency leads to a deviation from consumption intentions at home when the advance choice is reconsidered from a present perspective (immediate choice). This deviation implies that the consumption of healthier food items is postponed by at least one time period, and that these healthier food items are stored longer than intended. Given predetermined perishability, the likelihood that these food items are wasted increases.

Second, I collect unique data that add to a better understanding of the type and extent of food waste generated in households. The availability of data is low since wasting food at home is a private decision and difficult to observe. Previous studies rely on using self-assessed food waste measures directly asking participants about their waste behavior (Secondi et al., 2015) or infer food waste indirectly from using biological measures such as height, weight and age to predict an expected food consumption that is compared to food purchasing data (Hall et al., 2009; Yu & Jaenicke, 2020). Backed by the conceptual framework, this paper provides detailed data on individual consumption and waste habits, captures characteristics about individual lifestyle and the food environment, and elicits economic preferences. It thereby contributes to a holistic understanding of food consumption and waste behavior along the food consumption process.

Third, this study provides new insights to innovations in food policy. The aim of recent policy changes is to foster healthier nutrition by committing individuals to their advance food choices. An example is the policy change by the US Department of Agriculture (USDA) to allow online pre-ordering under the Supplemental Nutrition Assistance Program (SNAP) targeted at low-income communities.[1] This goal might not be achievable by solely focusing on grocery shopping behavior without taking into account the actual at-home consumption of healthier food. As unintended consequence, dynamically inconsistent individuals might not consume the healthier food they purchased at home. This policy change could rather increase waste of healthy food. In this regard, the paper conceptually contributes to a small list of papers (Danzer & Zeidler, 2023) that focuses on dynamic inconsistencies in actual food consumption choices. It seeks to integrate and extent the perspective taken by Read and Van Leeuwen (1998) and Sadoff et al. (2020) who mainly focus on grocery shopping choices.

Using novel nationally representative survey data from Germany, the paper assesses the incidence of food waste along the different stages of the food consumption chain: from grocery shopping to food storing, processing and eating. Unique survey items are designed to capture food consumption patterns and waste behavior among different food categories. I further collect granular information on household and socio-economic characteristics, economic preferences, consumption habits and the food environment. The data were collected in 2021 in February/March (wave 1) and June/July (wave 2). While the greater part of the analysis focuses on wave 1 data with over 1,200 observations, selected survey items can be analysed in wave 2 and allow for an

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

assessment over time.

To examine the relation between dynamically inconsistent time preferences and food waste behavior, this study applies the (β, δ) model formalized by Laibson (1997) and O'Donoghue and Rabin (1999) to estimate a dynamic inconsistency parameter at the individual level. The computation is based on exploiting variation in the self-assessed amount of money necessary for being willing to delay a payment of €1,000 for one month vs. one year. The plausibility of this measure is demonstrated by computing correlations between the dynamic inconsistency parameter and relevant intertemporal behaviors: Less inconsistent individuals have a higher tendency to hold a tertiary education degree, are less likely to be a smoker, have a lower body mass index and follow a healthier diet.

I test the conceptual framework empirically by first running a reduced form analysis: Three different food waste metrics are regressed on a dynamic inconsistency parameter and different sets of control variables capturing time and risk preferences, socio-demographic and household characteristics, food behavior and individual lifestyle and the current Covid-19 pandemic situation. Conceptually derived, all food waste measures target food items being stored for a too long time at home: food going bad (dairy, meat and fish and bakery products as well as fruits and vegetables), food being wasted because the best before date is exceeded and leftovers being wasted that where stored with the intention to be eaten. The goal of the second step is to pin down a mechanism rationalising the findings from reduced form regressions. Guided by the framework, I first investigate the link between consumption planning behavior and dynamic inconsistency. I then focus on the question whether inconsistent individuals deviate more from their own consumption intentions than rather consistent respondents. Based on the survey data, I derive an index capturing individual deviation behavior in the domain of at-home food consumption. In a third step, I regress the three food waste measures on the deviation index. The last part of the analysis focuses on potential threads to a causal identification of effects and provides robustness checks.

The paper first documents substantial heterogeneity in the incidence of food waste along the food consumption chain. The vast majority of food is wasted at the storing stage pointing to the relevance of intertemporal inconsistency in food consumption behavior as explanatory factor: 57% of individuals state that they have discovered food items at home within the last seven days that went bad. Twenty-four per cent of individuals state that they have thrown away food items because the best before date was exceeded. And 20% of respondents report to have thrown away leftovers that were stored in the fridge or freezer for further consumption. Not time related food waste figures at other stages of the food consumption chain are far smaller: Asked for general behavior, 3% of individuals state to throw away food being leftover from cooking. Only 14% of respondents report to throw away plate leftovers after eating.

Based on an Ordinary Least Squares (OLS) regression framework, I observe highly significant relations between dynamically inconsistent time preferences and individual food waste metrics: An increase in the dynamic inconsistency parameter by 10% is associated with a decrease in food going bad by 2%. More inconsistent individuals also show a significantly higher tendency to through away food because the best before date has expired (1.8%), and they have a higher likelihood to discard already prepared food that was stored earlier in time for further consumption (1.6%). The results are stable over time: dynamically inconsistent behavior is systematically associated with food waste patterns revealed in the second wave four to five months later. My results suggest that individuals with dynamically inconsistent time preferences indeed have a higher tendency to waste food. Long-run patience, on the other hand, expressed through the exponential discounting parameter, is not associated with food waste behavior.

Even though I find a highly significant correlation between dynamically inconsistent time preferences and food waste behavior, effect sizes are relatively small. One determining factor might be the Covid-19 pandemic situation potentially making it more difficult to detect an effect if dynamically inconsistent individuals waste less food compared to pre-pandemic times. Taking into account the pandemic situation suggests that coefficients constitute lower bound estimates. On the other hand, I will give a discussion about potential biases that might lead to an overestimation of the true effects. To investigate this topic, I suggest an alternative measure of dynamic inconsistency by applying questions about the level of self-assessed procrastination taken from the German Social Economic Panel (GSOEP). The question whether estimated coefficients represent (unbiased) lower bound estimates or whether they are even upward biased cannot be conclusively determined but will be discussed in the paper.

Summarizing results for control variables, risk preference is positively associated with food waste. Individuals living together with a child below the age of 12 in a household also indicate to waste significantly more food. As further factors, the number of grocery purchases and the number of out-of-home eating occurrences is positively associated with food waste generated at home. The number of days an individual indicates to work remotely from home correlates positively with food wasted in wave 2 but not in wave 1. Age is the only variable that is systematically negatively associated with food waste in both waves. Living in a single household is negatively correlated with food waste in wave 2, but not in wave 1.

Besides providing reduced form results, I find empirical evidence supporting the mechanism suggested in the conceptual framework: First, dynamically inconsistent individuals do not differ in their consumption planning behavior compared to consistent respondents. This finding suggests that inconsistent individuals do make plans for at-home consumption in the future. Second, I show that the dynamic inconsistency parameter is systematically correlated with the index measuring deviations from own at-home consumption intentions. Third, regression results suggest a highly significant correlation between the deviation index and individual food waste behavior.

The remainder of the paper is structured as follows: Section 2 describes the conceptual framework. Section 3 provides information on the data set used in this study, and gives a detailed description of outcome, explanatory and control variables. Section 4 provides reduced form results, explores mechanisms and implements robustness checks before Section 5 concludes.

2 Conceptual Background

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.

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 considered the relatively healthy 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 (present) and $t+k$ (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 $c_{t+k} < 0$. From an *advance* perspective $t-1$, a present-biased individual *wants* to consume according to equation 1:

$$U(c_t, c_{t+k}) = \beta\delta c_t + \beta\delta^2 c_{t+k} \geq 0. \tag{1}$$

The individual consumes if the sum of discounted future payoffs is positive.[2] The parameter δ captures long-run patience and indicates how impatient an individual is with respect to postponing consumption today to consume more in the future. From an economic rationale, δ lies between 0 and 1: a fully patient individual ($\delta = 1$) is indifferent between consuming today and tomorrow. The lower δ, the stronger is the individual preference to consume today instead of tomorrow. The parameter β captures dynamic inconsistency. It is a constant that is added to every time period lying in the future. From an *ex-ante* perspective, all payments are in the future and β cancels out. Equation 1 can be simplified to equation 2:

$$c_t + \delta c_{t+k} \geq 0. \tag{2}$$

Equation 2 implies that from an advance choice perspective $(t-1)$, the consumption decision only depends on the level of individual patience.

Consumption plans depend on the relative payoff values c_t and c_{t+k}, and on the level of δ. To illustrate this point, consider the following example: Assume the payoff from consuming the apple today (in comparison to the chocolate bar) is -3. Because consuming the apple today delivers future health benefits, the relative payoff in the future is +5. The level of patience shall be set at $\delta = 0.9$. From an advance choice perspective in $t-1$, the individual plans to eat the apple one period later in t since $1.5 > 0$.

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

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*). This can be illustrated by analyzing actual consumption choices. In period t, the individual consumes according to equation 3:

$$c_t + \beta\delta c_{t+k} \geq 0. \tag{3}$$

Since the present bias parameter β refers to all payoffs received in the future, the individual is overly discounting c_{t+k} 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 $\beta\delta c_{t+k} < \delta c_{t+k}$. Coming back to the example, assume $\beta = 0.65$. Equation 3 now implies that the utility from consuming the apple today is $-0.075 < 0$.[3] While the present-biased individual planned to eat the apple in $t-1$, by re-evaluating the choice in period t the individual switches to consuming the chocolate bar because the future health benefits from consuming the apple are overly discounted. This example illustrates the present bias in action; the discounting between the present and the future is higher than between any other two future time periods.

As this example demonstrates, food consumption is not a single shot decision, but a process that sketches over time. It involves making decisions at different stages in different time periods: from purchase planning over grocery shopping and storing to food processing and eating. Daily food consumption decisions can therefore be modelled as a sequence of single consumption choices that are made at different points in time along the food consumption chain. This process is depicted in Figure 1. 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 already deviate from her plans and include relatively more tempting food items in the food basket.

[insert Figure 1 here]

As Figure 1 depicts, buying more tempting food in the grocery store is a result of dynamically inconsistent time preferences at the shopping stage. The underlying choice set at this part of the food consumption chain is formed by all food items available at the grocery store. A consequence of this dynamic inconsistency is a choice set including more tempting food items than actually intended by the individual before entering the grocery store. Read and Van Leeuwen (1998) and Sadoff et al. (2020) provide evidence for the existence of dynamic inconsistencies at the grocery shopping stage.

In my framework, individuals not only choose a food basket from an immediate choice perspective. At the shopping stage, they make a second advance choice: They consider *when* to actually consume the food items at future points in time at home. These consumption intentions

[3] $-3 + 0.9 \times 0.65 \times 5 = -0.075$

might be less explicit and more of implicit nature. I assume that individuals buy food items in the grocery store with the intention to eat them at home in a certain time interval. This assumption implies that individuals can order which food items they intend to eat first, second, third,... over time.

Considering this second part of the food consumption process, present-biased individuals make an advance choice to eat a relatively less tempting meal at home in the future. As Cutler et al. (2003) point out, the near future can refer to a few days or even a few hours. 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.[4] A present-biased individual now deviates from her consumption intention by preferring a relatively more tempting meal. Danzer and Zeidler (2023) provide evidence of this type of dynamic inconsistencies at the eating stage. As a result, the consumption of relatively less tempting food items is postponed by at least one time period, and these food items are stored longer than intended.

What does a longer storage time imply? To answer this question, I take a deeper look on the understanding of temptation. Related studies investigating dynamic inconsistencies in food choices consider temptation through the lens of food healthiness (Read & Van Leeuwen, 1998; Sadoff et al., 2020). The apple is healthier than the chocolate bar because it is nutrient-rich. To link dynamic inconsistencies and food waste, I go one step forward and focus on the implications of food being healthy: Food being healthy implies not only being rich in nutrients. It also implies that the food has less additives that make it more perishable (Bucher et al., 2015), and that it is not processed and requires more time and effort to process it in order to eat it (Cutler et al., 2003).

Applying this holistic understanding of temptation, dynamically inconsistent individuals plan to eat healthy food in advance. As a consequence, they choose nutrient-rich perishable foods that have to be further processed to be eaten. I assume that individuals have correct beliefs about the predetermined perishability and effort *category* when making food purchases at the grocery store. This implies knowing that rather less tempting food items like fruits and vegetables and other raw ingredients for meals like bread, dairy products and meat are more perishable and require more processing effort than convenience food. Coming back to the example, the apple implies higher costs of food processing because eating it involves additional preparation steps like washing the peel, cutting and washing the knife afterwards.[5] In comparison, the chocolate bar can be eaten right away by just unwrapping it. Time costs of food preparation are especially relevant for at-home food consumption considering the household production framework of Becker (1965): Individuals do not derive utility directly from purchasing food inputs in the grocery store. They rather derive utility from processing food inputs and turning them into meals.

[4] I assume the choice set for at-home consumption is determined at the grocery store, consisting of all groceries that were purchased during the last shopping trip.

[5] Costs of food processing depend on individual preferences. Some individuals might want to wash and cut the apple in order to eat it while others would eat the apple right away.

Present-biased behavior leads to postponing the consumption of healthier food by at least one time period. Since healthier food is more perishable, a longer storage time directly increases the likelihood of food going bad and being thrown away.[6] Summarizing the reasoning, a consequence of dynamically inconsistent time preferences at the eating stage is an increased likelihood of food going bad and being wasted.

