Katholische Universität Eichstätt-Ingolstadt

Preferences, Individual Decision-Making and Government Interventions

Kumulative Dissertation

zur Erlangung des akademischen Grades

Doktor rerum politicarum (Dr. rer. pol.)

an der

Katholische Universität Eichstätt-Ingolstadt
Wirtschaftswissenschaftliche Fakultät

vorgelegt von

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Einreichung Dissertation: 21.03.2023
Mündliche Prüfung: 28.06.2023

Statement of Own Contribution

Chapter 1 "Present bias in choices over food and money: Evidence from a framed field experiment." is joint work with Alexander Danzer. This project is based on a joint research idea of Alexander Danzer and the author. The experimental design was developed by the author. The conception of the paper were joint tasks. The data collection and the identification strategy were conducted by the author. The author carried out the data preparation and empirical analysis. Literature work and first draft writing were joint tasks. Final chapter writing was done by the author.

Chapter 2 "Dynamic inconsistencies and food waste: Assessing food waste from a behavioral economics perspective." is a single-authored project by the author.

Chapter 3 "Economic behavior under containment: How do people respond to Covid-19 restrictions?" is joint work with Alexander Danzer and Matthias Holzmann. This project is based on a research idea by Alexander Danzer and the author. The survey design was a joint task by Alexander Danzer and the author. The data collection and data preparation were mainly done by the author with partial contribution of Matthias Holzmann. The empirical analyses was mainly done by Matthias Holzmann. The literature work and first draft writing as well as final chapter writing were joint tasks.

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Preface

Societies are facing serious challenges that have the potential to fundamentally change our way of life. The first challenge constitutes ensuring global food security. A growing world population and increasing occurrences of extreme weather events due to climate change put immense pressure on food production (Mbow et al., 2019). The second challenge describes the sustainability transition in all domains as the most fundamental prerequisite for future generations to thrive. This conversion requires an overhaul of established ways of thinking; especially conventional farming practices put immense pressure on the environment by exploiting scarce resources, hazarding the consequences of a biodiversity loss, and intensively applying fertilizer that is the basis for some of the most important non-CO_2 greenhouse gases (FAO, 2019; IPBES, 2019; Rockström et al., 2009; Westhoek et al., 2016). The third challenge targets the transformation to healthy societies to reduce widespread lifestyle diseases such as obesity and malnutrition. The World Health Organization (WHO) already speaks of a global obesity epidemic that increases the risk of cancer, cardiovascular diseases, and diabetes, and affects almost 60% of adults and one in three children in the European region (WHO, 2022).

While current dietary patterns and agricultural production structures are threatening both people and planet, a radical transformation of the food supply and demand side can be the single strongest factor to progress on all three challenges simultaneously: A shift in current diets towards healthier, more plant-based diets can enable feeding the world population a healthy diet while staying within earth's resource boundaries for food production (EAT-Lancet Commission, 2019; Willett et al., 2019). Unhealthy eating habits cause tremendous economic and social costs also from a public health perspective: The consumption of nutrient-poor foods negatively impacts labour productivity (Bütikofer et al., 2018), and puts a huge financial burden on public health systems (Finkelstein et al., 2009). A shift towards healthier diets is therefore likely to result in major health benefits for people.

Enabling consumers to adopt a healthier diet is a key point in transforming societies. According to the EAT-Lancet Commission (2019), the conversion to healthy diets requires a substantial increase in the consumption of healthy foods such as fruits, vegetables, legumes and nuts, and a huge reduction of less healthy foods such as added sugars and red meat. But why are consumers not just changing what they eat? Proposed in the 1930s by Samuelson (1937), economists assumed that people are exponential discounters and behave consistently over time: If they make plans for the future, they will realize those plans as soon as the future becomes present. But the existence of a billion dollar dieting industry rather suggests that people have difficulties in changing their consumption behavior over time. Indeed, several studies going back to the late 1990s (Della Vigna & Malmendier, 2006; Read et al., 1999; Read & Van Leeuwen, 1998) have empirically documented inconsistent behavior over time: People want to exercise more or eat healthier only in the future. Reconsidering future plans today, they stick to their old habits and deviate from their intentions. Different models have been developed to explain these empirically observed preference reversal; Cohen et al. (2020) provide the most recent overview of all approaches. In this thesis, I focus on an approach first suggested by Strotz (1955) and developed further by Akerlof (1991), Laibson (1997), and Phelps and Pollak (1968) suggesting that self-control problems are reflecting a series of non-overlapping selves that do not agree about the preference ranking of future and present consumption paths. As a consequence, time preferences are dynamically inconsistent.

Facing these enormous transitional challenges and given the evidence that individuals have problems to follow their good intentions in their everyday decision-making, the most relevant question from a public policy point of view then is: How can effective policies be designed that support individuals in changing their dietary habits? According to O'Donoghue and Rabin (1999), individuals might value commitment devices if they are not too naive about their dynamic inconsistency; and if commitment devices are sufficiently inexpensive to obtain (Laibson, 2015). Commitment policies enable individuals to self-select into the most favorable option from a future self perspective. This feature distinguishes commitment policies from other rather 'light' government interventions such as nudges that face the criticism to be paternalistic (Thaler, 2018). A recent example for a commitment policy is the food policy change administered 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] The aim is to foster healthier nutrition by enabling SNAP recipients to commit to their advance (online) food choices that they make for the future (next grocery shopping trip).

This thesis is composed of three essays focusing on the nexus between preferences, individual decision-making and government interventions. While chapters 1 and 2 examine the relation between preferences and individual decision-making, and derive implications for effective policy design, chapter 3 examines the effects of government interventions on individual decision-making and preferences. Chapter 1 focuses on commitment policies itself and asks the question: Who is taking up the commitment device? It presents results from a field experiment investigating dynamically inconsistent time preferences over food choices and commitment take-up over time. The second chapter is concerned with unintended negative consequences of food commitment policies by providing and empirically testing a framework that links dynamic inconsistencies, food consumption decisions and food waste. Chapter 1 and 2 contribute to investigating the behavioral foundations of individual decision-making by theoretically and empirically studying dynamically inconsistent time preferences over real food consumption choices. The question of how individuals make decisions based on their preferences is most fundamental to economic theory. The first two chapters indeed provide evidence more likely speaking against the effectiveness of commitment policies to successfully navigate the transition to healthier consumption patterns. The third chapter is concerned with the question whether severe, heavily paternalistic government interventions are effective in changing individual decision-making of individuals. Besides providing a causal analysis of effects for behavior in different economic and health domains, this chapter additionally examines behavioral side effects such as potential impacts on preferences.

Chapter 1 is concerned with the question who is taking up the commitment device. The answer to this central question determines the prospects for success of commitment policies since the value of public policies to alter economic behavior depends on individuals' responses to interventions. If those individuals with the greatest self-control problems do not demand commitment, take-up would be concentrated among those for whom the policy has only little effect. The evidence on this central question is indeed mixed: While Augenblick et al. (2015), Avery et al. (2022), Bai et al. (2021), and Kaur et al. (2015) document a positive relation, the studies of Royer et al. (2015) and Sadoff et al. (2020)

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

suggest the opposite: Dynamically inconsistent individuals are less likely to take up a commitment device. Related to this topic is the question why dynamically consistent individuals would take up the commitment device? Are they immune to temptation or do they actively exert internal control when external commitment is absent? This question has not gained much attention in the literature so far; theoretical and empirical work of Benhabib and Bisin (2005) and Sjåstad and Ekström (2021) suggests that dynamically consistent individuals actively exert self-control without available commitment device.

To investigate the relation between self-control problems and beliefs thereof, chapter 1 presents the design of an intertemporal choice experiment that records food choices over time and offers a commitment device allowing subjects to stick to their choices made for the future one week ahead. This chapter adds methodologically to the literature by proposing a holistic experimental design to measure dynamic inconsistency. It observes real food choices in a natural environment: Subjects are college students that choose their lunch in the college canteen and eat their lunch in the dining hall after an experimental session is over. Much of the previous literature has relied on abstract tasks, without ensuring the actual consumption of experimental rewards (Cohen et al., 2020). Considered rewards are often monetary or involve a rather abstract effort vs. leisure allocation over time. Some papers focus on food choices but only offer binary snack choices instead of food choices enabling a continuum of healthiness (Alan & Ertac, 2015; McClure et al., 2007; Read & Van Leeuwen, 1998; Sadoff et al., 2020). Except for McClure et al. (2007), they also cannot observe the actual consumption of food. This chapter joins a small list of recent field experiments seeking to operationalize economic theory more directly (Andreoni et al., 2022).

Based on the granular data on revealed preferences over real consumption choices in a natural setting, the study reveals behavioral patterns suggesting a negative relation between self-control problems and beliefs thereof: Subjects choosing the commitment device seem to already enforce internal self-control before commitment is offered. Non-committing subjects show dynamically inconsistent behavior over single food categories when commitment is not available. These results suggest that non-committing subjects are at least partially naive about their self-control problem while subjects demanding commitment show dynamically consistent behavior. Second, the study provides evidence that internal and external commitment strategies are substitutes: Committing individuals actively enforce internal self-control when commitment is absent. The behavioral pattern is consistent with a mental accounting strategy to meet self-imposed dietary goals (Koch & Nafziger, 2016; Thaler, 1999).

Chapter 1 provides new perspectives on the evaluation of recent changes in public food policies. Coming back to the aforementioned example of the USDA to allow online pre-ordering of grocery purchases for SNAP recipients, the study suggests only limited effects of the commitment policy for individuals with self-control problems: The results reveal that those individuals that would benefit the most do not take up the commitment device. Those individuals that do take it up apply internal self-control strategies in the absence of the policy.

Chapter 2 provides evidence that recent changes in food commitment policies can even have unintended negative effects. Even if dynamically inconsistent individuals would purchase more healthy food in the grocery store as a result of the commitment policy, due to their inconsistent time preferences they might not actually consume it at home. Instead, the healthy food might go to waste. In this case, the government policy that was actually introduced to shift diets to a more sustainable path could have the opposite effect: It might make food consumption even less sustainable by increasing food waste but leaving actual consumption patterns unaffected. Food waste, indeed, already constitutes a major problem in the global food system. Estimates of Gustavsson et al. (2011) suggest that around 30% of the global food production 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 for example are responsible for over 50% of total waste along the food value chain (Scherhaufer et al., 2012; Stenmarck et al., 2016). This translates to around 95 kg of food waste per capita and year (Gustavsson et al., 2011). Recognizing the devastating consequences of food waste, the United Nations (UN) have set the sustainable development goal to halve household and retail food waste by 2030.[2]

To investigate the relation between dynamic inconsistency and food waste, the second chapter first provides a conceptual framework that links food consumption decisions, dynamically inconsistent time preferences, and food waste. It suggests that dynamically inconsistent individuals have intentions about when to consume healthier food items at home. This choice is made at the grocery shopping stage for (future) consumption at home and results from the always present desire to adapt a healthier diet (in the future). Dynamic inconsistency leads to a deviation from consumption intentions at home when

[2]SDG 12.3: https://www.fao.org/sustainable-development-goals/indicators/1231/en/

the advance choice is reconsidered from a present perspective (immediate choice). This deviation implies that the consumption of healthier food items is postponed, and that healthier food items are stored longer than intended. Given predetermined perishability, the likelihood of waste increases for these healthy food items. This chapter therefore takes the view that food waste is an unintended consequence of dynamically inconsistent consumption choices along the food consumption chain.

In a second step, chapter 2 assesses the conceptual implications empirically by capitalizing on a rich data set from a nationally representative survey that captures individual food consumption behavior, waste behavior, economic preferences and a rich set of different control variables. 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 assessment over time. To examine the relation between dynamically inconsistent time preferences and food waste behavior, the study estimates a dynamic inconsistency parameter based on the model of Laibson (1997) and O'Donoghue and Rabin (1999) and constructs targeted measures of time-related food consumption and waste behaviors along different stages of the food consumption chain: from grocery shopping to food storing, processing and eating.