As second potential consequence, the time interval between two grocery shopping trips might become shorter because the more tempting food is consumed earlier in time and the relatively less tempting food might have gone bad already. Whether dynamically inconsistent time preferences affect the time interval is an empirical question and depends on the kind of deviation from intentions. Imagine an individual planning to eat pasta with a sauce including vegetables. In her immediate choice she deviates by leaving out the vegetables as the least tempting ingredients of the meal. Since she will still eat the pasta and sauce in time, this deviation should have no effect on the shopping interval. Now imagine an individual planning to eat a big salad bowl. She deviates in her immediate choice by switching from salad to pizza that she actually planned to eat at a later point in time. The pizza is consumed earlier in time while the salad might already go bad after one round of postponed consumption. In this case, the individual might need to go shopping again - earlier than intended.

3 Empirical Strategy

3.1 Data Set

While the focus of Section 2 lies on the theoretical foundation of the relation between dynamic inconsistencies and food waste, in this and the following subsections, I will describe the strategy to investigate the aforementioned relation empirically.

3.1.1 Data Overview I use a unique survey data set from the 'Grocery Shopping and Consumption in Germany' (ELKiD) study conducted at the chair of economics at Catholic University Eichstaett-Ingolstadt.[7] Goal of the project is an in-depth study of food purchasing and consumption behavior among households in Germany. The data are nationally representative and comprise two interviews per respondent: wave 1 of the survey was implemented in February-March 2021, followed by wave 2 in June-early July 2021. The survey was conducted online by Respondi, an established market research company with a representative pool of respondents in Germany, and applied stratified random sampling of individuals by gender, age and state of residency. The surveys take about 20 minutes to respond, for each wave.

[6] For simplification, I assume that perishability is predetermined. I abstract from potentially incorrect individual storage behavior that might further reduce storage life of perishable food at home since the implications of dynamically inconsistent time preferences do not change.

[7] https://www.ku.de/wfi/mikro/forschungsprojekt-lebensmittelkonsum

In the analysis, I focus mainly on outcomes collected in wave 1 since this wave not only contains detailed survey items about food planning, shopping, food processing and eating behavior but also time and risk preferences and demographic and household characteristics. Wave 2 includes a subset of items repeating questions on food consumption and waste behavior, individual characteristics and personal lifestyle. In addition, I connect wave 1 measures of time preferences with wave 2 measures of food waste to investigate the relation between dynamic inconsistency and food waste over time. I assume that time preference measures are stable over time. In the robustness section, I will also discuss a test of stability of inconsistency over time.

In wave 1, 1,322 individuals participated in the survey. I exclude 49 observations that have implausible values in either one of three variables: household size, age and long-run patience δ. More specifically, I filter out subjects that state living together with more than two partners or more than three parents, indicating an age below 18 or above 79 years, or having an estimated δ of above 1.1. With respect to long-run patience, I set the threshold at 1.1 since values above 1 run against economic intuition, but marginally higher values than 1 might still be reasonable. Including the 35 observations with economically implausible values of δ above 1.1 does neither change the results, nor affect the conclusions drawn from the analysis.[8]

After carefully cleaning the data, I have information on 1,273 individuals across Germany. When analyzing food waste behavior over time, I focus on a balanced sample of 869 individuals that also responded in wave 2. The dropout rate from wave 1 to 2 is 32%. To analyze those individuals that did not respond in wave 2, I regress an attrition dummy on a set of socio-economic (age, gender, education, employment dummy) and household characteristics (single household dummy, small child dummy, income, city dummy). I apply an OLS framework with robust standard errors and report the results of this regression in Table A1 in the Appendix. To summarize my findings, attrited individuals are significantly younger and more likely to have a child below the age of 12. There is no effect of being female, having a higher education degree, being employed, logarithmized income, being a single household or living in a city on the likelihood to drop out in wave 2.

Based on the rich data set gained with the survey, I start the analysis by providing some general numbers on food consumption behavior along the food consumption process. Considering shopping behavior over the last four weeks, 73% of respondents state that they purchase groceries exclusively in supermarkets while 12% report to also buy food at weekly markets or gourmet food stores. Respondents report to go grocery shopping on average 2.3 times a week. Eighty-three per cent of respondents state to regularly shop groceries at discounters, and 4% state that they also receive groceries from food banks. The majority of respondents (83%) state to spend below €500 on groceries per month. Relating it to household monthly income, this number translates to 65% of individuals spending less than 15% of their income on grocery purchases. Regarding organically produced food, one-third of respondents state to buy between 1-10% of groceries labeled organic. One-fifth of respondents buy between 11-20% of organic food.

[8] The results are available upon request.

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% of respondents state to have not prepared a single dish. Looking at the difference between eaten and prepared dishes at home, only 4% of respondents ate more than 3 dishes in excess to dishes they prepared for themselves or other household members. These numbers suggest that individuals in the sample are able to make informed statements about their food consumption and waste habits at home.

3.1.2 Summary Statistics The encompassing data set allows me to construct a detailed set of control variables that is summarized in Table 1. An overview of each variable can be found in Table A2 in the Appendix. First, I control for risk preferences since the future is inherently risky while the present is not (Andreoni & Sprenger, 2012b). 'Risk seeking' is a self-reported variable measured on an 11-point Likert scale ranging from 0 to 10 that measures the individual willingness to take risks. The risk assessment question is taken from the GSOEP. I further include age and gender as control variables. I report summary statistics for gender in Table 1 as female dummy and drop two observations indicating being diverse. In the regression, I consider all genders and only report differences between male and female. As Table 1 reveals, in wave 1 50% of individuals are female and the mean age of respondents is 44.7 years. Modelling 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 wasted in households. Following these studies, I include a tertiary education and employment dummy in the regression framework. I measure educational attainment with a dummy equalling 1 if a respondent has at least a tertiary education degree. Around 41% of survey respondents have a tertiary education degree. The employment dummy measures labour market activity at the extensive margin. It serves as an indicator for being more time constraint in everyday life that might affect the incidence and amount of food being wasted in a household. Around 70% of individuals are employed in the sample.

[insert Table 1 here]

As further part of socio-demographic control variables, I include household characteristics in the regression: I define a single household dummy being 1 if an individual is not living together with partners, children or other relatives like parents, siblings etc. I also count individuals living together with flat mates as individuals living in a single household since in shared apartments income and food resources are usually not shared but kept separate, and cooking and eating processes are usually not planned and executed together. In the survey, 48% of respondents indicate to live in a single household. Following Ellison and Lusk (2018), I further include a dummy variable equalling 1 if a child below the age of 12 lives in the household. As Table 1 reveals, in wave 1 13% of respondents report to live together with at least one child below the age of 12. Since Lusk and Ellison (2017) and Morris and Holthausen Jr (1994) emphasize the role of income in modelling food waste, I additionally consider household income. I use the natural logarithm of total household income in all regression specifications. The self-reported household income is at around €2,660. Since income is only observed as categorical variable, I calculate the mean for all categories and treat it as numeric information. I further include a dummy variable indicating whether the household lives in a city compared to a county. The last variable in this category is the walking distance to the next grocery store measured in minutes. It serves as proxy for the general food availability. The average walking distance is around 13 minutes.

As third control category, I consider food behavior and lifestyle characteristics. First, I include a vegetarian dummy as measure for a vegetarian or vegan diet. Individuals following a vegetarian diet are considered 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, I include the share of organic food, and calculate a discounter index. The share of organic food is a categorical variable measuring the average share of organic food items bought during a grocery shopping trip within the last four weeks. The average category 2 refers to a share of 11-20%. The discounter index can take values between 0 and 1. It indicates how many grocery stores out of all grocery stores an individual regularly bought groceries in during the last four weeks were discounters. In the sample, individuals indicate that on average 47% of regularly visited grocery stores are discounters. I follow Lusk and Ellison (2017) suggesting in a theoretical model that preparation experience might matter. The variable food preparation experience indicates how often a respondent has prepared a dish for herself or others within the last two days. On average, individuals report to have prepared 3.3 dishes. Further variables included are the number of individual grocery purchases per week (both on-site and online), and the number of out-of-home eating occurrences that indicates how often individuals ate in offices, canteens, cafes, restaurants or other households within the last two days not including the survey day. Since the survey was conducted in 2021, Covid-19 containment measures limited the possibilities for individuals to eat out. The average number indicated is 0.4 times in wave 1 and 0.6 in wave 2. Due to the pandemic, capturing individual lifestyle arguably becomes easier since many aspects of a pre-pandemic lifestyle were restricted by political containment measures.

3.1.3 Covid-19 Pandemic The last control category build variables capturing the local Covid-19 pandemic situation. Both survey waves were conducted in the middle of the Covid-19 pandemic in the first half of 2021. To prevent the spread of the virus, the German government implemented a number of containment measures that heavily affected the daily live of individuals and restricted economic and social behavior in almost all areas.[9] Figure 2 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

[9]Daycare facilities and schools were closed, and many workplaces except for essential goods and services were shut down. Also private gatherings were restricted to a small number of people and public events were canceled. An international travel ban was introduced and internal movements were limited.

official measure of the number of individuals diagnosed with Covid-19 per 100,000 inhabitants within the last seven days.[10] 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.[11] It can take values between 0 (no measures) and 100 (strictest measures) with higher values indicating stricter containment policies.

[insert Figure 2 here]

The grey shaded areas highlight the data collection periods of the survey. Despite both survey waves were conducted during periods of rather low incidence rates[12], 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 at a relatively high level compared to 2020 index values. Figure 2 illustrates that the daily life in Germany at the time the survey was conducted was still very 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) note that especially during the first months of the pandemic panic food purchases occurred that might have increased food wasted at home. As time passed by, panic purchases decreased and people started accumulating more experience and knowledge with home food provisioning. As individuals were forced to spend more time at home due to working from home requirements and limited commuting, severe travel restrictions, closed restaurants, cafes and canteens, the accumulated experience with consumption taking mainly part at home might have rather reduced food waste levels. In the survey, I ask participants about changes in their consumption behavior before and after the pandemic.[13] Only 5% of respondents state that they would now waste more food compared to pre-pandemic levels. The remaining 95% of respondents indicate no change or a decrease in food waste levels: 20% of individuals state that they would waste slightly or strongly less food while 80% say the amount of food waste remained unchanged.

Results of Masotti et al. (2022) that conducted a study during the first lockdown also provide suggestive evidence that food waste rather decreased during the time of Covid-19-related lockdown. Lusk and Ellison (2017) emphasize that food waste models come to the conclusion that people with more time waste less food: if people spend more time at home, they become better in managing their daily food routines. Ellison and Kalaitzandonakes (2020) focus on the

[10] 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.

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

[12] 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.

[13] 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...".

positive relation between food waste and income: As many people lost their jobs, were on furlough or faced cuts in salary during the pandemic, food waste was more likely to decrease. They further add that rising food prices during the pandemic were also likely to reduce food waste for households at all income levels.

Roe et al. (2021) also point out that individuals might reduce the number of grocery shopping trips to obey with social distancing invocations. A decline in the number of shopping trips might increase food waste levels because relatively more food items are bought during a single trip and better meal planning and storing skills are necessary to manage increased time intervals during shopping trips. Asked for changes in the number of both on-site and online grocery shopping occurrences, 67% of survey respondents state no changes, 17% indicate less shopping occurrences and 14% say they purchase more often. Asked for changes only with respect to on-site grocery shopping trips, 65% of respondents indicate their behavior has not changed, 21% say the number of trips decreased and 15% state the number even increased (slightly or strongly).

In the econometric specification, I control for the number of online and on-site grocery purchases. Overall, taking these numbers and the aforementioned studies together, this evidence suggests that - if anything - due to the Covid-19 pandemic, I would measure 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 I 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.

To approach this concern, I first take data on the policy stringency index at the federal state level in Germany that were manually computed by Danzer et al. (2023) after the method described in Hale et al. (2020), and merge these data with the survey data based on the zip code information respondents provide in both waves. 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)[14] enabling federal states to enact Covid-19 restrictions. Due to this act, the design of disaster control and public health regulations mainly belongs to the state governments responsibility (IfSG, §32 & §54). As a consequence, the exact implementation of Covid-19 containment policies differs between states and induces variation in the policy stringency index at state level that I can exploit to control for the local pandemic situation. Indeed, during data collection in the first wave, the stringency index varied between 80.1 in Saxony and Brandenburg and 66.7 in North Rhine-Westphalia and Hesse. Since food waste measures refer to the last seven days prior to taking the survey, I consider the state policy stringency index 10 days prior to the respective survey dates in both waves.[15]

As a second variable capturing the individual pandemic situation, I 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). Respondents in survey 1 indicating to have an employment state to work on average 2 days remotely from home (Table 1). In wave 2, the mean is significantly lower at 1.7 days ($p < 0.01$).

3.2 Food Waste Metrics

In Section 2, I conceptually link dynamically inconsistent time preferences with postponing consumption of healthier food items at home. As a consequence, food items are stored longer and the likelihood of waste increases. To capture household food waste, I therefore focus on behavior at the storing stage. I use the following three outcome variables: a food going bad index, a waste best before dummy and a waste of leftovers dummy that can be computed for both waves. Figure 3 depicts the food consumption process and summarizes descriptive statistics for the different food waste measures.

[insert Figure 3 here]

The food going bad index is composed of four different variables: respondents were asked to state whether they detected food items within the last seven days that due to their texture or condition they would no longer want to eat (completely). They answered this question for

[14] https://www.gesetze-im-internet.de/ifsg/IfSG.pdf

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

different food categories: fruits and vegetables, dairy products, meat or fish products, bread and bakery products. Buzby et al. (2011) and Quested and Johnson (2009) provide empirical evidence that most food waste generated in households comes from these four food categories. Answers are coded as binary values and summed up to calculate the index. The index can take values between 0 and 4. A maximum index value of four implies that the respondent detected food items from all four categories going bad within the last seven days. A person stating that food from only one category went bad within the last seven days is assigned a value of 1. Table 1 reports summary statistics for all food waste variables. The mean value for the food going bad index is 1.22. As Figure 3 shows, 57% of respondents state that they have discovered food items at home within the last seven days that went bad. Asked for general behavior, 94% of individuals in the sample indicate to throw away at least parts of food items that go bad.