In line with the theory, the study reveals a positive relation between dynamic inconsistency and food waste. This finding is robust to different model specifications, and including a rich set of control variables. 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. Besides providing reduced form results, the paper finds 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, the dynamic inconsistency parameter is systematically correlated with an index measuring deviations from own at-home consumption intentions. Third, regression results reveal a highly significant correlation between the deviation index and individual food waste behavior.

Chapter 2 argues for a holistic perception of food consumption decisions. It points to the importance of understanding detailed behavioral mechanisms at different stages of the food consumption process to foster the intended effects of food policy changes (increase in healthy nutrition) and diminish unintended behavioral consequences (increase in food waste). An understanding is critical for a successful transformation towards a more sustainable global food system.

Results provided in chapter 1 and 2 suggest that commitment policies alone are not effective (enough) to enable and guide an overhaul of established structures in the food system. The question then is: What constitutes an adequate alternative policy? And how paternalistically should governments intervene in everyday individual decision-making to reach this goal? Identical questions smolder in almost every public debate about related adaption and mitigation policies targeting causes and consequences associated with climate change. To shed more light on this fundamental debate, chapter 3 seeks to provide a basis for this discussion by focusing on two central questions: First, are strict interventions effective? And second, do they have unintended behavioral consequences, for example by affecting behavioral outcomes such as preferences? Without evaluating these topics first, the above questions cannot be discussed properly.

To start the analysis, chapter 3 focuses on a period of unprecedentedly strict and fundamental government intervention in everyday decision-making: the Covid-19 pandemic. It assesses the importance of governmental regulation for behavioral changes in people's daily life to overcome and mitigate the risks and potential social costs of a global health crisis. It contributes to the literature by investigating the effects of fundamental government intervention in a real live setting and assessing behavior across different economic domains. It also adds to an understanding of the stability of reported economic preferences.

Using novel nationally representative longitudinal survey data from Germany, a country with substantial spatial and temporal variation in Covid-19 containment measures, the paper assesses behavioral changes in three economic domains: the labor market domain (i.e., workplace and childcare behavior), the shopping domain (i.e., food purchasing behavior), and the consumption domain (i.e., risky and dietary behavior). These three domains are selected because other economic and social activities were prevented by Covid-19 containment measures: In large parts of Germany, restaurants were closed, retail trade was forbidden (except for essential goods), and most market-based leisure activities were shut down (e.g., cinemas, concert houses, sports facilities) during substantial parts of the survey observation period. The study exploits variation in the policy stringency of Covid-19 containment policies across German federal states and over time to provide a link between government regulations and effects on individual behavior.

To account for potential endogeneity problems and establish causality, the paper applies an instrumental variable approach: It instruments policy stringency at the state level with the duration to the next state election exploiting exogenous variation through pre-determined election cycles. Using weeks to an upcoming federal state election as an instrument, it shows that Covid-19 containment policies become less strict with elections moving closer in time.

The chapter finds that policy regulation significantly changes economic behavior in the workplace and in household childcare: Government restrictions increase working from home and the provision of childcare at home. While labor market outcomes respond partly mechanically to containment measures since some workplaces and childcare facilities were shut down, individuals also respond to stricter measures by adapting their consumption behavior: They reduce the number of grocery shopping trips. The stringency of Covid-19 containment policies further affects self-reported risk preferences and fear of Covid-19 - a self-developed measure that is applied in the survey: Individuals report to become more risk averse and are more afraid of Covid-19 as consequence of government regulation becoming stricter. Federal state policies have no systematic impact on alcohol consumption or diet healthiness. The results are robust to several different model specifications and robustness checks.

The results of chapter 3 demonstrate that fundamental government interventions in everyday decision-making have the potential to effectively influence behavior - at least as long as restrictions are in place. Yet, the question is how long policy effects will prevail after regulations are lifted? Regarding potentially unintended effects, Casoria et al. (2023) focus on the development of social preferences over time during the Covid-19 pandemic. The authors find that lockdown measures had a negative effect on trust. This effect vanished nine months after lockdown measures were lifted. Comparing gender attitudes before and after Covid-19 containment measures, Huebener et al. (2022) also find only a temporary pandemic-related change in gender role attitudes towards maternal employment. With respect to behavior in the work domain, first studies suggest that the level of working from home will stay higher compared to pre-pandemic periods in the longer run (Aksoy et al., 2023; Barrero et al., 2021). This finding provides evidence that regulatory induced changes in demand and supply structures can stay if this turns out to be beneficial for both sides. In light of the above identified fundamental challenges for society - ensuring global food security and transforming to a sustainable and healthy lifestyle - the question whether comparably strict food policy interventions would be effective in enabling consumers (and producers) a transition to healthier consumption and production patterns in the long run provides an important avenue for future research. Since Covid-19 containment measures already evoked a division in society with respect to the appropriateness of interventions, it is questionable whether similarly strict and intervening policies would be indeed accepted again in democratic societies.

Briefly summarizing all chapters of this thesis, Chapter 1 investigates a central question in the design of commitment policies: Who is taking it up? The chapter suggests that those individuals being at least at risk to behave inconsistently demand the policy. Chapter 2 conceptually links individual decision-making in the food domain to preferences and points to unintended negative effects of government interventions. This chapter provides evidence that food policies targeted at fostering healthy diets might instead only increase food waste if inconsistent individuals take up the policy in the first place. Chapter 3 investigates the effects of a period characterized by fundamental government interventions on everyday decision-making. The results provided in this chapter suggest that the unprecedentedly strict regulations during the Covid-19 pandemic causally influenced everyday behavior in different domains of life.

To wrap up, the three essays in this thesis consider different aspects of the nexus between preferences, individual decision-making and government interventions. Chapters 1 and 2 theoretically and empirically investigate the relation between dynamically inconsistent time preferences and individual decision-making in the food consumption domain. While both chapters derive implications for a very light version of government interventions relying on self-selection into a commitment policy, chapter 3 targets the implications of fundamental government interventions from a broader perspective: It focuses on the effect of pandemic containment measures on individual decision-making in different domains - from food consumption to workplace and childcare behavior - and risk preferences. Similar to chapter 2, chapter 3 also points to potential unintended consequences of these interventions: Covid-19 containment measures influence stated risk preferences and the perception of fear of Covid-19 - at least in the short run.

1 Present Bias in Choices Over Food and Money: Evidence from a Framed Field Experiment

1.1 Introduction

Not to comply with own intentions and resolutions seems human. Almost everybody has experienced or heard of unfulfilled new years resolutions, failed diet plans, or futile attempts to quit smoking. Economists explain such failures with dynamically inconsistent behavior (Akerlof, 1991; Laibson, 1997; Loewenstein & Prelec, 1992; Loewenstein & Thaler, 1989; O'Donoghue & Rabin, 1999; Strotz, 1955). A vast literature has documented and tested time inconsistencies (Frederick et al., 2002). Yet, this literature almost exclusively exploits monetary decisions and rewards to identify such inconsistent behavior. This is a direct consequence of the many advantageous features of money (e.g., costless exchangeability); however, some features are less desired and make monetary experiments less suitable to study real-world consumption decisions (e.g., almost infinite storability, one-dimensionality). Recent research has made substantial progress towards modelling real consumption decisions more realistically, focusing on consumption goods such as leisure (Augenblick et al., 2015) or food (Cherchye et al., 2020; Sadoff et al., 2020). Understanding whether behavior in monetary rewards proxies well for behavior in food is of utmost importance if we are to understand various relevant human behaviors, not least owing to the tremendous economic and social costs of unhealthy eating (Finkelstein et al., 2009). Food choices are not only a matter of taste; the consumption of nutrient-poor foods negatively impacts individual health and labour productivity (Bütikofer et al., 2018; WHO/FAO, 2003).

In this paper we take this literature one step further and provide a test of dynamically inconsistent behavior for a continuous convex non-monetary budget in an entirely natural environment: food decisions in a real canteen set-up. Our experiment features over 3,600 different real consumption choices out of 213,525 different possible combinations (merely focusing on three-item lunch menus). Compared to earlier studies, we not only allow for a full continuum of healthy or unhealthy foods without choice restrictions; we also explicitly design the consumption stage to comply with the consume-on-receipt assumption which has often been disregarded in the existing literature (Cohen et al., 2020). The paper also sheds light on consumers‘ tendency to utilize different types of control devices to commit to personal consumption plans. In a second step, we compare inconsistent behavior between convex food and convex money choices to investigate the applicability of monetary reward studies to natural behavior.

This paper makes three major contributions. First, we add to the literature by proposing a holistic experimental design to measure dynamic inconsistency. We explicitly address four relevant dimensions simultaneously: structurally estimating a time inconsistency measure, in a natural task and environment, offering a convex choice set, and enforcing true consumption choices on receipt by design. We join a small list of recent field experiments seeking to operationalize economic theory more directly (Andreoni et al., 2022). Related studies specialize on a subset of the aforementioned dimensions: One strand summarized in Frederick et al. (2002) focuses on measuring a present bias parameter using monetary rewards in the laboratory. While results deliver precise estimates for dynamic inconsistency, a common concern is the limited ecological validity owing to abstract tasks and simulated lab settings. It is also unclear whether monetary rewards are immediately transferred into true consumption. A second strand summarized in Imai et al. (2021) focuses on lab experiments conducted with effort-evoking tasks. These tasks do imply consuming effort (leisure) on receipt but in an overly stylized experimental setting: Artificial tasks are conducted in front of a computer limiting the applicability to real world behavior. A third strand focuses on behavior in true field settings by observing snacks choices (Alan & Ertac, 2015; Read & Van Leeuwen, 1998; Sadoff et al., 2020). We add to this literature in two ways. On the one hand, these papers do not offer fully convex choice sets. In fact, their designs focus on a limited number of snacks and are implemented with choice restrictions. In Sadoff et al. (2020) for example, subjects are required to choose 10 out of 20 food items in advance choice and are allowed to make only up to four changes in immediate choice. Subjects in our experiment can choose without choice restrictions (except a budget constraint) from a choice set containing 25 food items on average. Over the whole time period of the experiment, 135 unique dishes are offered in the canteen with its highly standardized setting. On the other hand, these studies do not ensure the actual consumption of food at the time of reception. Indeed, Sadoff et al. (2020) report post-survey results suggesting that most food items were consumed only within three days after delivery. In this respect, our experimental design is more comparable to the work of Belot et al. (2018) and Belot and James (2011) who study health behaviors, preferences and educational achievements with real meal consumption in a familiar canteen or at-home setting, respectively.

Second, we add to the understanding of the relation between factual self-control problems and subjective beliefs thereof. The value of public policies to alter economic behavior depends on individuals' responses to interventions, such as commitment devices. The existing evidence on this nexus is mixed: While Avery et al. (2022), Bai et al. (2021), and Kaur et al. (2015) document a positive relation, the studies of Royer et al. (2015) and Sadoff et al. (2020) suggest the opposite: present-biased individuals are less likely to take up a commitment device. Related to this topic is the question why time-consistent individuals would take up the commitment device? Are they immune to temptation or do they actively exert internal control when external commitment is absent? Our granular data on revealed consumption preferences enable us to shed light on the tendency to utilize internal and external control strategies as substitutes. This question has not gained much attention in the literature so far. In a recent study, Sjåstad and Ekström (2021) show in an online experiment that individuals with high internal trait self-control have a higher probability of demanding commitment. The finding is in line with the work of Benhabib and Bisin (2005) who model active internal self-control mechanisms in dynamic consumption-saving decisions.

Third, by going to the individual level we compare choices over food with choices over money. In order to make this feasible, we design our experiment in a way that allows convex time budgets in money and food. We study the fundamental question whether dynamic inconsistency in real consumption choices is reflected in intertemporal behavior derived from monetary rewards. We contribute to the literature that mainly focuses on comparing money with effort choices elicited in a rather abstract lab setting: Augenblick et al. (2015) find dynamic inconsistencies in the effort but not the money task; individual behavior between tasks is not correlated. Alan and Ertac (2015) and Cheung et al. (2022) compare money and snack choices in a rather abstract setting. They find evidence for a significant correlation between both tasks.