As second measure of food waste, I consider a waste best before dummy equalling 1 if an individual indicates to have thrown away food within the last seven days because the best before date was exceeded. Although the food might still be edible after the best before date has been exceeded, consumers might throw it away out of safety concerns or a lack of knowledge (Neff et al., 2015; Quested & Johnson, 2009). Results of Ellison and Lusk (2018) suggest that the expiration date affects the decision to throw away food. Since the conceptual framework is based on postponing consumption of less tempting food again and again, having more food exceeding the best before date is a direct consequence. As depicted in Figure 3, around 24% of individuals agree on this behavior (in wave 1), and 21% of respondents indicate in wave 2 to have thrown away food because the best before date was exceeded (Table 1).

The third outcome variable is a waste leftovers dummy equalling 1 if an individual states to have thrown away leftovers from cooking or eating that were stored in the fridge or freezer with the intention to eat them. This variable is included because eating leftovers might also be the less tempting choice if the portion size is too small to serve another full portion and additional food preparation effort is needed to integrate the leftovers into a full meal. Ellison and Lusk (2018) observe that individuals are less likely to throw away leftovers if there is enough left for a whole meal. As indicated in Table 1, 20% of respondents indicate to have thrown away leftovers within the last seven days in wave1, and 22% in wave 2.

Figure 3 further shows the incidence of food being thrown away at other consumption stages. At the processing stage, 72% of individuals state that the last time they cooked too much this was intended. Asked for general behavior, only 3% of individuals state to waste food after processing it; 87% of respondents state to rather store the food as leftovers in the fridge or freezer. Asking for leftovers after eating, 11% of respondents had leftovers on their plate the last time they ate a dish. Only 14% of individuals indicate to throw away plate leftovers in general; 51% of individuals store the leftovers in the fridge or freezer for later consumption. These numbers suggest that the majority of food is indeed wasted at the storing stage.

Contrary to other studies (Secondi et al., 2015), instead of direct questions asking for the amount of food wasted by individuals this paper relies on dummy variables capturing food waste behavior. While dummy variables lack the ability to measure differences at the intensive margin, the proposed method is based on the insight that many people underestimate the amount of food they waste (Neff et al., 2015; Quested et al., 2011). Other methods applied in the literature include food waste diaries (Koivupuro et al., 2012), waste composition analyses in municipalities (Lebersorger & Schneider, 2011; Schneider & Obersteiner, 2007) and more macroeconomic food purchasing-consumption comparisons based on biological measures (Hall et al., 2009; Landry & Smith, 2019; Yu & Jaenicke, 2020). While diaries itself might affect behavior and reduce food waste due to an attention effect, waste composition analyses are cumbersome and difficult to link with individual behavior. An in-out comparison of food consumption based on purchasing surveys and individual metabolic information (height, weight, gender and age) to estimate the physical need to eat provides only rough estimates of food waste.

This study instead relies on questions about waste behavior that are formulated in a way to prevent respondents from under-reporting; with precise contextual information, and over a specific period of time (seven days). They are embedded into survey items asking detailed information about food purchasing, processing and eating behavior. By these means, I seek to generate most accurate waste information that can be linked to an economic preference framework. This approach is most comparable to the study of Ellison and Lusk (2018) that uses a vignette approach.

3.3 Dynamic Inconsistency Measure

Based on the (β, δ) model introduced in Section 2, I capture dynamic inconsistencies in time preferences by calculating the β and δ parameter. In the literature, there exist different approaches how 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 this method has gained increasingly popularity, it is especially suited for an experimental setting since it requires additional instructions to understand the more complex task. This procedure is less feasible in surveys. An alternative approach is provided in the study of Falk et al. (2018) that use the 'staircase' method developed by Cornsweet (1962). This approach relies on a series of five interdependent hypothetical binary choices to measure long-run patience. To measure a present bias subjects would have to go through the staircase questions twice - with different time horizons. This procedure would again be very long and time consuming.

Out of these reasons, I follow Courtemanche et al. (2015) who apply two questions on hypothetical intertemporal money trade-offs from the 2006 NLSY (National Longitudinal Survey of Youth), a panel administered by the US Bureau of Labor Statistics. Based on these two questions, a patience and inconsistency parameter can be calculated. The first questions asks:

> Imagine: Suppose you have won a prize of €1000, which you can claim immediately. However, you can also wait for a year 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 one year to convince you to wait instead of claiming the prize now? Enter this additional amount of money in the text box.

Taking this amount which I will refer to as *amount1*, I adopt the calculation of Courtemanche et al. (2015) and compute a discount factor ($DF1$) for each respondent as follows:

$$DF1 = \frac{1,000}{(1,000 + amount1)}. \tag{4}$$

While the first question is referring to a time delay of one year, the second question asked for the amount to wait for one month. The decisive information is underlined in the survey and both questions are in consecutive order to additionally highlight the different time framing. The second question asks:

> Now imagine: Suppose you have won a prize of €1000, which you can claim immediately. However, you can also wait a month 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 one month to convince you to wait instead of claiming the prize now? Enter this additional amount of money in the text box.

Using the amount of this question (*amount2*), I compute an annualized discount factor ($DF2$) for each respondent as follows:

$$DF2 = \left[\frac{1,000}{(1,000 + amount2)}\right]^{12}. \tag{5}$$

To measure dynamic inconsistencies in time preferences, I exploit the two different time dimensions in questions 1 and 2. While question 1 is an intertemporal discounting question over an annual time interval, question 2 refers to a monthly time interval. A dynamically consistent individual should have the same (annualised) discount factor over the monthly interval as 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.

Applying the quasi-hyperbolic discounting framework of Laibson (1997) and O'Donoghue and Rabin (1999), an individual discounts an outcome that is τ periods away 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 $\beta < 1$, an individual behaves present-biased resulting in deviating from one's plan made for the future in favor of an action leading to immediate gratification today. Because future costs are overly discounted, the planned action that is more beneficial from an advance point of view is postponed and eventually never realized. Assuming annual periods, an individual's responses to the two questions imply the following relations:

$$\beta\delta = \frac{1,000}{(1,000 + amount1)} \tag{6}$$

and

$$\beta\delta^{\frac{1}{12}} = \frac{1,000}{(1,000 + amount2)}. \tag{7}$$

Solving for β and δ, this leads to

$$\beta = \frac{1,000}{[\delta(1,000 + amount1)]} \tag{8}$$

and

$$\delta = \left[\frac{(1,000 + amount2)}{(1,000 + amount1)}\right]^{\frac{12}{11}}. \tag{9}$$

Summary statistics for the two time preference parameters as well as the two discount factors are shown in Table 2. The mean discount factor for the annual delay question is 0.74 and for the monthly delay question it is 0.43, corresponding to an annual interest rate of 35% and 132%, respectively. The average individual in the sample is more patient over longer delays which is in line with diminishing impatience over time predicted by quasi-hyperbolic discounting. Although both interest rates are high, this result seems to be rather usual given evidence by Loewenstein (1988), McAlvanah (2010), and Shelley (1993) that preferences are sticky towards a status quo option. Since both preference elicitation questions explicitly establish receiving money immediately as intertemporal reference point, measuring patience with this willingness to delay method is expected to yield smaller discount factors compared to methods that do not impose an intertemporal reference point. Calculated interest rates in Courtemanche et al. (2015) that use an identical elicitation technique are twice as high as in this study suggesting that subjects in the survey answer both questions deliberately.

[insert Table 2 here]

The mean of the estimated present bias parameter β is 0.89. The estimate for the long-run patience parameter δ has a mean of 0.83. This implies 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. Figure 4 depicts the distributions of the two parameters. The two vertical lines mark the value 1. Ninety-six per cent of individuals have a β value at or below 1. The average value for β of 0.89 is a lower compared to structural estimates gained in experiments with money (Imai et al., 2021). Four per cent of respondents show a future bias with values $\beta > 1$. Ninety-eight per cent of individuals have a δ value at or below 1. From the original data set with 1,322 individuals, I exclude 37 observations with implausible values for δ (threshold of 1.1). This corresponds to 2.8% of observations from the original sample.

[insert Figure 4 here]

3.4 Econometric Specification

My empirical strategy is based on an OLS regression framework. By exploiting individual variation in the dynamic inconsistency parameter β, the regression equation can be formalized as

$$\text{Food waste}_i = \alpha_0 + \alpha_1 \beta_i + \mathbf{X}_i \alpha_2 + \epsilon_i, \tag{10}$$

with i indexing the individual and α_0 being the constant. The parameter β is the regressor of interest. I consider three different food waste measures as outlined in Subsection 3.2: First, a 'food going bad' index measuring the incidence of food going bad in four different categories. The second outcome variable is the 'waste best before date' dummy indicating whether an individual threw away food because the best before date was exceeded. The third measure is a 'waste leftovers' dummy equalling 1 if a respondent states to have thrown away leftovers stored with the intention to consume it. All three outcome variables are observed in wave 1 as well as in wave 2 enabling an analysis over time by regressing food waste measures from wave 2 on the dynamic inconsistency parameter measured in wave 1. The error term ϵ captures noise such as surprises or unpredictability in daily life that might affect the amount of food going to waste.

The vector $\mathbf{X}$ includes four distinct categories of control variables. First, I control for long-run patience δ and risk preference. The second group is reflecting socio-demographic and household characteristics and contains the variables age, gender, tertiary education dummy, employment dummy, single household dummy, child below 12 dummy and distance to the next grocery store. The third category consists of food behavior and individual lifestyle controls including the variables vegetarian dummy, share of organic food, discounter index, food preparation experience, number of grocery purchase and the number of out-of-home eating occurrences. The last category contains two variables reflecting the Covid-19 pandemic situation: working from home measured in days and the Covid-19 stringency index measured at state level.

Table 3 presents correlations between the dynamic inconsistency measure β, long-run patience parameter δ as well as the discount factors $DF1$ and $DF2$ with economic variables that have an intertemporal component. As Table 3 shows, almost all correlation coefficients go into the expected direction suggesting that the time preference measures I apply do not reflect simply noise but are able to capture true intertemporal preferences.

[insert Table 3 here]

Table 3 first shows an expected stronger correlation between $DF1$ with long-run patience δ ($\rho = 0.65$) and $DF2$ with the present bias parameter β ($\rho = 0.96$). Contrary to my expectation, the parameters β and δ are not systematically correlated, but both discount factors are ($\rho = 0.78$). Third, Table 3 shows that more present-biased individuals ($\beta \downarrow$) have a lower likelihood of obtaining a tertiary education degree, are rather smokers and have a higher body mass index indicating overweight. They also have a more unhealthy diet compared to less present-biased individuals. Although correlation coefficients are relatively small they are comparable to coefficients reported in Courtemanche et al. (2015) who also show highly significant correlations applying the identical time preference elicitation method.

Interestingly and contrary to my expectations, the long-run patience parameter δ is not systematically associated with intertemporal outcome variables while the discount factor $DF1$ shows the expected correlations except for tertiary education. These differences might stem from a response error that δ is subject to due to an annualization of monthly delay. In an alternative specification, I use both discount factors directly instead of the computed parameters. The results do not change qualitatively.[16]

4 Results

4.1 Dynamic Inconsistency and Food Waste

I start the analysis by reporting results of regressing the food going bad index on the present bias parameter β and as well as control variables. As Table 4 shows variables from the four control categories are gradually added. In column 1, only β is considered. In column 2, preference controls are taken into account. In columns 3-5, socio-demographic and household characteristics, food behavior and lifestyle characteristics and Covid-19 controls are added to the regression. All columns are based on OLS regressions with robust standard errors in parenthesis.[17] The coefficient of interest, β, decreases slightly as more control variables are added, but stays highly significant throughout all specifications.

[insert Table 4 here]

As Table 4 shows, as β increases (present bias decreases), the food going bad index decreases suggesting that less food is going bad if individuals are less present-biased. In terms of effect sizes, an increase of β by 10% is associated with a decrease in the food going bad index by 0.1 units or 2% (column 5).[18] The long-run patience parameter δ has no significant effect. In accordance with the theoretical considerations made in section 2, these results suggest that indeed behavioral inconsistencies over time are more relevant for assessing food waste behavior than long-run patience. Summarizing coefficients for control variables, respondents indicating to be more risk seeking, to be employed, to have at least one child below the age of 12, respondents indicating a higher number of grocery purchases as well as individuals that eat out of home more often experience systematically more food going bad. A higher age, living in a city, and more food preparation experience are associated with less food waste.

[16] Results are available upon request.

[17] Due to missing observations in two control variables, the sample for the regression analysis consists of 1,261 observations in wave 1 and 867 observations in wave 2.

[18] The effect size is calculated as following: If β increases by 1.11 units from 0.01 (minimum) to 1.12 (maximum), the food going bad index decreases by 1.002 units or $1/5 = 20\%$. If β increases by 0.11 units (moving from the mean estimate of $\beta = 0.888$ to time consistency with $\beta = 1$ is equivalent to this 10% increase), the index value decreases by 0.1 units or $0.1/5 = 0.02$.

Table 5 summarizes results for all three outcome variables. All regressions are based on the most specified regression equation that is shown in column 5 of Table 4. While the first three columns apply to wave 1 food waste measures, columns 4-6 are based on second wave outcomes. In each column, results for one of the three outcome variables are shown. The following control variables are measured in wave 1 *and* wave 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time.

[insert Table 5 here]

Wave 1 coefficients for β are highly 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 being thrown away because the best before date is exceeded by 1.75%.[19] A similar increase in β correlates with a decrease in the likelihood of having stored leftovers thrown away by 1.55%. Turning to wave 2 outcomes, coefficients stay significant: An increase in β from 0.88 to 1 correlates with a decrease in the food going bad index by 1.36%, followed by a decrease in food waste because the best before date is exceeded by 2.90%. The effect on the waste of stored leftovers dummy is -1.83%. Long-run patience measured by δ has no effect on any food waste measure in wave 1 or 2, and more risk seeking individuals in the sample waste more food.

Changes in coefficient size over time might be (partially) driven by attrition from wave 1 to wave 2. A correlation analysis reveals significant associations between dropping out in wave 2 and preference measures: $\rho = -0.10$ ($p = 0.00$) for β, $\rho = -0.10$ ($p = 0.00$) for δ and $\rho = 0.13$ ($p = 0.00$) for the risk preference measure, and attrition and food waste outcomes: $\rho = 0.10$ ($p = 0.00$) for the food going bad index, $\rho = 0.10$ ($p = 0.00$) for food waste because the best before date is exceeded and $\rho = 0.09$ ($p = 0.00$) for waste of leftovers. These results suggest attrition of individuals with larger dynamic inconsistencies and higher impatience that also show a tendency to waste more food. Although coefficient estimates for β vary between wave 1 and 2, this difference is only significant for the food going bad index: Results from a joint regression of the food going bad index 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 ($p = 0.034$). For the other two comparisons (columns 2 vs. 5 and 3 vs. 6), the difference in estimates for β is statistically not significant ($p = 0.778$ and $p = 0.964$).

Detailed results for single coefficients of all control variables are displayed in Table A3 in the Appendix. Age has a negative effect on food waste: older individuals waste less food compared to younger ones. This finding is also very robust in the literature (Jörissen et al., 2015; Koivupuro et al., 2012; Piras et al., 2021; Quested et al., 2013; Secondi et al., 2015). I find no systematic

[19] The effect size is calculated as following: An increase in β by 1.11 units (from min to max value) leads to a decrease in the dummy by 0.159 units or $1.11 \times -0.159 = 0.1765$. A 10% increase in β is equivalent to a 0.11 unit change. The effect therefore is $0.11 \times -0.11 = 0.01749$ or 1.75%.

effect of gender or higher education which is contrary to Buzby et al. (2002) and Secondi et al. (2015) and Landry and Smith (2019), Piras et al. (2021), and Secondi et al. (2015) that observe women and better educated individuals to waste more food. Contrary to Grainger et al. (2018) and Secondi et al. (2015) who show that employment status matters, employed individuals in my sample do not show a systematic tendency to waste more food. The single household dummy is systematically associated with less food waste in wave 2. Studies often also find an income effect: individuals with higher income tend to also waste more (Buzby et al., 2002; Koivupuro et al., 2012; Piras et al., 2021; Secondi et al., 2015). In this study, the evidence is mixed. While the coefficient for wasting food that exceeded the best before date is significant and positive in wave 1, there is a systematically negative association for food going bad in wave 2. Having a child below the age of 12 increases food waste for all three measures and in both waves. This finding is in line with results of Ellison and Lusk (2018), Grainger et al. (2018), and Piras et al. (2021) but contrary to Landry and Smith (2019). I observe no systematic tendency that individuals living in cities report more food waste than respondents living in rural areas. This is in line to results of Landry and Smith (2019) but contradicts findings of Secondi et al. (2015).

Out of the food behavior and individual lifestyle control category, three variables are systematically related to food waste behavior: Respondents with more food preparation experience report to waste less food. Also the number of own grocery purchases and the number of out-of-home eating occurrences are significantly associated with food waste. As both numbers go up, also waste increases. In the last control category, the working from home coefficient is significant in the second wave but not the first: As individuals spend more days working from home, they also waste more food. The Covid-19 stringency index at state level has no systematic effect.

Although I include many control variables in the regression, estimated coefficients reported in Table 5 can only be interpreted as correlations if I cannot rule out a bias. While I control for a potential influence of the Covid-19 pandemic on both dynamic inconsistency measure and food waste behavior, one potential source of an omitted variable bias that might distort coefficient estimates upwards is limited attention (DellaVigna, 2009). This potential source of bias is more difficult to capture, and I will take a deeper look at the causal identification of effects in the robustness section. To summarize the finding from the robustness tests, I cannot entirely rule out an omitted variable bias caused by limited attention. But the main findings and overall conclusions do not change after running several robustness checks. They suggest a very robust relation between dynamic inconsistency and individual food waste behavior (despite a small potential overestimation of true effects).

As pointed out in Section 2, a second potential consequence of dynamically inconsistent time preferences is a shorter distance between two grocery shopping trips leading to an increase in grocery spending. To investigate this link, Table 6 summarizes results by again gradually adding control variables to the variable of interest β. The dependent variable is the logarithmized monthly grocery spending measured in Euros at household level (monthly average over the last six months). The results suggest that age, household income, having a child below the age of 12, the distance to the next grocery store, food preparation experience, the number of own grocery purchases and the number of days an individual works remotely from home are positively associated with grocery spending. Being a single household, shopping at discounters more often and eating out more often is associated with lower grocery spending. While these effects seem reasonable, the results also show that present-biased behavior is not systematically correlated with grocery spending. This finding suggests that present-biased individuals deviate from their consumption intentions by rather leaving out single healthier food items instead of completely replacing healthier meals with unhealthier alternatives.

[insert Table 6 here]

4.2 Mechanism Exploration

The goal of Section 4 is to investigate the relation between dynamically inconsistent time preferences and food waste. So far, the evidence provided indeed suggests a systematic link. The goal of this subsection now is to move from the reduced form results reported in Table 5 to a more holistic testing of the mechanisms suggested in Section 2. Summarizing the reasoning that links dynamic inconsistency and food waste[20], present-biased individuals have intentions about when to consume food items. This advance choice is made at the grocery shopping stage. Dynamic inconsistency leads to a deviation from those intentions at home when the advance choice is reconsidered from a present perspective (immediate choice). This deviation implies that the consumption of healthier food items is postponed by at least one time period, and that these healthier food items are stored longer than intended. Given predetermined perishability, the likelihood that these food items are going to waste increases.

To investigate this reasoning, I proceed in three steps. First, I provide evidence suggesting that dynamically inconsistent individuals indeed plan their at home food consumption at the shopping stage. Second, I show that dynamically inconsistent individuals deviate from their intentions and postpone consumption of healthier food items at home. And third, I link deviations from consumption intentions to individual food waste behavior.

Coming to the first step, respondents make plans (advance choices) for at-home consumption by looking in the fridge before going to the grocery store, writing a shopping list and purchasing fruits and vegetables in advance. Asked for planning habits with respect to the last grocery shopping trip, 78.5% of respondents indicate to have checked how full the fridge is before going to the grocery store. And 79.1% of individuals indicate to have written a shopping list. Two-thirds of respondents did both, checking the fridge and writing a shopping list. Asked for the average number of days they buy fruits and vegetables in advance, respondents indicate to buy fruits and vegetables for an average of four days in advance.

Table 7 provides evidence that dynamically inconsistent individuals are not different in their planning behavior than dynamically consistent individuals. For this analysis, I regress the three

[20]Figure 3 summarizes the reasoning graphically.

outcome variables for planning behavior on the dynamic inconsistency measure. For each outcome variable, I look at two different specifications. First, I take the parameter β as in the regressions before. Second, I follow the studies of Ashraf et al. (2006) and Meier and Sprenger (2010) suggesting to create a present bias dummy variable. In their experimental study applying CTB sets, Augenblick et al. (2015) use the threshold of 0.99 to create the dummy variable. Applying this threshold to the survey data, 80% of respondents in my sample would be classified as being present-biased. With this threshold, Augenblick et al. (2015) only classify 33% of subjects as being present-biased over money and 56% as being present-biased over effort. Since the suggested elicitation method in this study has a tendency to be sensitive in relation to experimental elicitation techniques[21], I suggest an alternative threshold at $\beta < 0.95$. With this definition, 49% of individuals are classified as being present-biased in my sample. The results summarized in Table 7 are not sensitive at all to the threshold specification.[22]

[insert Table 7 here]

Focusing on the first outcome variable (fridge checking dummy) in Table 7, dynamically more inconsistent individuals (columns 1) as well as individuals with a present bias dummy equalling 1 do not show a systematic tendency to engage less in consumption planning behavior: Both coefficients are not statistically significant. Results for the second outcome variable (shopping list dummy) are similar: There is not systematic difference between dynamically inconsistent and consistent individuals in consumption planning behavior. The third outcome variable focuses on the number of days fruits and vegetables are purchased in advance. Here, the effects are comparable to the other two variables. Indeed, results in column 5 suggest that more inconsistent individuals (lower β) purchase for even more days in advance. But the coefficient is only marginally significant and the present bias dummy specification in column 6 again suggests that there is no effect.[23] Table A4 in the Appendix provides an overview of coefficient estimates for all control variables.

Coming to the second step, I provide evidence that dynamic inconsistency leads to deviations from intentions to consume healthier food at home. To test this proposition, I make use of five questions in the survey that aim at capturing actual behavior (immediate choice) deviating from intended behavior (advance choice). While the parameters δ and β are measured over money, these questions are tailored to food consumption behavior. Respondents can indicate their agreement to five separate statements on a 4-point Likert scale. The questions ask:

> We would now like to ask you to rate the following statements. On a scale from "Not at all true" to "Strongly true," you can indicate how likely a statement has been true for you in the last four weeks.

[21] Also the mean of β with 0.888 is lower compared to the estimate in Augenblick et al. (2015) with $\beta = 0.97$. In the meta-analysis of Imai et al. (2021), the average β is at 0.97.

[22] With a threshold at $\beta < 0.9$, 30% are classified as being present-biased. Irrespective of the threshold (0.99, 0.95, 0.90), results do not change.

[23] Regressions for the outcome variable 'purchasing in advance' are based on 1,241 observations since 20 respondents indicate to have not bought fruits and vegetables in advance during the last four weeks.

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 snack bars or picked up food myself instead of preparing something myself

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

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

[5]...left fruits and vegetables out longer than I intended.

While the first statement refers to deviating from own intentions in the grocery store, statements 2-5 apply to food consumption behavior at home. Specifically, these statements capture consumption behavior that should directly affect the amount of healthier food consumed because these behaviors lead to a consumption of more tempting food. Figure 3 summarizes descriptive statistics. Referring to food consumption behavior in the last four weeks, 58% of individuals in the sample rather or strongly agree to have bought sweets or snacks that they did not intend to buy when entering the grocery store. Focusing on the four statements referring to at home consumption, 17% of respondents indicate to have prepared fresh meals at home less often than intended. Around 43% have left fruits and vegetables out longer than intended. Around 17% of individuals report to have eaten more convenience food than intended, and 26% ordered more food from food delivery services than intended.

Considering statements 2-5, I construct a 'Deviating at home' index. I code the answer 'not at all true' as 1 and 'strongly true' as 4 and create dummies taking a 1 for values greater than 2 (a statement is rather or strongly true). I sum up the four dummy variables creating an index taking values between 0 and 4. The larger the index value is, the more often an individual deviates from consumption intentions at home. The mean index value is 1.02, with a standard deviation of 1.10. The deviate at home index is highly correlated with following a healthier diet: $\rho = -0.21$ ($p = 0.00$).

In Table 8, I regress the deviate at home index on β. From column 1 to 5, I gradually add control variables from the four categories summarized in Subsection 3.1. In all regression specifications, dynamically inconsistent behavior is significantly correlated with deviating more from own consumption intentions at home. In the full specification in column 5, an increase in β of 10% is associated with a decrease of the deviate at home index by 0.87%.[24] Also in line with expectations, more patient individuals with higher δ deviate less from their consumption plans. The evidence provided in Table 8 suggests that, indeed, individuals with higher dynamic inconsistencies deviate more from their consumption plans at home. Table A5 in the Appendix provides an overview of coefficient estimates for all control variables.

[insert Table 8 here]

[24] A change in β by 0.11 units (10%) is associated with a change of the index value by 0.0437 units. This is equivalent to $0.0437/5 = 0.00874$ or 0.87%.

In a third step, I regress the three food waste measures from wave 1 and 2 on the deviate at home index (measured in wave 1) to test whether postponing consumption of healthier food items at home is correlated with individual food waste behavior. Table 9 summarizes results from this exercise. In all regression specifications, the index coefficient is highly significant. In column 1, an increase in the deviate at home index by one unit is associated with an increase in the food going bad index by 0.372 units or 7.44%. It follows that an increase in the deviate at home index by 10% is associated with an increase in the food going bad index by 3.72%. A similar increase is associated with a 3.52% increase in the likelihood of food waste because the best before date is exceeded (column 2). The likelihood to waste stored leftovers increases by 2.36% (column 3). Columns 4-6 refer to wave 2 food waste measures and report similar results: An increase in the deviate at home index of 10% is associated with an increase of food going bad by 2.85%. The likelihood of wasting food because the best before date is exceeded increases by 3.36%, and the likelihood of wasting stored leftovers increases by 2.64%. Coefficient estimates between columns 1 and 4 are statistically significant from each other ($p = 0.076$); differences from the other two comparisons (columns 2 vs. 5 and 3 vs. 6) are not significant ($p = 0.572$ and $p = 0.512$). Similar to results reported in Table 5, there is no systematic effect of long-run patience δ on food waste measures, and risk seeking individuals waste more food. Table A6 in the Appendix provides an overview of coefficient estimates for all control variables. Taking the evidence from all three steps together, I find empirical support for the conceptual reasoning introduced in Section 2.