We measure dynamic inconsistency in food consumption choices by conducting a longitudinal field experiment in a college canteen. Over a total period of six weeks, we observe 73 subjects making repeated food choices for lunch using tablet computers. Based on different budget endowments subjects construct a food bundle for immediate lunch (after the session) and for advance lunch (one week apart) from a choice set of 25 food items offered in the canteen. Each subject is completing three sessions with one week spacing in between (same day and time). The design constitutes a within-subject experiment with 219 individual-session observations allowing to compare individual food choices over time. Our main analysis is based on 3,666 observations: 73 individuals make 25 decisions (on average) to choose a food item for two different time perspectives (today vs. in one week). Our research design features similar power as, for instance, the study of Augenblick et al. (2015) on leisure consumption. Importantly, every food bundle that could be constructed in the advance choice session was really available at the time of the immediate choice one week later. We therefore identify dynamic inconsistencies as violations of revealed preferences between advance and immediate choices. In particular, the advance choice of the first week is compared to the immediate choice of the second week (without choice reminder), and so on. Among the individual lunch bundles selected at the computer, one lunch is randomly chosen in an incentive compatible way; we collect the food in the canteen area and issue it to the subjects for consumption (for free).

After constructing advance food bundles in week 2 (for week 3), participants are offered a commitment device. If they choose to take the device, they switch off the possibility to make immediate lunch choices in week 3, restraining themselves to their advance choices made in week 2.

We categorize the design as a framed field experiment (Harrison & List, 2004) with participants conducting a natural task (choosing lunch at lunch time) in a natural environment (college canteen). Since we focus on a college context, our natural subject pool are college students. Subjects were aware of taking part in a research study. After constructing food consumption baskets, individuals allocate money over time.

To operationalize a test of dynamically (in)consistent behavior in food consumption, we build on the psychological insight that consumers tend to mentally separate dish categories, such as main dishes, side dishes and desserts (Flores et al., 2019; Wansink & Hanks, 2013), and that they keep mental records over nutrients and balance accounts (Bublitz et al., 2010). Consequently, we initially analyze choices at the food item (dish) level. Thereafter, we investigate full meal sets (containing several items each) at the aggregate food basket level to test for the use of nutritional accounts and to link our findings to the existing literature on non-monetary rewards. In a final step, we compare inconsistent behavior between convex food and convex money choices at the individual level.

To measure dynamic inconsistencies in food choices, we follow Sadoff et al. (2020) and implement a structural estimation approach that allows to test whether *inconsistent* food choices arise by chance under time *consistent* preferences. We apply a standard random utility model that derives the value of a food item from food characteristics and a random utility shock (Beggs et al., 1981). To assess food healthiness, we collect nutritional information about all food items, and focus on calories, fat and the quota of fruits and vegetables at the dish and meal level. We additionally calculate the Nutrient Profile Score (NPS) as a holistic healthiness measure taking into account seven different nutrients (Cherchye et al., 2020; Rayner et al., 2009). To analyse money allocation choices over time, we apply four Convex Time Budget (CTB) sets (Andreoni & Sprenger, 2012a) and interpret choices by focusing on the (β, δ) model (Laibson, 1997; O'Donoghue & Rabin, 1999).

We document three main findings. First, our results provide evidence for a balancing of food item healthiness over dish categories: While unhealthier main dishes are preferred in the advance choice, the opposite is true for desserts. In the immediate choice, subjects prefer unhealthier main dishes even more strongly. To the contrary, unhealthier desserts are even less strongly preferred. This finding suggests that subjects treat food items differently depending on the dish category (main dish vs. dessert). Since nutrients are balanced over different dish categories we do not find significant differences in food bundle healthiness between advance and immediate choices when looking at aggregate food baskets (meals).

Second, individuals choosing the commitment device show internal self-control in their food choices when commitment is absent. They do so by balancing food healthiness between different dish categories: they show a systematic tendency to simultaneously value unhealthier main dishes and healthier desserts in immediate choices. Indeed, only (later) committing individuals balance food bundle healthiness in immediate food choices when temptation should be greatest. These subjects seem to be control-enforcing: they apply an internal self-control strategy before the commitment is offered and choose the external commitment device as soon as it becomes available. The behavioral pattern is consistent with a mental accounting strategy to meet self-imposed dietary goals. This finding suggests that internal and external commitment strategies are substitutes for committers; and that they actively enforce self-control. Non-committing individuals do not seek control. They do not choose the commitment device and do not exercise internal self-control by balancing food bundle healthiness. This group displays present-biased behavior over single food categories: they prefer even unhealthier main and side dishes in immediate choices in the first choice comparison. In the second choice comparison, they exhibit systematic present-biased behavior with respect to unhealthier desserts.

Third, we compare within-individual choices from the food and money task at the individual level. Focusing on the money allocation task, our results suggest that subjects do not behave dynamically inconsistent when allocating money over time. In the choice comparison, we find that the distribution of the food inconsistency measure is more dispersed than the distribution of the money inconsistency measure. The latter is strongly concentrated around time consistency. The difference between the distributions is statistically significant ($p < 0.001$). Focusing on the correlation between tasks, we do not find a significant relationship between behaviors in the money allocation and food consumption tasks. We also examine whether subjects that take up the commitment device in the food consumption task show a different allocation behavior in the money task. Estimates of dynamic inconsistency in the money allocation tasks for committing vs. non-committing individuals are not statistically different from each other.

The remainder of the paper is structured as follows: Section 1.2 describes the experimental design and the underlying theoretical background. Section 1.3 provides the results for the food consumption and money allocation tasks at the aggregate and individual level. We also discuss the robustness of our results. Section 1.4 concludes.

1.2 Empirical Design

1.2.1 The Experiment

To examine time-inconsistencies in real food consumption choices, we conduct a longitudinal framed field experiment at a college canteen in Bavaria, Germany. In three separate sessions with one week spacing, participants are asked to choose food items from the canteen's menu for immediate and prospective consumption, and subsequently consume their received lunch in the dining hall.

1.2.1.1 Design Details

Subjects can choose from the entire canteen menu without choice restrictions, apart from the limited budget endowment. Depending on condition, subjects face a budget constraint of either 4€ or 5€. In effect, individuals make choices for both budget conditions before the computer randomly selects a choice. Time inconsistencies are identified from comparing *advance food choices* that are made in the first week for the second week (advance choice perspective) with *immediate food choices* that are made in the second week for the second week (immediate choice perspective). We expect time inconsistent individuals to switch from healthier food items in advance choice to unhealthier food items in immediate choice given the desire to adapt a healthier diet (in the future) (DellaVigna, 2009). The experimental design is summarized in Table 1.1. Subjects go through three separate sessions. In each session, subjects make food consumption choices for the respective day and for the next session one week ahead. After the lunch choices in sessions 1 and 2, subjects allocate money over time in the second part of the experiment. There is no money allocation in session 3.

To get familiar with the food choice task, in session 1 subjects first make *immediate* lunch choices ($t_1 t_1$ choices) for the same day from the regular canteen menu (which is published for the entire week on Monday). They choose twice - one lunch for up to 4€ and the other lunch for up to 5€. The high budget condition is introduced to allow participants to also choose higher priced dishes in the canteen. Subjects are informed that they can choose without further restrictions: they are allowed to choose food items

Table 1.1: *Summary of Experiment*

Session 1 $\equiv t_1$	Session 2 $\equiv t_2$	Session 3 $\equiv t_3$
Lunch choices t_1t_1 for budgets $b = 4$ and $b = 5$ *(immediate)*	Lunch choices t_2t_2 for budgets $b = 4$ and $b = 5$ *(immediate)*	C=0: Lunch choices t_3t_3 for budgets $b = 4$ and $b = 5$ *(immediate)*
Lunch choices t_1t_2 for budgets $b = 4$ and $b = 5$ *(advance)*	Lunch choices t_2t_3 for budgets $b = 4$ and $b = 5$ *(advance)*	C=1: No lunch choices t_3t_3
	Commitment decision for t_3 (C)	
Convex Time Budget sets t_1t_2 and t_1t_3 *(immediate)* and t_2t_3 *(advance)*	Convex Time Budget set t_2t_3 *(immediate)*	

Notes: The table summarises the sequences of the experiment between sessions (columns) and within sessions (rows). All participants were present at three consecutive sessions. Within each session, they make choices for the present and the future (one week later). In session 1, participants initially make four lunch choices: they first choose lunches from today's canteen menu for today (t_1t_1). After that, they make advance lunch choices for next week based on next week's canteen menu. For each point in time, they choose food items for a low budget (4€) and a high budget (5€). This implies two lunch choices for $t = 1$ of which one is randomly chosen for implementation with equal probability (p=0.5). In session 2, participants make lunch choices for session 2 from an immediate perspective. This implies four lunch choices for session 2 $t = 2$ (two immediate and two advance choices from the prior week) of which one is randomly chosen for implementation with equal probability (p=0.25). In session 2, after making advance choices for session 3, participants are offered a commitment device. If they commit, they switch off the possibility to make immediate lunch choices in session 3. Participants also make money choices (trading off earlier and later payments) in session 1 and 2 using four CTB sets.

multiple times, and to choose the same food items for both budget conditions. We further inform subjects that one of the two immediate t_1t_1 choices will be randomly selected by the computer with probability 0.5, and delivered to them for free at the end of the session. By randomly drawing one lunch choice out of several choices made by an individual, we incentivize participants to choose according to their preferences.

After making these immediate lunch choices, subjects make *advance* lunch choices (t_1t_2 choices) for the same weekday and time next week (from the prospective canteen menu which is not publicly available until next Monday). Advance choices are stored and retrieved in session 2. In session 2 (denoted by t_2), subjects again make two immediate lunch choices (t_2t_2 choices). The difference between t_1t_2 and t_2t_2 choices is the choice perspective: while t_1t_2 choices are made from an advance perspective for the upcoming week in session 1, t_2t_2 choices are made from an immediate perspective in session 2. We follow Augenblick et al. (2015) and inform subjects in session 1 about the repeated decision making in session 2 to avoid subjects being surprised about immediate decision making. We choose a strategy without prior disclosure: subjects in session 2 are not reminded of their session 1 choices. This guarantees that advance and immediate choices are made in isolation, and that subjects do not integrate advance and immediate choices (Halevy, 2015). Reminders of prior choices might also undesirably enforce consistency across time. We advise subjects that the total number of lunch choices for session 2 is four (two choices from session 1 and two choices from session 2) and that they receive one meal based on a random draw with equal probability of 25%. In the main analysis, we focus on the comparison of advance choices from session 1 (t_1t_2 choices) and immediate choices from session 2 (t_2t_2 choices) to identify violations of revealed preferences.

In Session 2, after making advance lunch choices for session 3 (t_2t_3 choices), we offer subjects an externally enforced commitment device. If they choose to commit, they switch off the possibility to make immediate lunch choices in session 3 (t_3t_3 choices). By choosing the commitment device, they can thus abstain from choosing again when temptation should be greatest. If they do not choose to commit, they will again make immediate lunch choices in the next session. In session 3, the computer randomly draws one out of two advance choices for committing individuals ($C = 1$) with probability 0.5, and one out of four advance and immediate choices for non-committing individuals ($C = 0$) with probability 0.25.

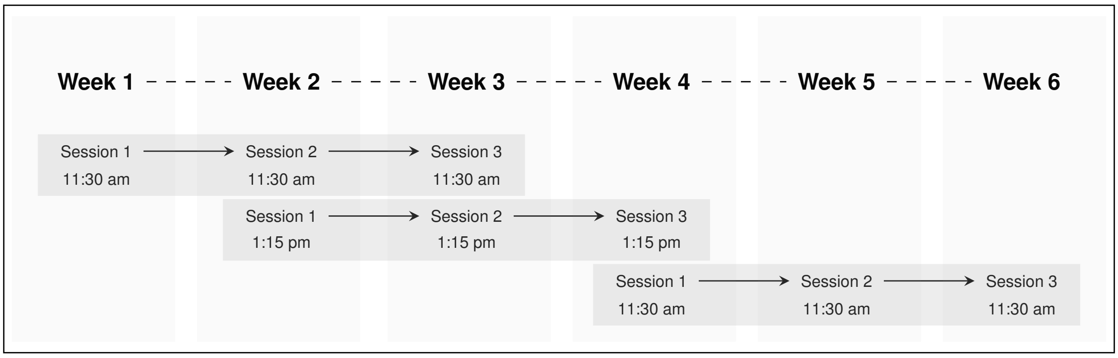
After choosing food bundles for lunch, in the second part of the experiment subjects allocate money over a one-week and two-week time horizon. Overall, subjects make 28 money allocation decisions: for seven different interest rates ranging from 1.00 to 2.00, they allocate money using four different CTB sets. Additional to the show-up fee that is paid out cash at the end of each session, subjects can receive up to 20 € in the money allocation task. As summarized in Table 1.1, in session 1 subjects allocate money between session 1 and session 2 (t_1t_2) and session 1 and session 3 (t_1t_3) from an immediate choice perspective since the allocation decisions include the current session date. In Session 1, they additionally allocate money between session 2 and 3 (t_2t_3) from an advance perspective. In Session 2, subjects allocate money between session 2 and session 3 (t_2t_3) from an immediate perspective. There is no money allocation in week three. Subjects are informed that one out of 14 decisions from the t_1t_2 and t_1t_3 set is chosen in session 1 with equal probability (≈ 0.07). They are further informed that in session 2, one out of 14 money decisions from the t_2t_3 (prospective) and the t_2t_3 (immediate) set is chosen.

1.2.1.2 Setup and Timeline

All university students received an e-mail invitation sent out by the college administration. We further advertised the experiment using a roll-up banner placed at the entry of the college canteen. Subjects registered for the experiment via email and were assigned the same session day and (lunch) time for three consecutive weeks, according to their preferences. Each participant attended for three sessions with one week spacing. Subjects were made aware of participating in an experiment which involves a free lunch for consumption in each of the three experimental sessions. They were asked to not eat for at least two hours preceding the experiment. For participating in all three sessions, subjects receive a total show-up fee of 25.50 €, of which 5 € are paid in sessions 1 and 2 and 15.50 € in session 3. The large fee in the last session is the attrition penalty.

The experimental timeline is depicted in Figure 1.1. The experiment was conducted over six weeks between Nov. 11 and Dec. 20, 2019. Subjects entering the experiment in week 1 and 4 start their sessions at 11:30am. Subjects entering in week 2 start at 1:15pm. Both slots were scheduled to fit the timetable of students during regular canteen opening hours. In total, 86 students signed up for the experiment. Since 13 did not show up or dropped out, the analysis is based on more than 3,600 single food choices made by 73 subjects in 219 individual sessions.

Figure 1.1: *Experimental Timeline*

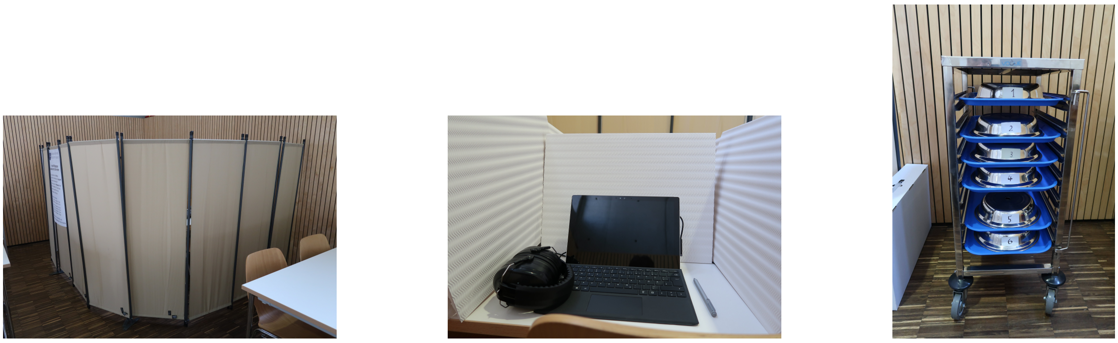


Note: The figure summarises the timeline of the experiment. Th experiment was conducted rollingly over a time span of six weeks. Participants went through three consecutive sessions with one week spacing in between. They were allocated to the same time and day for all three sessions. Participants could either start in week 1, week 2 or week 4. Different time slots were offered to best fit the schedule of college students.

Figure 1.2 depicts the experimental setup. At the beginning of a session, subjects enter an experimental booth specifically erected in the dining hall for the time of the study (a). They are placed around tables with visual covers to ensure that all choices are made in private (b). Subjects first make food choices on-screen using tablet computers. Then, they answer short questionnaires about their socio-economic background, consumption routines and preferences, followed by the allocation of money over time. In the meantime, research assistants collect the computer-selected lunch menus in the canteen and deliver them under a steel tableware cloche to the experimental booth using a cart (c). At the end of each session, participants receive money payments in cash (show-up fee + money task yield) as well as a tray with their lunch choice for free. Subjects leave the experimental booth and consume their dish in the regular seating area of the canteen. The experiment is programmed in Python and executed with the software o-tree (Chen et al., 2016).

By design, we do not observe the eating process itself to ensure natural choices and prevent distractions during the eating process. However, using a unique tray colour and tray identifier we collect the trays in the dish-washing area after the meals were consumed. This allows us to merge information about eating behavior with the food decisions made in the experimental booth. Out of 219 possible tray observations, we have data on 210 trays; in 9 cases, trays were cleaned by the canteen staff before we

Figure 1.2: *Experimental Setup*



(a) Booth (b) Desk (c) Serving Cart

Note: The figure depicts the experimental setup. Panel a) shows the experimental booth that was built in the dining hall. Participants enter the booth to make food and money choices. Panel b) shows an example desk participants were located to in order to make their choices using a table computer. Panel c) depicts the serving cart that was used to purchase the randomly selected food choice of each participant in the university canteen and serve it at the end of each session.

could analyse them. In all 210 cases, dishes were consumed (with a varying amount of plate waste).

1.2.1.3 Food Categories

In the regular college canteen, consumers choose from different food categories reflecting main dishes, side dishes and desserts. Eating behaviors often follow certain habits as humans try to minimize cognitive resources spent on everyday tasks (Khare & Inman, 2006; Wood & Neal, 2009). Disturbing individual eating routines might therefore lead to unusual choice behavior. We thus seek to mimic the natural choice setting as closely as possible by presenting lunch menus in the most familiar way with food items being sorted into the three dish categories: main dishes, side dishes and desserts. A further display convention in the canteen is to show main dishes at the top of the menu, followed by side dishes and desserts that are displayed last. We follow this convention in the experiment by fixing the order of the respective food columns: main dishes are listed first, side dishes and desserts are shown in the second and third place. Within each food category, we randomize the presentation order of food items.

Figure 1.3 depicts an extract of an example canteen menu (for 4€ $t_1 t_2$ choice made in session 1). Subjects can choose items from the food categories main dishes, side dishes and desserts. Participants can select or delete food items by clicking on the green plus or red minus button. Prices for food items correspond to regular canteen prices and are displayed in the cell right to a respective food item. The total price of the chosen lunch is automatically calculated and displayed at the bottom of the menu.[1] If the total price exceeds the price limit, the go-on button disappears and the lunch order cannot be submitted until the given budget is met.[2] Before choosing a lunch for the first time and after reading the instructions, subjects answer several control questions to ensure an understanding of the food choice task.[3]

The studies of Flores et al. (2019) and Wansink and Hanks (2013) show that the appearance order of food items matters for food choices: Individuals are influenced by the first item they see and tend to make their subsequent food choices on the basis of this first item. Research in psychology further shows that consumers use internalized heuristics to facilitate decision making: restraint eaters rather consider the food category than the food itself when making food choices (Knight & Boland, 1989). This evidence suggests that consumers tend to mentally separate dish categories, such as main dishes, side dishes and desserts. Table 1.2 indeed shows that the three dish categories are different not only with with respect to average dish size, but also with respect to nutritional information. While desserts are rather rich in sugar and fat, main and side dishes are saltier and provide more vegetables. We therefore analyze food choices by focusing on food categories separately.

To measure food choice healthiness, we collect the following nutritional information for all food items (dishes): energy (calories), saturated fats, sugar, salt, fiber, proteins and the quota of fruits/vegetables. Nutrients are collected for single ingredients, summed up and weighted according to recipes. Most recipes are provided by the canteen operator. In case recipes are not provided, we search for comparable dishes. For example, most desserts are based on products by a large German supplier of bake and cake processed products

[1] To circumvent the potential problem that specific food items are sold out, participants are also asked to choose replacement alternatives.

[2] The example menu only shows a subset of food items. A full example canteen menu including all food items is shown in Figure 1.A.1 in the Appendix.

[3] We ask for the number of food options they would select from an immediate choice perspective in session 1, the probability that a $t_1 t_1$ choice will be chosen, whether lunches would be delivered for free, whether it would be possible to choose a food item more than once or repeatedly over different options. After answering each control question and independent of the actual answer, the correct answer is displayed. Ninety-six per cent of answers subjects submitted were correct.

Figure 1.3: *Example Food Choice Task*

Select the dishes for your canteen lunch that you will receive at the end of the second session on [*date of 'today in one week'*] with a probability of 25%. Your seleced items must not exceed the total value of €4.00. Your chosen budget is indicated below the canteen menu. Click on the plus or minus sign to add an item, discard an item or change the amount.

Note: A large mixed salad has approximately 260 grams. If a dish is offered in the self-serving area, the plate will be fully filled by eye. The portion sizes of all other dishes are set by the canteen operator.

Main Dishes	**€**	**Amount**	**Side Dishes**	**€**	**Amount**	**Desserts**	**€**	**Amount**	**Sides**	**€**	**Amount**
Vegan Thai noodle vegetable pan with peanuts in coconut sauce	1.92	0	Rice	0.70	0	Fresh Fruit	0.50	0	Mayonnaise	0.20	0
Chicken breast with onion cream sauce	2.35	0	Green leaf salad	0.70	0	Fruit quark	0.70	0	Ketchup	0.20	0
Alaska pollock fillet in batter with tomato sauce and rice	2.81	0	Cucumber salad	0.70	0	Natural yogurt with muesli	0.70	0			
Vegetarian soup of the day large with roll	1.20	0	Spaetzle	0.70	0	Pudding	0.80	0			
Large mixed salad (green leaf lettuce, carrots, tomatoes, cucumber) with dressing	2.21	0	Carotts	0.70	0	Mousse/ Creme	1.10	0			

Sum: 0 Euros

Note: The figure shows an example of the food choice task (translated from German). Subjects can click on the green plus or red minus to add or delete food items. There are no choice restrictions except that the price of the food basket must not exceed the price limit of 4 € or 5 €, respectively. Following standard procedures in the canteen, we present food items in the main food categories main dishes, side dishes and desserts.