[insert Table 9 here]

4.3 Robustness Tests

So far, I have interpreted results reported from regressions of the food waste measure on the dynamic inconsistency parameter β as causal effects given a rich set of control variables also including Covid-19 controls that might otherwise lead to biased estimates. But maybe Covid-19 related factors are not the only source of bias. In this subsection, I will now lead a discussion about further factors that might potentially bias coefficient estimates in Table 5. In the second part of this subsection, I will provide empirical evidence for the assumption that dynamic inconsistency stays constant over time.

4.3.1 Causal Identification First, one potential bias might stem from measurement error. The parameter identification for β relies on only two questions. In experimental studies, usually more allocation choices per individual are taken to identify a present bias. The two applied hypothetical elicitation questions[25] might also be more difficult to answer compared to money allocation choices in experiments that are truly paid out. If the regressor of interest (β) would

[25] See Subsection 4.1 for the exact wording.

suffer from measurement error, estimated coefficients would be downward biased in absolute terms and I would estimate lower bounds of the true effects.

Second, a more severe bias might result from limited attention. Attention in everyday life is a limited resource. Following DellaVigna (2009), a reduced salience or the number of competing stimuli might systematically distract attention away from recognizing how much food one is wasting at home. It might also result in a wrong perception of the two questions on monetary amounts included in the survey to calculate β. Following this reasoning, respondents not paying full attention would systematically underestimate food waste incidences, and at the same time they might give identical answers in the two money questions resulting in β being too low by construction.[26] This omitted variable would bias coefficients reported in Table 5 upwards.

A check of the number of respondents that state the exact same amount in both questions reveals that around 20% of individuals give identical answers. To alleviate concerns about a potential overestimation of the true effect of β on food waste behavior, I first exclude all observations with equal monetary amounts indicated in both money questions from the sample and re-run the analysis with the rest 80% of the sample.

Summarizing the results from this exercise, when regressing the three food waste measures on β, I still observe highly significant coefficients for two outcome measures: the food going bad index and waste best before date dummy. Coefficients for the waste leftovers dummy turn insignificant but were also estimated with least precision in the main analysis in Table 5. Concerning coefficient size, the evidence is not entirely clear. All coefficients increase for wave 2 outcomes (in absolute terms) speaking against a bias due to limited attention: For the food going bad index, the coefficient now is $1.641 > 0.680$. The coefficient of the waste best before dummy now changes to $0.585 > 0.264$, and the coefficient for the waste leftovers dummy changes to 0.184 (insignificant) > 0.166. Two out of three wave 1 coefficients become smaller in absolute terms: the coefficient for the food going bad index changes to $0.964 < 1.002$. Also the coefficient for the waste leftovers dummy reduces to 0.078 (insignificant) < 0.141. The coefficient for the waste best before dummy increases to $0.236 > 0.159$. If anything, a potential bias in wave 1 estimates would be rather small.

Since this evidence does not clearly rule out a potential overestimation of true effects, I suggest an alternative measure for dynamic inconsistency as a second robustness check: The survey includes two items measuring the level of procrastination and patience. Both variables are 11-point Likert scale preference measures taken from the GSOEP, a large-scale longitudinal data set managed by the German Institute for Economic Research. The procrastination variable asks how much individuals agree to the statement 'I tend to put off tasks even when I know it would be better to do them right away'. The value 0 indicates no agreement at all, while 10 means full agreement. The patience variables asks how much an individual would be willing to give up something that benefits her today in order to benefit more in the future. Willingness increases from 0 (not at all willing) to 10 (totally willing). I use procrastination as a proxy for

[26] See Subsection 4.1 for the calculation of β.

dynamic inconsistency because this measure captures the aspect of postponing unpleasant tasks and deviating from own plans made for the future. I include the patience variable to proxy the level of long-run discounting. I re-run the analysis and report results in Table 10.

[insert Table 10 here]

Columns 1-3 again refer to food waste measures from wave 1 while columns 4-6 report results for wave 2 outcomes. Table 10 shows that the procrastination coefficient is highly significant across all specifications. The estimate in column 1 implies that a 10% increase in procrastination is associated with a 0.96% increase in the food going bad index. A similar increase in procrastination leads to an increase in the likelihood of food being wasted because the best before date is exceeded by 1.54% (column 2), and results in a 1.76% higher likelihood of stored leftovers being wasted (column 3). Wave 2 results are very similar with effect sizes of 1.06%, 1.32% and 1.87%. Compared to results reported in the main analysis in Table 5, the effect size for the food going bad index and waste best before dummy slightly decreases in both waves while it increases slightly for the waste leftovers dummy. Table A7 in the Appendix provides an overview of coefficient estimates for all control variables.

With respect to effect sizes, the evidence provided from both robustness tests cannot rule out the existence of an omitted variable bias resulting in a small overestimation of true effects. Both tests suggest that the findings and overall conclusions are very robust to these alternative model specifications: Coefficients from a regression of individual food waste behavior on dynamic inconsistency are statistically highly significant.

4.3.2 Stability of Inconsistency So far, I assumed that dynamic inconsistency is constant over time. While I can calculate the two parameters β and δ only for wave 1, I observe the procrastination measure in both waves. Looking at the association over time, the correlation coefficient is large in size and highly significant: $\rho = 0.65$ ($p < 0.00$) providing evidence that, indeed, dynamically inconsistent behavior has a constant component over time. In a second step, I repeat the regression analysis from Table 10 but now use the wave-specific measure of procrastination to test whether estimates over time are significantly different from each other. Table 11 reports the results from this exercise. A comparison of column 1 vs. 4, 2 vs. 5 and 3 vs. 6 reveals no systematic difference between the estimates: the interaction term of procrastination and wave is statistically not significant with $p = 0.46$, $p = 0.99$ and $p = 0.41$. This finding provides some evidence that the correlation of dynamically inconsistent preferences and food waste behavior is stable over time.

[insert Table 11 here]

5 Conclusion

This paper analyzes the link between dynamically inconsistent time preferences and individual food waste behavior. Conceptualizing food waste as unintended consequence of deviating from own intentions to consume healthy food at home, I show that more present-biased individuals waste more food. This result is robust to different model specifications including different sets of controls, and using alternative measures for present-biased behavior. Based on my conceptualization, I further provide evidence supporting reduced form results: More present-biased individuals make plans for at-home food consumption, but deviate from their plans when the future becomes present by consuming unhealthier food and postponing the consumption of healthier food at home. Finally, I show that individuals deviating more from consumption intentions also waste more food at home.

The extent of present bias is not systematically correlated with the level of grocery spending. This finding suggests that more present-biased individuals do not shop groceries more often. It implies that inconsistent individuals deviate from their consumption intentions by rather leaving out single meal ingredients instead of replacing full meals potentially necessitating to shorten the time interval between two shopping trips (and to increase grocery spending).

Based on the theoretical conceptualization, the novel data set and empirical analysis, this paper adds a new behavioral economic perspective on household food waste and contributes to an understanding of possible determinants and drivers. It is important to recognize that this study cannot entirely rule out identification biases. Although I consider a rich set of control variables, factors such as limited attention might induce an upward bias of coefficient estimates. Even tough highly significant effects across different model specifications and over time strongly support the relevance of dynamically inconsistent time preferences for food consumption and waste behavior at home, topics focusing on a causal identification of different behavioral determinants of individual waste behavior provide an important avenue for future research.

This research is critical for a holistic understanding of the unintended effects of food policy innovations. The aim of recent food policy changes is to foster healthier nutrition by committing individuals to healthier food choices made in advance of the actual grocery shopping trip. An example is the policy change by the USDA to allow online pre-ordering under SNAP. An unintended negative effect of this policy innovation can be the increase of food going to waste. The results of this study suggest that dynamically inconsistent time preferences not only affect grocery shopping but also food consumption behavior at home. Even though individuals might make healthier food purchasing choices they might not eat the healthier food at home. Instead, these food items might go bad and end up being wasted. Thus, as unintended consequence of this policy innovation, instead of fostering a healthier nutrition only food waste goes up (with negative environmental and societal consequences). This 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.

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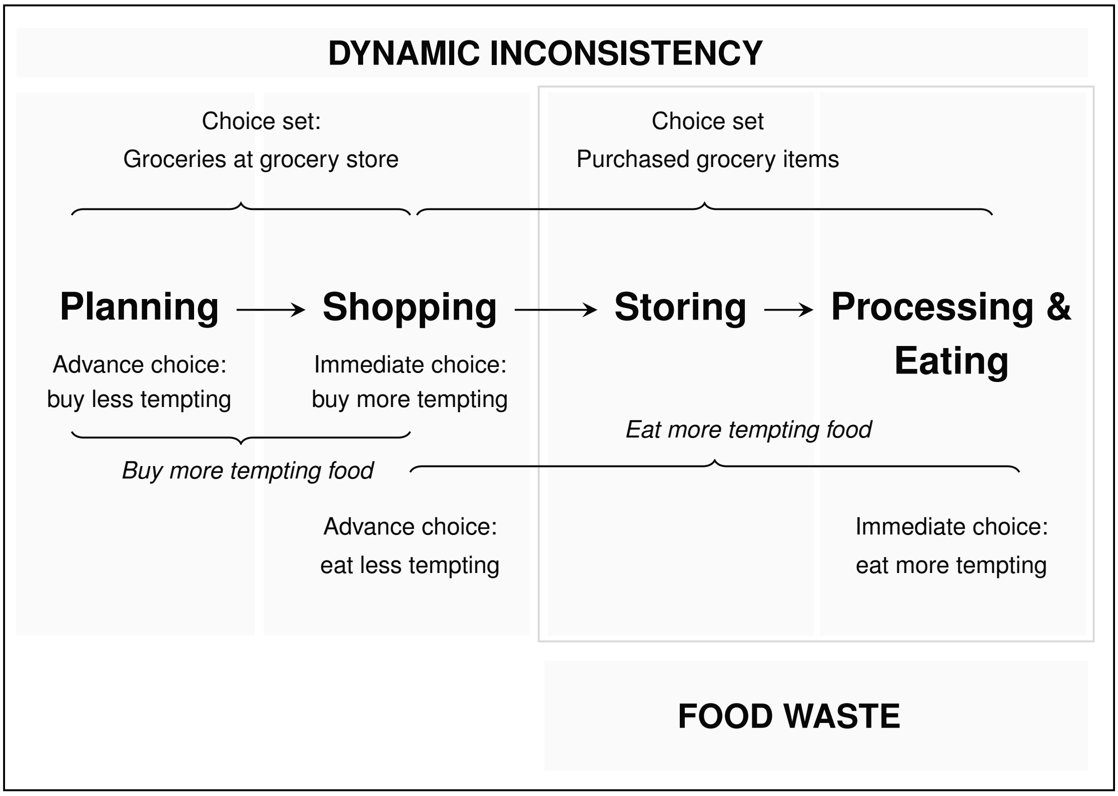
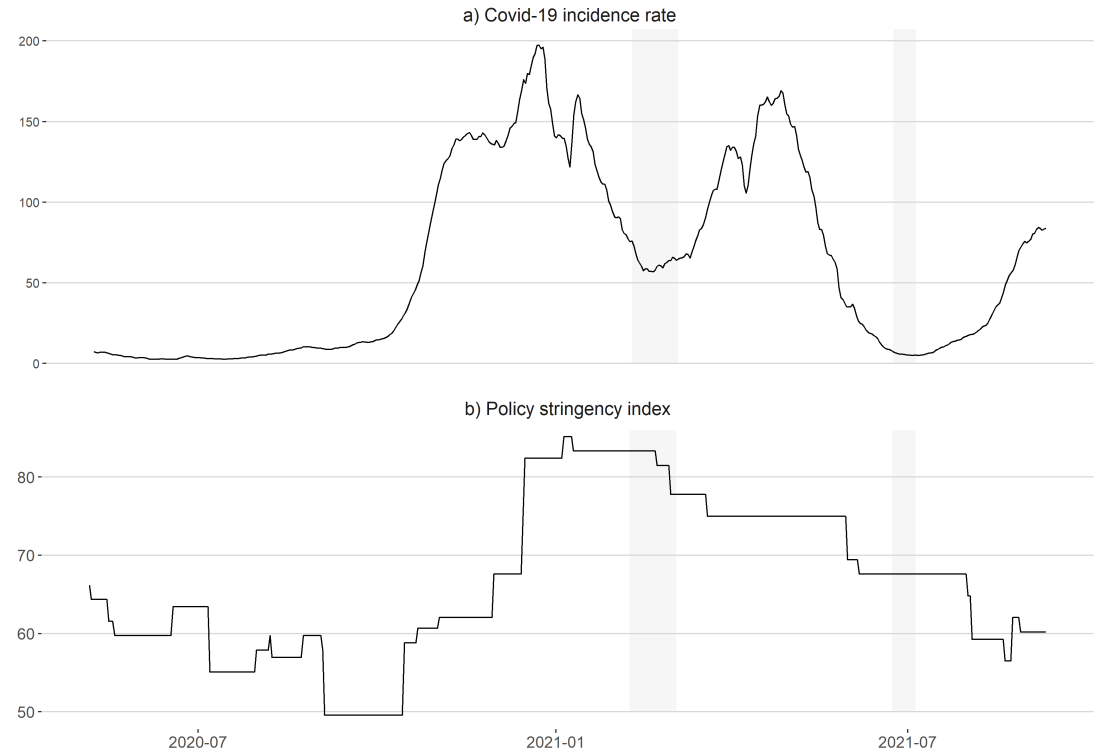
Figure 1: *Food consumption and dynamic inconsistencies*