Table 1.2: *Summary of Nutrients: Dish Categories*

Food Category	Nutrient Profile Score	Calories (Kcal)	Sugar (g)	Saturated Fats (g)	Proteins (g)	Salt (Sodium in mg)	Veg Quota (%)	Item Size (g)	Price
A: weight (g)									
Main Dish	12.07	482.18	11.03	7.13	21.42	1190.98	45.59	368.18	2.26
Side Dish	-2.16	168.05	3.62	1.23	4.15	382.98	48.16	145.02	0.68
Dessert	9.33	247.39	21.29	5.61	6.77	109.31	16.67	169.83	0.75
B: per 100g									
Main Dish	-0.31	120.98	2.89	1.88	5.60	299.44	45.59	100	0.65
Side Dish	-1.68	142.48	2.36	0.80	3.85	363.78	48.16	100	0.57
Dessert	2.67	149.10	13.01	3.18	3.80	66.00	16.67	100	0.47

Notes: The table depicts average nutrient profile scores, average single nutrients, the average size and average price of the three dish categories offered during the experiment at the university canteen. In panel A, all nutrient information are based on the average weight measured in grams. Panel B reports all information per 100 grams. Nutrient profile scores range between -15 (most healthy) and +40 (most unhealthy).

from which we obtain recipes online. Nutritional information were hand-collected online and additionally provided by a commercial supplier platform. We follow Cherchye et al. (2020) and also compute the Nutrient Profile Score (NPS) for each food item. The score was developed by nutritionists (Arambepola et al., 2008; Rayner et al., 2005; Rayner et al., 2009; Scarborough et al., 2007) and converts a multidimensional nutrient profile consisting of the aforementioned seven nutrients into a single score ranging from -15 (most healthy) to +40 (most unhealthy).[4]

Within each dish category, subjects can choose from a number of food items. An average choice set comprises 25 food items: five main dishes, 14 items from the side dish category and six desserts. The canteen menu is highly standardized: Every day, as main dish options the canteen offers at least one vegetarian main dish, a salad buffet, two main dishes containing meat and a vegetarian soup bowl. As dessert options, the canteen always offers pudding, mousse, fruit quark, yoghurt with and without sugar and a fruit (apple or banana). As side dish options, there is always one sort of vegetables and a constant variety of small salads (cucumber, peppers, tomato, mixed, green salad), different sorts of buns (pretzel, wheat, grain), a small vegetarian soup bowl as well as at least one hot side dish such as noodles, rice, potatoes or fries. We summarize nutritional information, prices and dish sizes for different food items in Table 1.A.1 in the Appendix. Since the types of vegetable, soups and hot main dishes vary on a daily basis, the canteen

[4] As an example application, the NPS system is used by governmental authorities in UK and Australia/New Zealand to regulate health claims in TV advertisements mainly watched by children.

setup delivers a between-dish comparison based on 135 unique dishes.

1.2.2 Structural Estimation

We analyse food consumption behavior over time by focusing on differences between food choices made from an advance and immediate choice perspective. By applying a simple Ordinary Least Squares (OLS) regression framework, however, we might mistakenly consider inconsistencies in food choices as evidence for inconsistencies in time preferences. But inconsistent choices might also be driven by random shocks to utility under time consistent preferences. Indeed, to make decision environments over time as comparable as possible, subjects are told not to eat two hours before a session starts, and attend the experiment always on the same week day and at the same time. But there might still be unobservable factors affecting subjects' utility over time differently. To account for such random shocks, we follow Beggs et al. (1981) and Sadoff et al. (2020) and apply standard random utility techniques to structurally analyse food choices.

In a random utility model (Walker & Ben-Akiva, 2002), the value of each food item is derived from a set of underlying characteristics and a random utility shock:

$$V_j = \mathbf{X}_j \phi + \epsilon_j \quad j \in 1, .., J,$$

where $\mathbf{X}_j$ represents a vector of food characteristics and ϵ_j is a random utility shock drawn iid from a Type-1 extreme value distribution. The parameter vector ϕ represents the weights given to attributes. Food choices can now be summarized by orderings. In a first step, consider the probability that a given food item j is preferred to all alternative food items $1, ..., J-K-1$:

$$F_j[x_1, ..., x_{J-K-1}; x_j; \phi] = \frac{exp(\mathbf{x}_j \phi)}{exp(\mathbf{x}_j \phi) + \Sigma_{i=1}^{J-K-1} exp(\mathbf{x}_i \phi)}.$$

Now consider a subject choosing K unique food items from the choice set. We order all food items and summarize it in a ranking $r \equiv \{1, ..., J\}$. The probability of observing this ranking is

$$Prob(r, \mathbf{x}, \phi) = \prod_{j=J-K}^{J} F_j[x_1, ..., x_{J-K-1}; x_j; \phi].$$

We can calculate the log-likelihood of observing a certain number of rankings N as

$$L(\phi) = \Sigma_{i=1}^{N} log(Prob(r_i, \mathbf{x}_i, \phi))$$

by applying a rank-ordered Logit regression model estimated via maximum likelihood. For $N = 73$ subjects, we construct 73 orderings from advance and 73 orderings from immediate food choices. The coefficients ϕ_A and ϕ_I can be estimated simultaneously and we can test the null hypothesis H_0 that $\phi_A = \phi_I$ given a random error structure. Exploiting within-individual switches between healthier and unhealthier food items over time, rejecting the null provides evidence for violations of revealed preferences accounting for random shocks to utility.

By definition, the framework assumes that any included items are preferred over all excluded items. Since we have a dummy variable indicating whether or not a certain food item is included by an individual, we do not have an ordering within the sets of included and excluded items. The ranks within both sets are tied since no explicit ranking exists and all possible rankings are consistent with observed behavior. We use the method of Efron (1977) to handle ties in rank order data.

Since subjects were not restricted to choose a fixed amount of food items for lunch, the number of included and excluded items might vary within individuals over time resulting in a varying sum of ranks. According to Allison and Christakis (1994), the sum of the ranks must not be constant over individuals as long as tied items are assigned the same number. We can therefore apply this setup to estimate utility weights for all of our subjects; independent of the number of items included.

1.3 Results

The paper first provides evidence on dynamic inconsistencies in food choices (Section 1.3.1), before comparing food consumption with money allocation choices (Section 1.3.2). Finally, we provide several robustness tests (Section 1.3.3).

1.3.1 Dynamic Inconsistency in Food Consumption

To assess the extent of time inconsistency in food choices, we follow Ashraf et al. (2006), Augenblick et al. (2015), and Sadoff et al. (2020) and consider choices made prior to offering commitment. Subjects in our experiment make food choices from an advance and immediate perspective. In session 1, they choose food items for lunch for session 2 (advance choice perspective). In session 2, they choose lunch for session 2 from an immediate choice perspective. To evaluate time-inconsistencies in food choices, we compare advance choices from session 1 made for session 2 with immediate choices from session 2. Throughout our analysis, we focus on the quota of fruits and vegetables, calories, saturated fats, and nutrient profile scores as outcome variables. All of these measures are established indicators of diet healthiness, with nutrient profile scores being the most holistic metric.

1.3.1.1 Food Choices

Table 1.3 shows the results of our structural estimation approach. To operationalize the random utility model introduced in Section 1.2.2, we run rank-ordered Logit regressions that are estimated with maximum likelihood. First, we focus at the three food categories (main dishes, side dishes, desserts) separately. Results of this exercise are reported in columns 1-3 of Table 1.3. In each panel A-D, we assume either the quota of fruits and vegetables, calories, saturated fats or nutrient profile scores to drive utility. Standard errors are clustered at individual level. In each panel, estimates of the utility weight given to food items in advance choice, ϕ_A, are shown first. Our main estimate of interest is given by the interaction term that calculates the difference in utility weight between immediate and advance choice ($\phi_I - \phi_A$).

Table 1.3: *Utility Weight Estimates*

	Main dish	Side dish	Dessert	Full meal
A: Vegetables/Fruit Quota				
Veg Quota ($\hat{\phi}_A$)	-1.093***	-0.192	0.698***	-0.024
	(0.395)	(0.205)	(0.257)	(0.149)
Immediate choice ×	-0.893***	-0.064	0.593**	-0.032
Veg Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.296)	(0.226)	(0.281)	(0.126)
Log-likelihood	-332.630	-647.175	-243.514	-2171.461
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 9.082$	$\chi^2(1) = 0.082$	$\chi^2(1) = 4.450$	$\chi^2(1) = 0.066$
	($p = 0.003$)	($p = 0.775$)	($p = 0.035$)	($p = 0.798$)
B: Calories				
Calories ($\hat{\phi}_A$)	0.110***	0.180***	-0.409***	0.142***
	(0.025)	(0.031)	(0.142)	(0.015)
Immediate choice ×	0.031*	0.025	-0.333*	0.018
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.016)	(0.023)	(0.172)	(0.011)
Log-likelihood	-327.004	-618.033	-242.415	-2087.843
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 3.709$	$\chi^2(1) = 1.175$	$\chi^2(1) = 3.746$	$\chi^2(1) = 2.368$
	($p = 0.054$)	($p = 0.278$)	($p = 0.053$)	($p = 0.124$)
C: Fat				
Fat ($\hat{\phi}_A$)	0.008	0.120***	-0.069**	0.045***
	(0.015)	(0.017)	(0.029)	(0.007)
Immediate choice ×	0.028***	0.009	-0.082**	0.003
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.011)	(0.015)	(0.041)	(0.006)
Log-likelihood	-349.825	-612.403	-244.886	-2146.090
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 6.668$	$\chi^2(1) = 0.393$	$\chi^2(1) = 3.954$	$\chi^2(1) = 0.192$
	($p = 0.010$)	($p = 0.531$)	($p = 0.047$)	($p = 0.661$)
D: Nutrient Profile Score				
Nutrient Profile Score ($\hat{\phi}_A$)	0.034***	0.054***	-0.026*	0.038***
	(0.010)	(0.010)	(0.016)	(0.005)
Immediate choice ×	0.016**	0.003	-0.034*	0.003
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.007)	(0.009)	(0.019)	(0.004)
Log-likelihood	-325.927	-620.344	-250.213	-2105.038
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 4.655$	$\chi^2(1) = 0.165$	$\chi^2(1) = 3.189$	$\chi^2(1) = 0.477$
	($p = 0.031$)	($p = 0.685$)	($p = 0.074$)	($p = 0.490$)
# Observations	730	1780	864	3666
# Rankings	146	146	146	146
# Clusters	73	73	73	73

Note: The table presents results from rank-ordered Logit regressions estimated with maximum likelihood. We report results for different potential utility drivers: quota of fruits and vegetables, calories, saturated fats and nutrient profile scores. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice (ϕ_A). The interaction term indicates a utility weight change between immediate and advance choice. The null hypothesis tests whether the interaction coefficient is different from 0. Results are first reported for the three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Column 4 shows results at the food basket level (looking at all food categories simultaneously. In column 4, the data set comprises 3,666 observations: On average, subjects choose food items from a set of around 25 different food items resulting in an overall sample size of $25.11 \times 73 \times 2 \approx 3666$. Levels of significance: *0.10, **0.05, ***0.01

As columns 1-3 reveal, the choice pattern between food categories is highly heterogeneous. Assuming the quota of fruits and vegetables to drive utility (panel A), subjects put significant more weight on main and side dishes with less vegetables in advance choice. At the same time, they favor healthier desserts with more fruits. These different inclusion probabilities reveal that subjects in advance choice favor unhealthier main dishes but healthier desserts. This choice pattern suggests a preference for mixed bundles with respective to bundle healthiness. There exist significant differences between immediate and advance choices indicated by the interaction term $\phi_I - \phi_A$: While the utility weight for healthier main dishes significantly decreases (-0.893), the opposite is true for desserts. Here, the utility weight for healthier desserts increases even more compared to advance choices. This choice pattern suggests that subjects value main dishes with relatively more fruits and vegetables less in immediate choice (compared to advance choice) while at the same time they the opposite effect is observed for desserts: healthier desserts are preferred even more from an immediate choice perspective. This choice pattern is observed in all panels, irrespective of the utility driver used.

Three conclusions can be drawn. First, Table 1.3 provides evidence that subjects treat food categories differently. This finding is resonating with the literature (Flores et al., 2019; Wansink & Hanks, 2013). Second, subjects seem to balance the healthiness of food items over dish categories: main dishes become less healthy in immediate choice while desserts become healthier. Third, the magnitude of significant utility weight differences is higher compared to Sadoff et al. (2020): focusing on the quota of fruits and vegetables, the utility weight for more healthy main dishes significantly decreases by 82%, while the utility weight for more healthy desserts significantly increases by 85%. This finding suggests a more intense change in utility weight over time.

In a second step, we collapse food category choices and focus at the meal level. Results are reported in column 4 of Table 1.3. As expected after observing the diverging choice pattern at food category level, we find a null effect in all panels: Analyzing food choices across food categories at the same time, we do not observe a significant difference in meal healthiness between immediate and advance food choices. The aggregate analysis at food basket (meal) level hides within-meal heterogeneity in choice behavior.

1.3.1.2 Commitment Demand

To investigate the relation between self-control problems and beliefs thereof, we now consider the demand for a commitment device. Subjects decide in session 2 whether to use a commitment device that ties them to their advance choices made in session 2 for session 3. If they choose to commit, one out of two food choices made from an advance choice perspective in session 2 is randomly chosen and served in session 3. Subjects that choose not to commit make an additional two food choices from an immediate perspective in session 3. In this case, one out of four choices is randomly selected and implemented. In the experiment, 52% (38) of subjects demand the commitment device. This number is comparable to Augenblick et al. (2015) and Sadoff et al. (2020) who report commitment take-up of 53% or 59%, respectively.

In Table 1.4, we repeat the analysis from Section 1.3.1, and additionally split the data set based on commitment device take-up. Columns 1-3 show structural estimation results for all choices made by committing individuals. Columns 4-6 on the other hand report utility weight estimates for non-committing individuals. Results are reported for food categories separately: main dishes, side dishes and desserts. Note, that all results are based on choices *before* the commitment device was offered. Table 1.4 reports structural estimation results for four different utility drivers: quota of fruits and vegetables (panel A), calories (B), saturated fats (C) and nutrient profile scores (D).

Focusing on advance food choices, both committing and non-committing subjects prefer unhealthier main dishes, but healthier desserts. This result echos the findings from Section 1.3.1.1: Subjects treat food categories differently and balance food healthiness over food categories suggesting a preference for mixed bundles for both committing and non-committing individuals. This pattern of opposing signs for utility weight estimates in advance choices can be observed for all utility drivers: subjects prefer unhealthier main or side dishes but healthier desserts. Focusing on the comparison of immediate and advance choices ($\phi_I - \phi_A$), we observe differences in behavior between committing and non-committing subjects. To give an example, we focus on utility weight estimates based on the quota of fruits and vegetables as utility driver (panel A). Committing individuals show an even stronger preference for unhealthier main dishes ($\phi_I - \phi_A = -0.727$, $p = 0.080$), while they give even more weight to more healthier desserts ($\phi_I - \phi_A = 0.916$, $p = 0.017$) in immediate choice. They seem to offset unhealthier main dishes by choosing

Table 1.4: *Utility Weight Estimates and Commitment Demand*

	Committer=1			Committer=0		
	Main dish	Side dish	Dessert	Main dish	Side dish	Dessert
A: Vegetables/Fruit Quota						
Veg/Fruit Quota ($\hat{\phi}_A$)	-1.321**	-0.390	0.590	-0.862*	0.023	0.807**
	(0.623)	(0.287)	(0.359)	(0.504)	(0.298)	(0.375)
Immediate choice ×	-0.727*	-0.022	0.916**	-1.060**	-0.108	0.276
Veg/Fruit Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.414)	(0.319)	(0.384)	(0.423)	(0.327)	(0.414)
Log-likelihood	-173.803	-337.902	-119.994	-158.605	-308.372	-123.086
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 3.075$	$\chi^2(1) = 0.005$	$\chi^2(1) = 5.702$	$\chi^2(1) = 6.272$	$\chi^2(1) = 0.110$	$\chi^2(1) = 0.445$
	$(p = 0.080)$	$(p = 0.945)$	$(p = 0.017)$	$(p = 0.012)$	$(p = 0.740)$	$(p = 0.505)$
B: Calories						
Calories ($\hat{\phi}_A$)	0.130***	0.199***	-0.449**	0.091**	0.143**	-0.365
	(0.028)	(0.036)	(0.180)	(0.039)	(0.059)	(0.225)
Immediate choice ×	0.010	0.013	-0.542***	0.051*	0.049	-0.143
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.013)	(0.031)	(0.200)	(0.028)	(0.031)	(0.283)
Log-likelihood	-171.145	-317.113	-116.207	-155.559	-300.512	-124.920
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.634$	$\chi^2(1) = 0.170$	$\chi^2(1) = 7.372$	$\chi^2(1) = 3.381$	$\chi^2(1) = 2.531$	$\chi^2(1) = 0.257$
	$(p = 0.426)$	$(p = 0.680)$	$(p = 0.007)$	$(p = 0.066)$	$(p = 0.112)$	$(p = 0.612)$
C: Fat						
Fat ($\hat{\phi}_A$)	-0.003	0.124***	-0.081**	0.020	0.113***	-0.056
	(0.023)	(0.021)	(0.039)	(0.019)	(0.030)	(0.043)
Immediate choice ×	0.028**	-0.002	-0.131**	0.030	0.030*	-0.046
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.012)	(0.021)	(0.054)	(0.019)	(0.018)	(0.060)
Log-likelihood	-185.092	-317.520	-117.944	-164.126	-294.694	-125.684
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 4.941$	$\chi^2(1) = 0.007$	$\chi^2(1) = 5.975$	$\chi^2(1) = 2.498$	$\chi^2(1) = 2.965$	$\chi^2(1) = 0.590$
	$(p = 0.026)$	$(p = 0.934)$	$(p = 0.015)$	$(p = 0.114)$	$(p = 0.085)$	$(p = 0.442)$
D: Nutrient Profile Score						
Nutrient Profile Score ($\hat{\phi}_A$)	0.042***	0.068***	-0.014	0.028**	0.033**	-0.038*
	(0.015)	(0.012)	(0.023)	(0.013)	(0.017)	(0.022)
Immediate choice ×	0.012	-0.004	-0.056**	0.020	0.015	-0.012
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.008)	(0.012)	(0.028)	(0.012)	(0.014)	(0.027)
Log-likelihood	-169.567	-316.219	-124.332	-155.997	-302.265	-125.409
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 2.274$	$\chi^2(1) = 0.145$	$\chi^2(1) = 4.182$	$\chi^2(1) = 2.631$	$\chi^2(1) = 1.226$	$\chi^2(1) = 0.213$
	$(p = 0.132)$	$(p = 0.704)$	$(p = 0.041)$	$(p = 0.105)$	$(p = 0.268)$	$(p = 0.645)$
# Observations	380	934	450	350	846	414
# Rankings	76	76	76	70	70	70
# Clusters	38	38	38	35	35	35

Note: The table presents results from rank-ordered Logit regressions applying a random utility model that takes into account random utility shocks. We report results for different potential utility drivers: the quota of fruits and vegetables, calories, saturated fats and nutrient profile scores, and report results for committing and non-committing individuals separately. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the respective utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice. The interaction term indicates a utility weight change from advance to immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to advance choice (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

healthier desserts. The utility weight for healthier main dishes significantly decreases by 55%, while for healthier desserts the utility weight significantly increases by 155%. Committing individuals seem to balance food basket healthiness over food categories not only in advance, but also in immediate choice when temptation should be greatest.

Non-committing individuals on the other hand show an elevated preference for unhealthier main dishes in immediate choice that is not offset by choosing healthier desserts. Focusing on panel A, the estimated utility weight for healthier main dishes significantly decreases by 123% ($\phi_I - \phi_A = -1.060$, $p = 0.012$) while there is no significant difference in utility weight for healthier desserts. This choice pattern can be observed for all four utility drivers: while main or side dishes become unhealthier in immediate choice, the inclusion probability for unhealthier desserts does not change. This finding suggests dynamically inconsistent choice behavior for non-committing individuals.

Summarizing the estimates reported in Table 1.4, committing and non-committing individuals exhibit differences in their choice patterns in immediate choice. Committing subjects balance food bundle healthiness with a tendency to choose slightly healthier in immediate choice. This behavior suggests that committing individuals follow an internal self-control strategy when external commitment is absent. The observed behavior is in line with theoretical considerations of Benhabib and Bisin (2005) who take into account explicit self-control mechanisms in modelling dynamic consumption-saving behavior, and echos the findings of Sjåstad and Ekström (2021) who study internal and external commitment in a more stylized lab setting. The result suggests that internal and external commitment mechanisms are substitutes; and that committing individuals actively regulate their behavior when external devices are absent.

Non-committing individuals on the other hand choose unhealthier main or side dishes indicating dynamically inconsistent time preferences. They do not choose the external commitment device and do not seem to enforce self-control when commitment is absent. This finding suggests that non-committing individuals are at least partially naive about their inconsistency (O'Donoghue & Rabin, 2001). Our results suggest that present-biased individuals are less likely to take up a commitment device, thereby limiting the scope for effective policy interventions applying such devices. This finding is in line with the studies of Royer et al. (2015) and Sadoff et al. (2020) who also find a negative relation between self-control problems and beliefs thereof. It contradicts the findings of Avery et al. (2022), Bai et al. (2021), and Kaur et al. (2015) who find a positive correlation.

A further question is which internal self-control strategy committing individuals apply? While we cannot pin down the exact channel, one possible mechanism that is consistent with the data is mental accounting. While Thaler (1999) applies this strategy to financial activities, Tversky and Kahneman (1981) adopt a broader perspective and a literature has emerged that expands the application also to food choices (Cheema & Soman, 2006; Koch & Nafziger, 2016). According to this strategy, subjects set a healthiness goal for lunch. This goal defines a reference point that makes underperformance painful under the assumption of loss-aversion. Under narrow bracketing, the lunch choice is assessed in isolation and the loss cannot be compensated by later behavior, e.g. by overperforming at dinner (Koch & Nafziger, 2016). Food items for lunch are, hence, chosen against the background of a given nutritional account or budget. An underperformance in the main and side dish category needs to be offset immediately by overperforming in the dessert category. As a result, the same amount of nutrients is treated differently across different dish categories, and at the aggregate food bundle (meal) level, food bundle healthiness does not change from advance to immediate choice.

1.3.1.3 Stability of Inconsistency

So far, our analysis has focused on food choices made in session 1 (advance choices) and session 2 (immediate choices) to identify violations of revealed preferences over time. To investigate the stability of food choice behavior over more time periods, we now look at food consumption choices of non-committing individuals after commitment has been offered in session 2. More precisely, we compare food choices made from an advance perspective in session 2 with food choices made from an immediate perspective in session 3, and structurally estimate utility weights for immediate and advance choices applying the random utility techniques introduced in Section 1.2.2. We can only focus on non-committing individuals since committing individuals do not make food choices from an immediate perspective in session 3.

The results of this exercise are presented in Table 1.5. Columns 1-3 present utility weight estimates for the three food categories main dishes, side dishes and desserts while panels A to D show the estimates for the four assumed utility drivers: the quota of fruits and vegetables, calories, saturated fats and nutrient profile scores. Focusing on utility weight estimates in advance choice ($\hat{\phi}_A$), non-committing individuals favor unhealthier main and side dishes while they prefer healthier desserts. This pattern of opposing coefficient signs between rather salty and sweet food categories is constant for all utility drivers assumed. It suggests a preference for mixed bundles in advance choice.

Focusing on the comparison of advance and immediate choices ($\hat{\phi}_I$-$\hat{\phi}_A$), a choice pattern is revealed by looking at calories, saturated fats and nutrient profile scores while results are less precise for the quota of fruits and vegetables: There is no significant change in the inclusion probability of unhealthier main or side dishes, but unhealthier desserts are significantly more likely to get chosen in immediate choice. Looking at calories, the difference in utility weight between immediate and advance choice is 0.535. This estimate implies a utility weight increase for unhealthier desserts by 75% in immediate choice.

Comparing second round results to first round estimates reported in Table 1.4, a similar behavioral pattern emerges between the two rounds: First, in advance choice non-committing individuals show a preference for mixed bundles in both rounds. Second, in immediate choice they favor unhealthier items from single food categories in both rounds. In the first choice comparison (Table 1.4), non-committing individuals receive more utility from including unhealthier salty food items from the main or side dish category into their immediate choice food bundles. In the second comparison (Table 1.5), individuals receive more utility from including unhealthier sweet food items from the dessert category in their immediate choice food bundles. As in round 1, we observe parts of food bundles becoming unhealthier. Interestingly, utility weight changes in immediate choice are driven by salty food items in round 1, but sweet food items in round 2. In both rounds, non-committing individuals show dynamic inconsistencies in food choices.