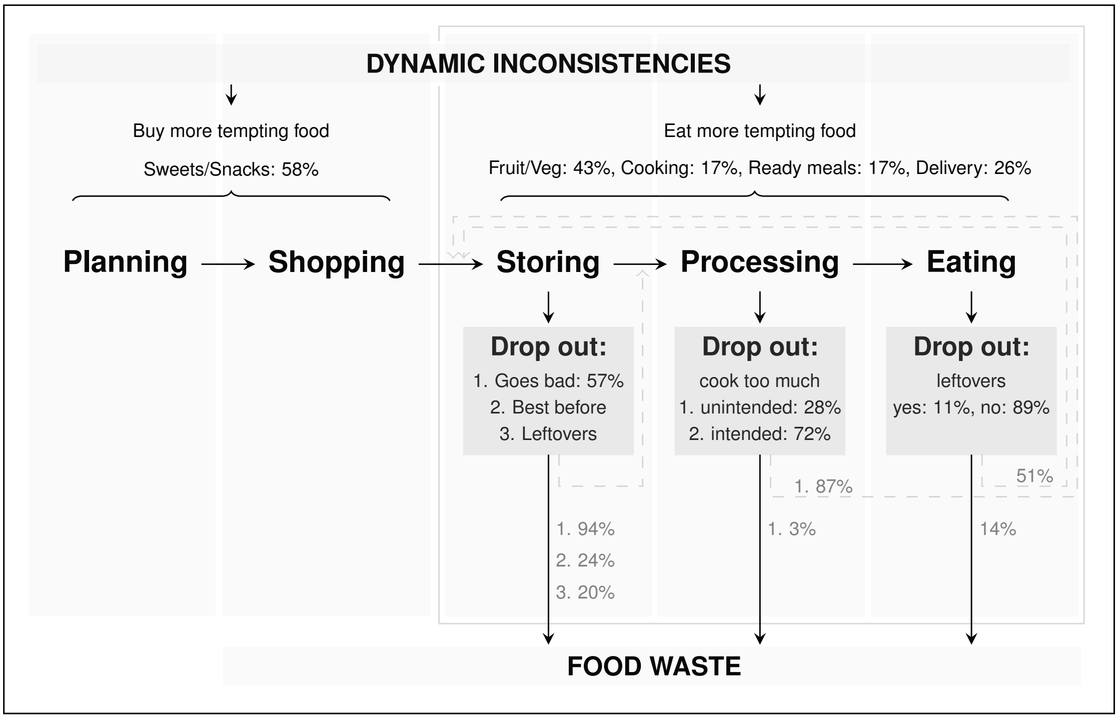
Note: The figure depicts the food consumption process. Daily food consumption decisions are modelled as a sequence of single consumption choices that are made at different points in time: from purchase planning, grocery shopping and storing to food processing and eating. Individuals have to make several 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.

Figure 2: *Covid-19 incidence rates and policy strigency index*



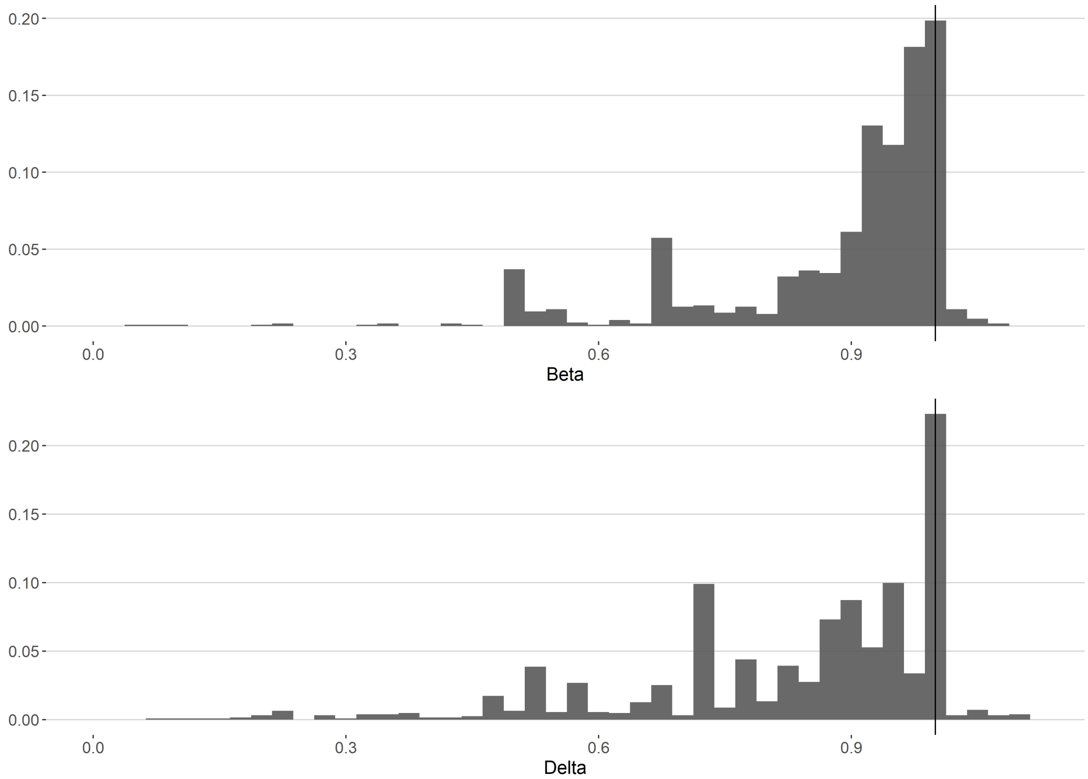
Note: The figure depicts the pandemic situation and stringency of policy response between May 2020 and September 2021 in Germany. Panel a) plots the development of the Covid-19 incidence rate while panel b) shows the Oxford Policy Stringency Index created by Hale et al. (2020). The index constitutes 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 grey 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.

Figure 3: *Dynamic inconsistency and food waste*



Note: The figure depicts the food consumption chain and summarizes figures based on the survey data with respect to two areas. First, present-biased individuals deviate from their intentions to consume healthier food in the future (upper part of the figure). Figures illustrating this deviation behavior are provided for the different stages of the food consumption chain. Second, present-biased individuals postpone the consumption of healthier food items which increases the likelihood of these items to go bad. Numbers illustrating food waste behavior are given for the different consumption stages in the lower part of the figure.

Figure 4: *Distribution of beta and delta*



Note: The figure depicts the distribution of the two time preference parameters. The distribution for 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 1: *Summary statistics*

Statistic	N	Mean	SD	Min	Max
Outcomes Wave 1:					
Food going bad index	1,273	1.222	1.366	0	4
Waste best before dummy	1,273	0.237	0.426	0	1
Waste leftovers dummy	1,273	0.199	0.399	0	1
Outcomes Wave 2:					
Food going bad index	869	1.067	1.341	0	4
Waste best before dummy	869	0.212	0.409	0	1
Waste leftovers dummy	869	0.217	0.413	0	1
Controls Wave 1:					
Risk seeking	1,273	4.483	2.349	0	10
Age	1,273	44.676	14.377	18	69
Female	1,271	0.501	0.500	0	1
Tertiary education dummy	1,273	0.412	0.492	0	1
Employment dummy	1,273	0.707	0.455	0	1
Single household dummy	1,273	0.478	0.500	0	1
Household income	1,273	2,661.322	1,648.027	250.000	10,001.000
Child below 12 dummy	1,273	0.134	0.341	0	1
City dummy	1,271	0.378	0.485	0	1
Distance grocery store	1,273	12.924	10.678	1	36
Vegetarian dummy	1,273	0.177	0.382	0	1
Share organic food	1,273	2.188	1.702	0	7
Discounter index	1,273	0.466	0.290	0.000	1.000
Food preparation experience	1,273	3.335	1.933	0	11
No. grocery purchases	1,263	2.310	1.915	0	10
No. out-of-home eating	1,273	0.397	0.876	0	7
Working from home (days)	1,273	1.445	2.049	0	5
Covid-19 stringency index	1,271	71.814	4.485	66.667	80.093
Controls Wave 2:					
Age	869	47.606	13.977	18	100
Female	868	0.483	0.500	0	1
Tertiary education dummy	869	0.514	0.500	0	1
Employment dummy	869	0.700	0.459	0	1
Single household dummy	869	0.510	0.500	0	1
Household income	869	2,676.254	1,626.789	250.000	10,001.000
Child below 12 dummy	869	0.154	0.361	0	1
City dummy	869	0.375	0.484	0	1
Share organic food	869	2.346	1.857	0	7
No. grocery purchases	869	2.992	2.606	0	20
No. out-of-home eating	869	0.618	1.083	0	7
Working from home (days)	869	1.191	1.883	0	5
Covid-19 stringency index	867	62.196	2.363	59.259	69.907

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 1,273 but reduces to 1,271 since two respondents do not indicate valid zip-code information and cannot be assigned a city dummy or stringency index value. In wave 2, for two observations no state can be assigned based on the zip-code information.

Table 2: *Summary statistics: dynamic inconsistency measures*

Statistic	N	Mean	SD	Min	Max
Main regressors:					
Beta β	$1,273$	0.888	0.151	0.005	1.121
Delta δ	$1,273$	0.832	0.183	0.081	1.100
Regressors robustness:					
Procrastination Wave 1	$1,273$	4.299	2.703	0	10
Procrastination Wave 2	869	4.265	2.833	0	10
Patience	$1,273$	5.946	2.147	0	10

Note: Table reports summary statistics for variables measuring dynamic inconsistency. 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.

Table 3: *Correlation of time preference measures with intertemporal variables*

	$DF1$	$DF2$	Beta (β)	Delta (δ)
$DF1$	–	–	–	–
$DF2$	$0.78***$	–	–	–
Beta (β)	$0.60***$	$0.96***$	–	–
Delta (δ)	$0.65***$	$0.17***$	-0.03	–
Tertiary education dummy	0.04	$0.08***$	$0.08***$	-0.03
Smoker dummy	$-0.06**$	$-0.08***$	$-0.08***$	0.00
Body mass index	$-0.05*$	$-0.05*$	$-0.05*$	-0.03
Healthy diet	$0.07***$	$0.10***$	$0.10***$	0.00

Note: The table provides pairwise Spearman correlation coefficients of the time preference measures $DF1$, $DF2$, 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

Table 4: *Food going bad and dynamic inconsistency*

	Food Going Bad Index				
	(1)	(2)	(3)	(4)	(5)
Beta (β)	-1.392^{***}	-1.381^{***}	-1.207^{***}	-1.008^{***}	-1.002^{***}
	(0.273)	(0.270)	(0.266)	(0.272)	(0.273)
Delta (δ)		0.041	0.167	0.146	0.142
		(0.222)	(0.223)	(0.225)	(0.225)
Risk seeking		0.084^{***}	0.060^{***}	0.052^{***}	0.052^{***}
		(0.017)	(0.017)	(0.017)	(0.017)
Age			-0.012^{***}	-0.010^{***}	-0.010^{***}
			(0.003)	(0.003)	(0.003)
Female			1.354	1.434	1.429
			(0.776)	(0.854)	(0.861)
Tertiary education dummy			-0.043	-0.038	-0.046
			(0.079)	(0.079)	(0.080)
Employment dummy			0.284^{***}	0.192^{**}	0.174^{*}
			(0.082)	(0.081)	(0.093)
Single household dummy			-0.015	-0.065	-0.063
			(0.093)	(0.093)	(0.093)
Log household income			0.067	0.067	0.063
			(0.058)	(0.057)	(0.058)
Child below 12 dummy			0.216^{*}	0.232^{**}	0.237^{**}
			(0.119)	(0.116)	(0.116)
City dummy			-0.179^{**}	-0.166^{**}	-0.162^{**}
			(0.080)	(0.078)	(0.079)
Distance grocery store			-0.001	-0.00003	0.0001
			(0.004)	(0.004)	(0.004)
Vegetarian dummy				-0.162	-0.166
				(0.099)	(0.099)
Share organic food				0.003	0.002
				(0.024)	(0.024)
Discounter index				-0.018	-0.018
				(0.135)	(0.135)
Food preparation experience				-0.045^{**}	-0.045^{**}
				(0.019)	(0.019)
No. grocery purchases				0.058^{***}	0.058^{***}
				(0.023)	(0.023)
No. out-of-home eating				0.250^{***}	0.254^{***}
				(0.054)	(0.055)
Working from home (days)					0.010
					(0.022)
Covid-19 stringency index					-0.006
					(0.008)
Constant	2.457^{***}	2.037^{***}	1.757^{***}	1.541^{***}	2.002^{**}
	(0.250)	(0.306)	(0.500)	(0.508)	(0.781)
N	1,273	1,273	1,271	1,261	1,261

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The food going bad 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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 5: *Food waste behavior and dynamic inconsistency*

	Food going bad index W1	Waste best before date dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β)	-1.002^{***}	-0.159^{**}	-0.141^{*}	-0.680^{**}	-0.264^{***}	-0.166^{*}
	(0.273)	(0.086)	(0.082)	(0.322)	(0.101)	(0.094)
Delta (δ)	0.142	-0.015	0.011	-0.236	-0.078	-0.001
	(0.225)	(0.069)	(0.063)	(0.277)	(0.086)	(0.080)
Risk seeking	0.052^{***}	0.015^{***}	0.008	0.051^{***}	0.021^{***}	0.011^{*}
	(0.017)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Constant	2.002^{**}	0.382	0.357	3.377^{***}	1.185^{***}	1.184^{***}
	(0.781)	(0.254)	(0.224)	(1.357)	(0.428)	(0.424)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Covid-19 situation	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.048	0.061	0.027	0.006	0.086
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 6: *Dynamic inconsistency and food spending*