1.3.2 Comparison of Food Consumption and Money Allocation Choices

In Section 1.3.1, we analyzed the extent and direction of dynamic inconsistencies in food choices. Subjects had to make real consumption choices (order lunch at lunchtime) in a natural setting (at a college canteen) that were consumed on receipt (eat dish in the dining hall) after each session. But how does this novel food choice task compare with a standard money allocation task? To answer this question, we proceed in two steps. First,

Table 1.5: *Utility Weight Estimates: Second Round Choices for Non-Committers*

	Main dish	Side dish	Dessert
A: Vegetables/Fruit Quota			
Veg Quota ($\hat{\phi}_A$)	-1.913***	-0.462**	1.050***
	(0.631)	(0.226)	(0.293)
Immediate choice ×	0.429	0.348	-0.329
Veg Quota ($\hat{\phi}_I - \hat{\phi}_A$)	(0.683)	(0.238)	(0.265)
Log-likelihood	-142.390	-349.731	-134.537
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.395$	$\chi^2(1) = 2.140$	$\chi^2(1) = 1.540$
	($p = 0.530$)	($p = 0.144$)	($p = 0.215$)
B: Calories			
Calories ($\hat{\phi}_A$)	0.161***	0.216***	-0.716***
	(0.038)	(0.040)	(0.145)
Immediate choice ×	-0.036	-0.013	0.535***
Calories ($\hat{\phi}_I - \hat{\phi}_A$)	(0.044)	(0.026)	(0.184)
Log-likelihood	-142.135	-336.615	-133.484
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.660$	$\chi^2(1) = 0.256$	$\chi^2(1) = 8.464$
	($p = 0.417$)	($p = 0.613$)	($p = 0.004$)
C: Fat			
Fat ($\hat{\phi}_A$)	0.032	0.129***	-0.186***
	(0.028)	(0.021)	(0.043)
Immediate choice ×	0.006	0.030	0.169***
Fat ($\hat{\phi}_I - \hat{\phi}_A$)	(0.030)	(0.022)	(0.035)
Log-likelihood	-151.208	-329.276	-131.367
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.046$	$\chi^2(1) = 1.841$	$\chi^2(1) = 23.415$
	($p = 0.830$)	($p = 0.175$)	($p = 0.000$)
D: Nutrient Profile Score			
Nutrient Profile Score ($\hat{\phi}_A$)	0.051***	0.051***	-0.081***
	(0.014)	(0.014)	(0.020)
Immediate choice ×	-0.009	0.003	0.067***
Nutrient Profile Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.017)	(0.014)	(0.018)
Log-likelihood	-139.696	-339.217	-133.060
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 0.262$	$\chi^2(1) = 0.047$	$\chi^2(1) = 14.147$
	($p = 0.609$)	($p = 0.829$)	($p = 0.000$)
# Observations	354	908	420
# Rankings	70	70	70
# Clusters	35	35	35

Note: The table presents results from rank-ordered Logit regressions for non-committing subjects after commitment was offered (and not taken). We regress an "Is chosen" dummy that equals 1 if a food item is chosen by an individual on the respective nutrient (panels A to D) and an interaction term between nutrient and immediate choice dummy. The advance choice coefficient in each panel represents the utility weight in advance choice. The interaction term coefficient indicates a utility weight change in immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to the utility weight from the advance choice perspective (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

we describe the money allocation task in more detail and analyse monetary discounting behavior in Section 1.3.2.2. We then examine the correlation between the two tasks at the individual level in Section 1.3.2.3.

1.3.2.1 Money Allocation Task

In session 1 and 2, subjects allocate money to a sooner and later point in time by choosing money allocations in CTB sets. The allocation task is summarized in Table 1.6. In total, subjects decide on money allocations in four separate CTB sets that differ with respect to the delay length k (one vs. two weeks) and choice perspective (advance vs. immediate choice). In session 1, subjects face three different CTB sets. In the first set, they allocate money between session 1 (today) and session 2 (in one week). In the second CTB set, money is allocated between session 1 and session 3 (in two weeks). In the third set, all allocation choices are made for the future: money has to be split between in one week and two weeks. CTB set 3 and 4 are identical except for the choice perspective: in CTB set 4, money is allocated from an immediate choice perspective involving today (session 2) and the next week (session 3).

Table 1.6: *Money Allocation Task: CTB Sets*

Experimental Session	CTB set	Sooner payment (c_t)	Later payment (c_{t+k})	Delay (k)
1	1: $t_1 \rightarrow t_1 t_2$	Today	In 1 week	1 week
1	2: $t_1 \rightarrow t_1 t_3$	Today	In 2 weeks	2 weeks
1	3: $t_1 \rightarrow t_2 t_3$	In 1 Week	In 2 weeks	1 week
2	4: $t_2 \rightarrow t_2 t_3$	Today	In 1 week	1 week

Note: The table shows the four CTB sets applied in the experiment. In each money allocation sheet, seven money allocation decisions are made given the following seven interest rates $(1 + r)$: $1.00, 1.05, 1.11, 1.18, 1.33, 1.43, 2.00$, and the budget constraint: $(1 + r)c_t + c_{t+k} = 10$. In session 1, CTB set 1 and 2 are displayed in random order.

Figure 1.4 depicts an example CTB set with a delay length of one week and immediate choice perspective (set 1 or 4 in Table 1.6). Subjects are informed to choose exactly one allocation in each row. In fact, they can only proceed if exactly one allocation per row is chosen. In each row, a different interest rate is implemented. Overall, the interest rates are given by $(1 + r) \in \{1.00, 1.05, 1.11, 1.18, 1.33, 1.43, 2.00\}$, and values are chosen for comparison with prior work (Andreoni et al., 2015; Augenblick et al., 2015; Lührmann et al., 2018). Between the first and last row, interest rates increase from 1 to 2 and reduce the amount of money that can be allocated to the sooner payment date. In all allocation decisions, the intertemporal budget constraint is given by

$$(1 + r)c_t + c_{t+k} = m \tag{1.1}$$

with the budget m being set to 10 €. Increasing interest rates imply that the implicit price for receiving money sooner compared to later in time goes up. By choosing the rightmost allocation, subjects will always receive 10 € at the future payment date. Before starting the money allocation task, subjects are informed about all contextual details in the instructions, see an example screen and answer several control questions to ensure an understanding of the task. After submitting an answer, the correct answer is given to subjects irrespective of their actual answer. The instruction displayed to subjects before the task starts is shown in Appendix B.

In designing our experiment, we implement a number of features to reduce potential confounding factors in measuring present bias in money. First, to alleviate the concern of *pay-out uncertainty*, we follow Andreoni and Sprenger (2012a) and explicitly guarantee all money payments by the university in the instructions. Second, we rule out *pay-out delay* as Augenblick (2018) and Balakrishnan et al. (2020) find that a delay of the initial payment by even a few hours reduces present bias significantly. In our experiment, each draw is paid directly at the end of the respective session. Third, since subjects always receive a show-up fee at the end of each session, there are no additional *transaction costs* for collecting pay-outs from the money allocation task that could potentially influence allocation behavior. Fourth, we reduce *task interference* by explicitly stating in the instructions that the food consumption task as part 1 and the money allocation task as part 2 of a session are independent of each other.

1.3.2.2 Monetary Discounting

Moving to the first analysis, Figure 1.5 graphically summarises money allocation behavior over time. The figure depicts the mean amount of money that is allocated to the sooner payment date for all seven different interest rates. The left panel displays all allocation choices with one-week delay while the right panel depicts allocations for

Figure 1.4: *Example CTB Decision Sheet*

Choose an allocation:

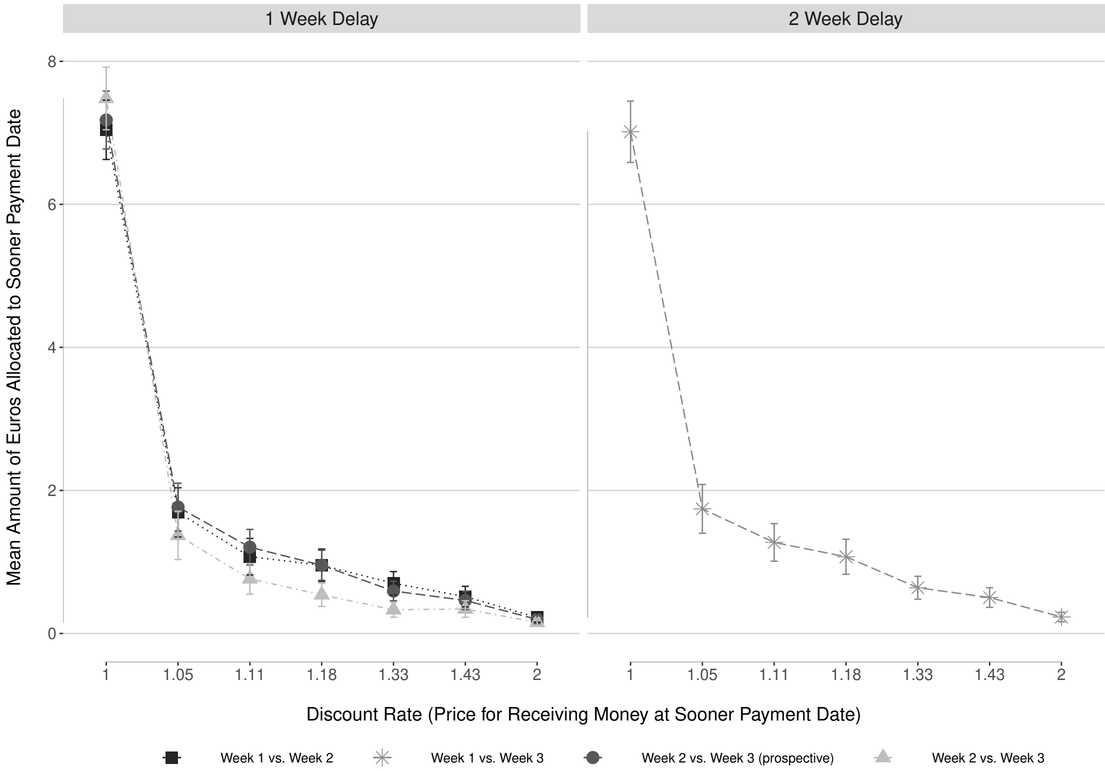
Please allocate money between **today** and **today in one week**. In each row, choose the amount of money you would like to receive today and on [*date of 'today plus one week'*] at the end of the respective session.

1	**Amount today**	**€10.00**	**€8.00**	**€6.00**	**€4.00**	**€2.00**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
2	**Amount today**	**€9.50**	**€7.60**	**€5.70**	**€3.80**	**€1.90**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
3	**Amount today**	**€9.00**	**€7.20**	**€5.40**	**€3.60**	**€1.80**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
4	**Amount today**	**€8.50**	**€6.80**	**€5.10**	**€3.40**	**€1.70**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
5	**Amount today**	**€7.50**	**€6.00**	**€4.50**	**€3.00**	**€1.50**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
6	**Amount today**	**€7.00**	**€5.60**	**€4.20**	**€2.80**	**€1.40**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**
7	**Amount today**	**€5.00**	**€4.00**	**€3.00**	**€2.00**	**€1.00**	**€0.00**
	and amount in one week	**€0.00**	**€2.00**	**€4.00**	**€6.00**	**€8.00**	**€10.00**

Note: The figure shows an example CTB set (translated from German). Participants make seven allocation decisions choosing a monetary amount paid out earlier and later after an experimental session. In each row, subjects face a different discount rate increasing the price for allocating money to the earlier payment date. In this sheet, subjects allocate 10 € between today and today in one week. All amounts are paid out cash to participants at the end of each session.

a two-week delay. Money allocation behavior reflects the law of demand: As $(1 + r)$ increases, the average money allocation to the sooner payment date decreases. In fact, 96% of choices are monotonically decreasing in $(1 + r)$ at the individual level and no participant exhibits more than three nonmonotonicities.[5]

Figure 1.5: *Monetary Discounting Behavior*



Note: The figure depicts the mean amount of money that subjects allocate to the sooner payment date - depending on the discount rate. As the discount rate increases, allocating money to the sooner payment date becomes more expensive. The left panel depicts money allocation choices with one week delay between sooner and later payment date. The panel on the right shows allocation decisions for the two week delay. The behavior follows the law of demand: As the price increases, the amount of money allocated to the sooner payment date decreases.