	Log Grocery Spending				
	(1)	(2)	(3)	(4)	(5)
Beta (β)	0.084	0.080	-0.049	-0.070	-0.059
	(0.114)	(0.112)	(0.098)	(0.099)	(0.097)
Delta (δ)		0.220**	0.057	0.045	0.038
		(0.092)	(0.081)	(0.079)	(0.078)
Risk seeking		0.017**	0.011*	0.011*	0.011*
		(0.007)	(0.007)	(0.007)	(0.007)
Age			0.003**	0.002*	0.002*
			(0.001)	(0.001)	(0.001)
Female			-0.502	-0.416	-0.424
			(0.109)	(0.122)	(0.135)
Tertiary education dummy			0.008	-0.009	-0.025
			(0.030)	(0.030)	(0.030)
Employment dummy			-0.038	-0.021	-0.060
			(0.032)	(0.032)	(0.036)
Single household dummy			-0.331***	-0.342***	-0.338***
			(0.036)	(0.035)	(0.035)
Log household income			0.235***	0.219***	0.212***
			(0.024)	(0.024)	(0.024)
Child below 12 dummy			0.079*	0.081*	0.090**
			(0.044)	(0.043)	(0.043)
City dummy			0.002	-0.005	0.002
			(0.031)	(0.031)	(0.030)
Distance grocery store			0.003**	0.003**	0.004**
			(0.001)	(0.001)	(0.001)
Vegetarian dummy				-0.032	-0.040
				(0.039)	(0.039)
Share organic food				0.016*	0.014
				(0.010)	(0.010)
Discounter index				-0.238***	-0.237***
				(0.052)	(0.052)
Food preparation experience				0.022***	0.021***
				(0.008)	(0.008)
No. grocery purchases				0.016**	0.016**
				(0.008)	(0.008)
No. out-of-home eating				-0.038**	-0.030*
				(0.017)	(0.017)
Working from home (days)					0.020**
					(0.008)
Covid-19 stringency index					-0.011***
					(0.003)
Constant	5.493***	5.236***	3.709***	3.890***	4.753***
	(0.103)	(0.130)	(0.201)	(0.205)	(0.310)
N	1,273	1,273	1,271	1,261	1,261

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. Logarithmized grocery spending measured in wave 1 is 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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 7: *Consumption planning behavior*

	Fridge Checking		Shopping List		Purchasing in Advance	
	Beta (β)	Present bias dummy	Beta (β)	Present bias dummy	Beta (β)	Present bias dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic inconsistency measure	-0.002	-0.017	0.113	-0.027	-0.610^{*}	-0.029
	(0.079)	(0.024)	(0.081)	(0.023)	(0.382)	(0.104)
Delta (δ)	-0.033	-0.037	0.013	0.004	-0.091	-0.089
	(0.067)	(0.068)	(0.068)	(0.069)	(0.293)	(0.296)
Risk seeking	-0.0001	-0.0001	-0.001	-0.001	-0.059^{***}	-0.058^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)
Constant	0.533^{**}	0.560^{**}	0.740^{***}	0.854^{***}	5.307^{***}	4.977^{***}
	(0.247)	(0.244)	(0.243)	(0.234)	(1.090)	(1.078)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Covid-19 situation	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.984	0.467	0.145	0.242	0.080	0.780
N	1,261	1,261	1,261	1,261	1,241	1,241

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The variables 'fridge checking dummy', 'shopping list dummy' and 'purchasing 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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 8: *Deviating from intentions at home*

	Deviate at Home Index				
	(1)	(2)	(3)	(4)	(5)
Beta (β)	-0.910^{***}	-0.890^{***}	-0.625^{***}	-0.427^{**}	-0.437^{**}
	(0.221)	(0.218)	(0.209)	(0.202)	(0.203)
Delta (δ)		-0.531^{***}	-0.272	-0.306^{*}	-0.305^{*}
		(0.170)	(0.172)	(0.170)	(0.171)
Risk seeking		0.052^{***}	0.032^{**}	0.029^{**}	0.028^{**}
		(0.014)	(0.014)	(0.013)	(0.013)
Constant	1.827^{***}	2.016^{***}	1.662^{***}	1.330^{***}	1.502^{***}
	(0.202)	(0.244)	(0.418)	(0.419)	(0.430)
Further controls					
Preference controls	No	Yes	Yes	Yes	Yes
Household characteristics	No	No	Yes	Yes	Yes
Food behavior & lifestyle	No	No	No	Yes	Yes
Covid-19 situation	No	No	No	No	Yes
p-value β	0.000	0.000	0.002	0.030	0.032
N	1,273	1,273	1,271	1,261	1,261

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 9: *Deviating from intentions and food waste behavior*

	Food going bad index W1	Waste best before dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Deviate at home index	0.372***	0.088***	0.059***	0.285***	0.084***	0.066***
	(0.039)	(0.013)	(0.012)	(0.048)	(0.014)	(0.015)
Delta (δ)	0.269	0.013	0.031	−0.121	−0.041	0.026
	(0.211)	(0.066)	(0.062)	(0.273)	(0.086)	(0.080)
Risk seeking	0.042***	0.013**	0.006	0.046**	0.019***	0.010*
	(0.016)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Constant	0.428	−0.066	0.035	2.215***	0.457***	0.432**
	(0.484)	(0.155)	(0.138)	(0.558)	(0.180)	(0.178)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Covid-19 situation	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.000	0.000	0.000	0.000	0.000	0.000
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 10: *Procrastination and food waste behavior*

	Food going bad index W1	Waste best before date dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before date dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.044***	0.014***	0.016***	0.048***	0.012**	0.017***
	(0.014)	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)
Patience	−0.019	−0.005	0.003	−0.020	−0.001	−0.004
	(0.020)	(0.006)	(0.006)	(0.023)	(0.006)	(0.007)
Risk seeking	0.053***	0.015***	0.005	0.052**	0.019***	0.010
	(0.018)	(0.005)	(0.005)	(0.021)	(0.007)	(0.006)
Constant	0.699	−0.060	−0.018	2.144***	0.427**	0.408**
	(0.494)	(0.153)	(0.142)	(0.544)	(0.182)	(0.174)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Covid-19 situation	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.001	0.001	0.000	0.003	0.023	0.001
N	1,261	1,261	1,261	867	867	867

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: GSOEP long-run patience measure, risk seeking behavior, (2) socio-demographic and household characteristics: age, gender, tertiary education dummy, employment dummy, single household dummy, log 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table 11: *Procrastination and food waste behavior over time*

	Food going bad index W1	Waste best before date dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before date dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination W1/W2	0.044***	0.014***	0.016***	0.073***	0.014***	0.020***
	(0.014)	(0.004)	(0.004)	(0.015)	(0.005)	(0.005)
Patience	−0.019	−0.005	0.003	−0.016	0.00003	−0.003
	(0.020)	(0.006)	(0.006)	(0.023)	(0.006)	(0.007)
Risk seeking	0.053***	0.015***	0.005	0.050**	0.019***	0.010
	(0.018)	(0.005)	(0.005)	(0.021)	(0.007)	(0.006)
Constant	1.166	0.171	0.117	2.203*	0.840**	0.903**
	(0.769)	(0.245)	(0.219)	(1.329)	(0.428)	(0.417)
Further controls						
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Food behavior & lifestyle	Yes	Yes	Yes	Yes	Yes	Yes
Covid-19 situation	Yes	Yes	Yes	Yes	Yes	Yes
p-value β	0.002	0.001	0.000	0.000	0.003	0.000
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Appendix

Table A1: Attrition analysis

	Attrition Dummy			
	(1)	(2)	(3)	(4)
Age	−0.008***	−0.008***	−0.009***	−0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Female dummy		0.025	0.023	0.020
		(0.025)	(0.025)	(0.025)
Tertiary education dummy			−0.020	−0.020
			(0.026)	(0.027)
Employment dummy			−0.031	−0.027
			(0.028)	(0.029)
Single household dummy				0.011
				(0.030)
Child below 12 dummy				0.094**
				(0.044)
Log household income				−0.007
				(0.020)
City dummy				0.001
				(0.026)
Constant	0.690***	0.672***	0.720***	0.739***
	(0.044)	(0.047)	(0.059)	(0.161)
N	1,273	1,273	1,273	1,271

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

Table A2: *Description of variables*

Variable name	Definition
Outcomes:	
Food going bad index (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 equalling 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.
Waste best before dummy (W1/W2)	Dummy equalling 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 equalling 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 equalling 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 equalling 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 equalling 1 if individual has a tertiary education degree.
Employment dummy	Dummy equalling 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 dummy	Dummy equalling 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 equalling 1 if at least one child below the age of 12 lives in the household.
City dummy	Dummy equalling 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 equalling 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.

Food preparation experience	Number of prepared meals for him/herself and others (household members, flat mates) within the last two days not including survey day; measured on a scale ranging from 0 to "more than 10" coded as 11.
No. grocery purchases	Number of own total grocery purchases (online and on-sight) per week (average over last four weeks).
No. out-of-home eating	Number of meals eaten out of the home (in canteens, restaurants, offices, cafes, other households) within the last two days not including survey day.
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.

Table A3: *Food waste behavior and dynamic inconsistency*

	Food going bad index W1	Waste best before date dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Beta (β)	-1.002^{***}	-0.159^{**}	-0.141^{*}	-0.680^{**}	-0.264^{***}	-0.166^{*}
	(0.273)	(0.086)	(0.082)	(0.322)	(0.101)	(0.094)
Delta (δ)	0.142	-0.015	0.011	-0.236	-0.078	-0.001
	(0.225)	(0.069)	(0.063)	(0.277)	(0.086)	(0.080)
Risk seeking	0.052^{***}	0.015^{***}	0.008	0.051^{***}	0.021^{***}	0.011^{*}
	(0.017)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Age	-0.010^{***}	-0.003^{***}	-0.003^{***}	-0.008^{**}	-0.002^{*}	-0.002^{**}
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	0.059	-0.005	0.036	0.115	-0.035	0.027
	(0.081)	(0.025)	(0.023)	(0.091)	(0.028)	(0.028)
Tertiary education dummy	-0.046	-0.010	0.019	-0.065	-0.027	0.004
	(0.080)	(0.026)	(0.024)	(0.091)	(0.029)	(0.029)
Employment dummy	0.174^{*}	0.007	0.004	-0.047	-0.050	-0.005
	(0.093)	(0.030)	(0.027)	(0.107)	(0.033)	(0.032)
Single household dummy	-0.063	0.034	-0.016	-0.478^{***}	-0.083^{***}	-0.105^{***}
	(0.093)	(0.029)	(0.026)	(0.095)	(0.031)	(0.030)
Log household income	0.063	0.043^{**}	0.022	-0.132^{**}	-0.010	-0.029
	(0.058)	(0.018)	(0.017)	(0.070)	(0.020)	(0.021)
Child below 12 dummy	0.237^{**}	0.066^{*}	0.095^{***}	0.235^{*}	0.127^{***}	0.135^{***}
	(0.116)	(0.041)	(0.041)	(0.133)	(0.045)	(0.045)
City dummy	-0.162^{**}	-0.003	-0.001	-0.066	-0.035	0.008
	(0.079)	(0.025)	(0.024)	(0.093)	(0.029)	(0.029)
Distance grocery store	0.0001	-0.001	0.001	-0.002	-0.001	0.001
	(0.004)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	-0.166	-0.056^{*}	-0.045	-0.160	-0.035	-0.029
	(0.099)	(0.031)	(0.031)	(0.106)	(0.033)	(0.036)
Share organic food	0.002	-0.015^{**}	-0.008	-0.037	-0.010	-0.003
	(0.024)	(0.007)	(0.007)	(0.023)	(0.007)	(0.007)
Discounter index	-0.018	-0.040	0.030	0.020	-0.066	-0.014
	(0.135)	(0.041)	(0.038)	(0.149)	(0.046)	(0.045)
Food preparation experience	-0.045^{**}	-0.001	-0.010^{*}	-0.040^{*}	-0.017^{**}	-0.009
	(0.019)	(0.006)	(0.006)	(0.024)	(0.007)	(0.007)
No. grocery purchases	0.058^{***}	0.007	0.019^{***}	0.107^{***}	0.014^{**}	0.023^{***}
	(0.023)	(0.007)	(0.006)	(0.019)	(0.006)	(0.006)
No. out-of-home eating	0.254^{***}	0.061^{***}	0.050^{***}	0.188^{***}	0.051^{***}	0.047^{***}
	(0.055)	(0.016)	(0.015)	(0.053)	(0.015)	(0.015)
Working from home (days)	0.010	0.002	0.009	0.073^{***}	0.010	0.017^{**}
	(0.022)	(0.007)	(0.007)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index	-0.006	-0.003	-0.003	-0.006	-0.007	-0.010^{*}
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Constant	2.002^{**}	0.382	0.357	3.377^{***}	1.185^{***}	1.184^{***}
	(0.781)	(0.254)	(0.224)	(1.357)	(0.428)	(0.424)
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table A4: Consumption planning behavior

	Fridge Checking		Shopping List		Purchasing in Advance	
	Beta (β)	Present bias dummy	Beta (β)	Present bias dummy	Beta (β)	Present bias dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Dynamic inconsistency measure	-0.002	-0.017	0.113	-0.027	-0.610^{*}	-0.029
	(0.079)	(0.024)	(0.081)	(0.023)	(0.382)	(0.104)
Delta (δ)	-0.033	-0.037	0.013	0.004	-0.091	-0.089
	(0.067)	(0.068)	(0.068)	(0.069)	(0.293)	(0.296)
Risk seeking	-0.0001	-0.0001	-0.001	-0.001	-0.059^{***}	-0.058^{***}
	(0.005)	(0.005)	(0.005)	(0.005)	(0.023)	(0.023)
Age	0.0005	0.0004	0.0004	0.0005	0.008^{*}	0.007^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Female	-0.669^{**}	-0.667^{**}	-0.215	-0.217	-0.549	-0.522
	(0.046)	(0.049)	(0.417)	(0.416)	(2.600)	(2.540)
Tertiary education dummy	0.033	0.033	-0.041	-0.040	0.177	0.165
	(0.025)	(0.025)	(0.025)	(0.025)	(0.113)	(0.113)
Employment dummy	-0.038	-0.037	-0.069^{**}	-0.068^{**}	-0.209	-0.207
	(0.030)	(0.030)	(0.029)	(0.029)	(0.138)	(0.138)
Single household dummy	-0.060^{**}	-0.060^{**}	-0.109^{***}	-0.109^{***}	0.137	0.132
	(0.027)	(0.027)	(0.026)	(0.026)	(0.125)	(0.125)
Log household income	0.014	0.013	-0.023	-0.023	-0.016	-0.031
	(0.018)	(0.018)	(0.018)	(0.018)	(0.084)	(0.084)
Child below 12 dummy	-0.013	-0.012	-0.042	-0.043	0.035	0.055
	(0.035)	(0.035)	(0.036)	(0.036)	(0.155)	(0.154)
City dummy	0.042^{*}	0.042^{*}	0.001	0.002	0.015	0.008
	(0.025)	(0.025)	(0.025)	(0.025)	(0.112)	(0.112)
Distance grocery store	0.0003	0.0003	0.003^{**}	0.002^{**}	0.022^{***}	0.023^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
Vegetarian dummy	-0.018	-0.019	-0.033	-0.033	-0.138	-0.151
	(0.032)	(0.032)	(0.031)	(0.031)	(0.136)	(0.136)
Share organic food	0.007	0.007	0.013^{*}	0.014^{*}	0.008	0.001
	(0.008)	(0.008)	(0.007)	(0.007)	(0.033)	(0.033)
Discounter index	0.005	0.005	-0.036	-0.036	-0.464^{**}	-0.464^{**}
	(0.043)	(0.043)	(0.043)	(0.043)	(0.187)	(0.186)
Food preparation experience	0.014^{**}	0.014^{**}	0.018^{***}	0.017^{***}	0.005	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.028)	(0.028)
No. grocery purchases	-0.010	-0.009	-0.016^{***}	-0.016^{***}	-0.315^{***}	-0.313^{***}
	(0.006)	(0.006)	(0.006)	(0.006)	(0.028)	(0.029)
No. out-of-home eating	0.001	0.002	0.018	0.017	0.016	0.026
	(0.014)	(0.014)	(0.013)	(0.013)	(0.062)	(0.062)
Working from home (days)	0.018^{***}	0.017^{***}	0.013^{*}	0.012^{*}	0.025	0.024
	(0.006)	(0.006)	(0.007)	(0.007)	(0.029)	(0.029)
Covid-19 stringency index	0.001	0.001	0.001	0.001	-0.003	-0.004
	(0.003)	(0.003)	(0.002)	(0.002)	(0.011)	(0.011)
Constant	0.533^{**}	0.560^{**}	0.740^{***}	0.854^{***}	5.307^{***}	4.977^{***}
	(0.247)	(0.244)	(0.243)	(0.234)	(1.090)	(1.078)
N	1,261	1,261	1,261	1,261	1,241	1,241

Note: The table summarizes results from Ordinary Least Squares regressions with robust standard errors. The variables 'fridge checking dummy', 'shopping list dummy' and 'purchasing 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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table A5: Deviating from intentions at home

	Deviate at Home Index				
	(1)	(2)	(3)	(4)	(5)
Beta (β)	-0.910^{***}	-0.890^{***}	-0.625^{***}	-0.427^{**}	-0.437^{**}
	(0.221)	(0.218)	(0.209)	(0.202)	(0.203)
Delta (δ)		-0.531^{***}	-0.272	-0.306^{*}	-0.305^{*}
		(0.170)	(0.172)	(0.170)	(0.171)
Risk seeking		0.052^{***}	0.032^{**}	0.029^{**}	0.028^{**}
		(0.014)	(0.014)	(0.013)	(0.013)
Age			-0.020^{***}	-0.017^{***}	-0.017^{***}
			(0.002)	(0.002)	(0.002)
Female			-0.309	-0.290	-0.265
			(0.243)	(0.297)	(0.312)
Tertiary education dummy			-0.111^{*}	-0.093	-0.112^{*}
			(0.062)	(0.061)	(0.061)
Employment dummy			0.062	-0.017	-0.067
			(0.069)	(0.068)	(0.074)
Single household dummy			0.136^{*}	0.095	0.097
			(0.071)	(0.070)	(0.070)
Log household income			0.090^{*}	0.097^{**}	0.097^{**}
			(0.047)	(0.047)	(0.047)
Child below 12 dummy			0.236^{**}	0.265^{***}	0.268^{***}
			(0.102)	(0.098)	(0.098)
City dummy			-0.007	0.022	0.019
			(0.063)	(0.061)	(0.061)
Distance grocery store			0.004	0.006^{**}	0.006^{**}
			(0.003)	(0.003)	(0.003)
Vegetarian dummy				-0.050	-0.056
				(0.087)	(0.087)
Share organic food				-0.025	-0.029
				(0.018)	(0.017)
Discounter index				0.053	0.050
				(0.104)	(0.104)
Food preparation experience				-0.056^{***}	-0.058^{***}
				(0.015)	(0.015)
No. grocery purchases				0.057^{***}	0.057^{***}
				(0.016)	(0.016)
No. out-of-home eating				0.256^{***}	0.262^{***}
				(0.041)	(0.041)
Working from home (days)					0.025
					(0.016)
Covid-19 stringency index					0.008
					(0.007)
Constant	1.827^{***}	2.016^{***}	1.662^{***}	1.330^{***}	0.798
	(0.202)	(0.244)	(0.418)	(0.419)	(0.633)
N	1,273	1,273	1,271	1,261	1,261

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

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

	Food going bad index W1	Waste best before dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Deviate at home index	0.372***	0.088***	0.059***	0.285***	0.084***	0.066***
	(0.039)	(0.013)	(0.012)	(0.048)	(0.014)	(0.015)
Delta (δ)	0.269	0.013	0.031	−0.121	−0.041	0.026
	(0.211)	(0.066)	(0.062)	(0.273)	(0.086)	(0.080)
Risk seeking	0.042***	0.013**	0.006	0.046**	0.019***	0.010*
	(0.016)	(0.005)	(0.005)	(0.020)	(0.006)	(0.006)
Age	−0.005	−0.002*	−0.002**	−0.003	−0.001	−0.001
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	0.021	−0.017	0.029	0.072	−0.046*	0.017
	(0.078)	(0.024)	(0.023)	(0.090)	(0.027)	(0.028)
Tertiary education dummy	−0.019	−0.003	0.023	−0.044	−0.022	0.008
	(0.078)	(0.025)	(0.024)	(0.090)	(0.028)	(0.029)
Employment dummy	0.200**	0.013	0.008	−0.029	−0.044	−0.001
	(0.090)	(0.029)	(0.027)	(0.103)	(0.032)	(0.032)
Single household dummy	−0.105	0.025	−0.023	−0.511***	−0.092***	−0.113***
	(0.090)	(0.028)	(0.026)	(0.093)	(0.030)	(0.030)
Log household income	0.010	0.032*	0.014	−0.177***	−0.025	−0.040*
	(0.056)	(0.018)	(0.016)	(0.070)	(0.020)	(0.021)
Child below 12 dummy	0.162	0.046	0.083**	0.206*	0.120***	0.128***
	(0.115)	(0.040)	(0.040)	(0.128)	(0.043)	(0.044)
City dummy	−0.179**	−0.006	−0.003	−0.065	−0.035	0.008
	(0.076)	(0.025)	(0.024)	(0.090)	(0.028)	(0.029)
Distance grocery store	−0.002	−0.001	0.0005	−0.003	−0.002	0.001
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	−0.161	−0.053*	−0.044	−0.176	−0.040	−0.033
	(0.091)	(0.030)	(0.030)	(0.105)	(0.033)	(0.036)
Share organic food	0.005	−0.014*	−0.008	−0.033	−0.009	−0.002
	(0.023)	(0.007)	(0.007)	(0.023)	(0.007)	(0.007)
Discounter index	−0.034	−0.044	0.028	−0.036	−0.083*	−0.026
	(0.129)	(0.041)	(0.038)	(0.146)	(0.045)	(0.045)
Food preparation experience	−0.021	0.005	−0.006	−0.025	−0.013*	−0.006
	(0.018)	(0.006)	(0.006)	(0.023)	(0.007)	(0.007)
No. grocery purchases	0.040**	0.002	0.016***	0.090***	0.009*	0.019***
	(0.022)	(0.006)	(0.006)	(0.020)	(0.005)	(0.006)
No. out-of-home eating	0.168***	0.040***	0.036***	0.149***	0.040***	0.038***
	(0.053)	(0.016)	(0.015)	(0.050)	(0.015)	(0.015)
Working from home (days)	−0.0003	−0.0001	0.007	0.065***	0.007	0.015*
	(0.022)	(0.007)	(0.006)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index	−0.010	−0.004	−0.003	−0.004	−0.007	−0.009
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Constant	1.185	0.237	0.239	2.509**	0.886**	0.978**
	(0.753)	(0.244)	(0.217)	(1.351)	(0.423)	(0.414)
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01

Table A7: *Procrastination and food waste behavior*

	Food going bad index W1	Waste best before date dummy W1	Waste leftovers dummy W1	Food going bad index W2	Waste best before date dummy W2	Waste leftovers dummy W2
	(1)	(2)	(3)	(4)	(5)	(6)
Procrastination	0.044***	0.014***	0.016***	0.048***	0.012**	0.017***
	(0.014)	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)
Patience	−0.019	−0.005	0.003	−0.020	−0.001	−0.004
	(0.020)	(0.006)	(0.006)	(0.023)	(0.006)	(0.007)
Risk seeking	0.053***	0.015***	0.005	0.052**	0.019***	0.010
	(0.018)	(0.005)	(0.005)	(0.021)	(0.007)	(0.006)
Age	−0.010***	−0.003***	−0.003***	−0.008**	−0.002*	−0.002*
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Female	0.088	0.001	0.043*	0.144	−0.024	0.033
	(0.081)	(0.025)	(0.023)	(0.090)	(0.028)	(0.028)
Tertiary education dummy	−0.068	−0.015	0.013	−0.074	−0.031	0.001
	(0.081)	(0.026)	(0.024)	(0.091)	(0.029)	(0.029)
Employment dummy	0.196**	0.014	0.015	−0.024	−0.042	0.004
	(0.093)	(0.030)	(0.027)	(0.106)	(0.033)	(0.032)
Single household dummy	−0.059	0.036	−0.015	−0.484***	−0.084***	−0.107***
	(0.094)	(0.029)	(0.026)	(0.094)	(0.031)	(0.030)
Log household income	0.061	0.044**	0.023	−0.143**	−0.016	−0.030
	(0.058)	(0.018)	(0.016)	(0.069)	(0.020)	(0.021)
Child below 12 dummy	0.284**	0.077**	0.103***	0.288**	0.142***	0.149***
	(0.117)	(0.041)	(0.040)	(0.132)	(0.045)	(0.045)
City dummy	−0.181**	−0.009	−0.005	−0.085	−0.040	0.004
	(0.079)	(0.025)	(0.024)	(0.092)	(0.029)	(0.029)
Distance grocery store	−0.0002	−0.001	0.001	−0.002	−0.001	0.001
	(0.004)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Vegetarian dummy	−0.168	−0.054	−0.045	−0.152	−0.037	−0.026
	(0.098)	(0.031)	(0.030)	(0.106)	(0.034)	(0.036)
Share organic food	−0.002	−0.016**	−0.009	−0.040	−0.012	−0.003
	(0.024)	(0.007)	(0.007)	(0.023)	(0.007)	(0.007)
Discounter index	0.003	−0.035	0.036	0.037	−0.063	−0.007
	(0.136)	(0.041)	(0.038)	(0.149)	(0.046)	(0.044)
Food preparation experience	−0.038**	0.001	−0.009	−0.037	−0.016**	−0.008
	(0.018)	(0.006)	(0.006)	(0.024)	(0.007)	(0.007)
No. grocery purchases	0.060***	0.007	0.019***	0.106***	0.014**	0.023***
	(0.023)	(0.006)	(0.006)	(0.019)	(0.006)	(0.006)
No. out-of-home eating	0.251***	0.057***	0.046***	0.187***	0.052***	0.047***
	(0.055)	(0.016)	(0.015)	(0.052)	(0.015)	(0.015)
Working from home (days)	0.004	0.0004	0.006	0.068***	0.008	0.016*
	(0.022)	(0.007)	(0.007)	(0.026)	(0.008)	(0.009)
Covid-19 stringency index	−0.007	−0.003	−0.002	−0.002	−0.006	−0.008
	(0.008)	(0.003)	(0.002)	(0.019)	(0.006)	(0.006)
Constant	1.166	0.171	0.117	2.350*	0.843**	0.898**
	(0.769)	(0.245)	(0.219)	(1.362)	(0.428)	(0.421)
N	1,261	1,261	1,261	867	867	867

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 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, food preparation experience, number grocery purchases, number out-of-home eating and (4) Covid-19 controls: working from home (days) and Covid-19 stringency index. The following control variables are measured in wave 1 *and* 2: employment dummy, single household dummy, log household income, child below 12 dummy, city dummy, share organic food, number grocery shopping, number out-of-home eating, working from home (days) and Covid-19 stringency index. For wave 2 outcomes, control variables measured in wave 2 are taken. Preference measures as well as age, gender and tertiary education dummy are assumed to stay constant over time. The Covid-19 stringency index indicated stringency of political containment measures due to Covid-19 at the federal state level. The value 10 days before an individual answered the survey is applied. Levels of significance: *0.10, **0.05, ***0.01