To estimate dynamic inconsistencies in choices over money, we apply the quasi-hyperbolic discounting framework ((β, δ) model) of Laibson (1997) and O'Donoghue and Rabin

[5]Subjects have 24 opportunities to violate monotonicity comparing two adjacent values of $(1 + r)$ in their 28 total CTB choices. 54 of 73 subjects have no identified nonmonotonicities. Of those 19 participants violating monotonicity, 10 participants only have one nonmonotonicity, six individuals have up to three nonmonotonicities.

(1999) and adopt the parametric approach of Andreoni and Sprenger (2012a) by assuming a constant relative risk aversion (CRRA) utility function with Stone-Geary background consumption parameters. Following Augenblick et al. (2015), we fix the minimum amount of background consumption at the level of the show-up fee that subjects receive at the end of each experimental session. Hence, the quasi-hyperbolic discounted utility from experimental payments at two payment dates, c_t, and c_{t+k}, is given by

$$U(c_t, c_{t+k}) = (c_t + \omega)^{\alpha} + \beta^{\mathbf{1}_{t=0}} \delta^k (c_{t+k} + \omega)^{\alpha}. \tag{1.2}$$

A risk-averse individual maximizes utility from two payments over time. While c_t is the payment delivered immediately, c_{t+k} is a future payment delivered with delay k and will therefore be discounted. The parameter δ captures long-run discounting, while β captures the degree of dynamic inconsistency. For $\beta = 1$, the quasi-hyperbolic discounting model nests the exponential discounting model. The variable $\mathbf{1}_{t=0}$ is an indicator that takes on the value of one if the earlier payment date, t, is the present, and zero otherwise. Background consumption is captured by ω. Maximizing equation 1.2 given the intertemporal budget constraint in equation 1.1 yields an intertemporal Euler equation that can be rearranged to obtain:

$$ln(\frac{c_t + \omega}{c_{t+k} + \omega}) = \frac{ln(\beta)}{\alpha - 1}\mathbf{1}_{t=0} + \frac{ln(\delta)}{\alpha - 1}k + ln(P). \tag{1.3}$$

Assuming an additive error, the Euler equation can be estimated at the aggregate or individual level:

$$ln(\frac{c_t + \omega}{c_{t+k} + \omega})_i = \eta_0 \times k + \eta_1 \times (\mathbf{1}_{t=0}) + \eta_2 \times ln(P) + \epsilon_i.$$

Discounting and utility function parameters can be recovered as nonlinear combinations of regression coefficients with standard errors estimated via the delta method:

$$\hat{\beta} = exp(\hat{\eta}_1/\hat{\eta}_2), \hat{\delta} = exp(\hat{\eta}_0/\hat{\eta}_2) \text{ and } \hat{\alpha} = 1 + 1/\hat{\eta}_2.$$

In each CTB set, subjects can only choose one out of six different allocation options: They can allocate either 100 percent, 80 percent, 60 percent, 40 percent, 20 percent or 0 percent to the sooner payment date. A different allocation to the sooner payment date is not possible by design. This restriction leads to interval censoring of the data and requires to adapt the estimation methodology. To account for censoring, we follow Andreoni et al. (2015) and Lührmann et al. (2018) and estimate utility function parameters applying an interval-censored Tobit regression model that is estimated with maximum likelihood.

Table 1.7 shows the results of this structural estimation, with standard errors being clustered at individual level. In column 1, the present bias parameter β, the long-run discounting factor δ as well as the degree of risk aversion α are estimated. The estimation is based on 2,044 observations: 73 subjects allocate money in four separate CTB sets with seven allocation choices each. In column 2, we additionally consider an error parameter in the estimation: We follow Lührmann et al. (2018) and allow subjects to make Fechner errors. Since our college students very likely face this money allocation task for the first time, they might not choose the available money ratio that is closest to their optimal ratio. With Fechner errors, the distance between the optimal and the available ratio is allowed to be evaluated stochastically. According to Von Gaudecker et al. (2011), a larger Fechner error implies that this distance is given less weight in decision making. As a consequence, decision errors are more likely to appear. In column 2, the stochastic decision making term τ is added to the model.

As reported in Table 1.7, the present bias parameter without including Fechner errors is estimated to be $\beta = 1.105$ (column 1). A Wald test reveals that $\hat{\beta}$ is not statistically different from 1 ($H_0 : \beta = 1$, $p = 0.375$). By considering Fechner errors (column 2), we estimate $\beta = 1.018$ that is again not statistically different from 1 ($p = 0.302$). Overall, the estimation of dynamic inconsistency does not seem to be sensitive to including errors in decision making. In the individual analysis that follows, we will therefore proceed by only focusing on the first specification (without Fechner errors).

Our results do not suggest dynamic inconsistencies in choices about money. This conclusion is consistent with the findings of Augenblick et al. (2015) and Imai et al. (2021) who also find no evidence for dynamically inconsistent behavior in allocating money over time.

Table 1.7: *Utility Parameter Estimates*

	Interval-Censored Tobit	Interval-Censored Tobit with Fechner error
	(1)	(2)
Utility parameters		
Present bias parameter ($\hat{\beta}$)	1.015	1.018
	(0.017)	(0.017)
Discount factor ($\hat{\delta}$)	1.023	1.022
	(0.005)	(0.005)
Curvature ($\hat{\alpha}$)	0.816	0.827
	(0.031)	(0.039)
Error parameter		
Fechner error ($\hat{\tau}$)		1.102
		(0.133)
# Observations	2044	2044
# Clusters	73	73
$H_0 : \hat{\beta} = 1$	$\chi^2(1) = 0.79$	$\chi^2(1) = 1.07$
	$p = 0.375$	$p = 0.302$

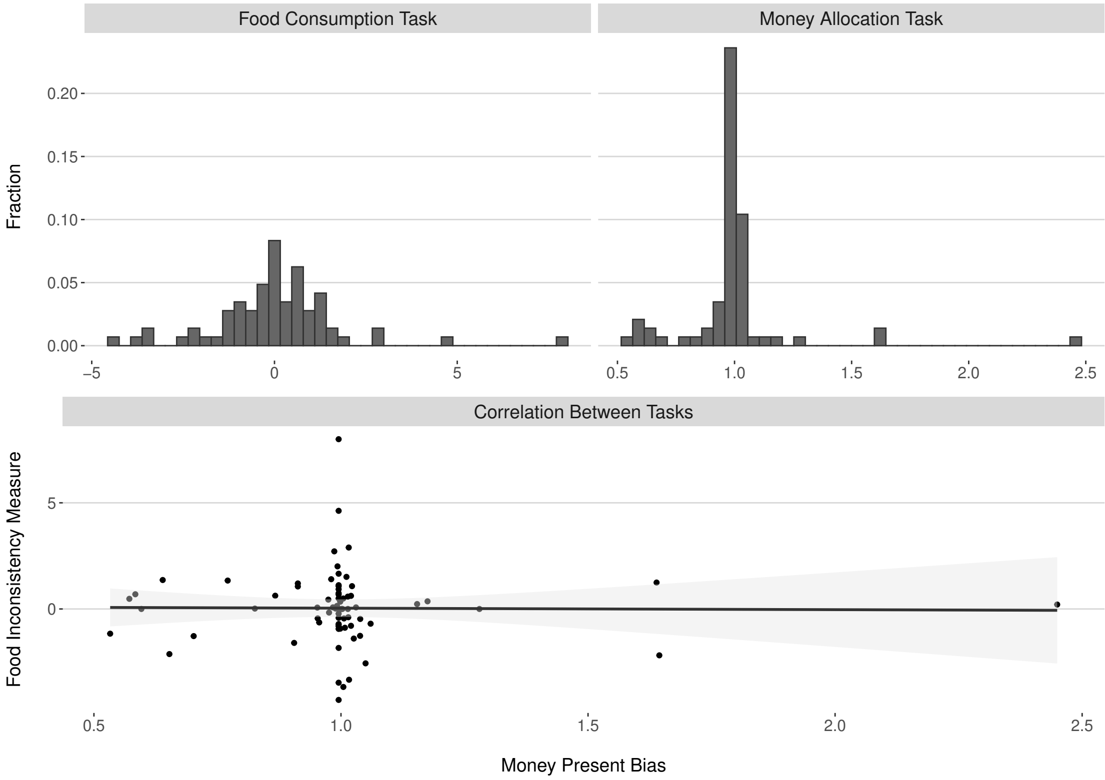
Note: The table shows results from an interval-censored Tobit regression. In the maximum likelihood estimation, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm is applied. Estimates are structurally based on the Euler equation $ln(\frac{c_t+\omega}{c_{t+k}+\omega}) = \frac{ln(\beta)}{\alpha-1}\mathbf{1}_{t=0} + \frac{ln(\delta)}{\alpha-1}k + ln(P)$, and a minimum amount of background consumption is considered by including the show-up fee paid at the end of each experimental session in the estimation. Parameters are computed as nonlinear combinations of regression coefficients. Standard errors are clustered at individual level and recovered via the delta method. For each column, results of a Wald-test are reported. The underlying hypothesis H_0 is: $\hat{\beta} = 1$.

1.3.2.3 Individual Analysis

On aggregate, we find evidence of dynamic inconsistency in the food consumption task but not in the money allocation task. We now turn to the comparison of behaviors to investigate the fundamental question whether dynamic inconsistency in real consumption choices is reflected in intertemporal behavior derived from monetary rewards. To operationalize this comparison, we re-run the structural estimation approaches at the individual level. More precisely, we apply the random utility approach introduced in Section 1.2.2 and run rank-ordered Logit regressions for each individual to obtain a measure of dynamic inconsistency over food choices. In a similar way, we apply the (β, δ) model introduced in Section 1.3.2.2 and run interval-censored Tobit regressions for each individual to estimate the present bias parameter β for choices over money.

In the money allocation task, we identify one observation with an extreme value of 22.83. We follow the approach of Lührmann et al. (2018) and exclude extreme observations with values below 0.01 and above 9.6. Since we do not have extremely low values, we will exclude one observation with $\beta_i = 22.83$ and look at a 99% sub-sample with 72 observations. Figure 1.6 presents individual estimates and their correlation assuming the quota of fruits and vegetables driving utility in the food choice task. The upper part depicts the distributions of the dynamic inconsistency measures for food (left) and money (right). The lower part shows the correlation between the individual estimates. Focusing on the upper panels, the figure illustrates a much more dispersed inconsistency distribution for the food consumption compared to the money allocation task. A Kolmogorov-Smirnoff test reveals that the difference between both distributions is highly significant ($p < 0.001$). This result is also obtained when considering the remaining healthiness criteria (calories, fats, nutrient profile scores). Results for the three remaining criteria are shown in the upper part of Figures 1.A.2, 1.A.3 and 1.A.4 in the Appendix. Note that for calories, saturated fats and nutrient profile scores we multiply the difference in utility weights $(\phi_I - \phi_A)$ with -1 for a better comparability: a negative difference now indicates a higher inclusion probability of unhealthier food items in immediate compared to advance choice. For the money allocation task, a parameter estimate $\hat{\beta}$ below 1 indicates present-biased behavior. After this conversion, for all inconsistency measures a negative value indicates choices to become unhealthier or present-biased, respectively. Table 1.A.2 in the Appendix summarises the distribution of estimated parameters for both tasks (for the full sample).

Figure 1.6: *Individual Estimates: Quota of Fruits and Vegetables*



Note: The figure summarises estimates of dynamic inconsistency at individual level for a 99% sub-sample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming the quota of fruits and vegetables as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

We follow Augenblick et al. (2015) and further compute two dummy variables indicating whether an individual shows dynamically inconsistent behavior in the expected direction: choosing unhealthier food and allocating more money to the sooner payment date in immediate choice. For the money allocation task, we apply the approach of the correlational studies of Ashraf et al. (2006) and Meier and Sprenger (2010) and define the dummy to take the value 1 if the individual estimate lies strictly below 0.99 (present bias). For the food consumption task, we define the dummy to take the value 1 if the individual estimate ($\phi_I - \phi_A$) lies strictly below 0.00 which indicates consistency. Considering the food choice task, we find that 44% of individuals show dynamic inconsistency in the expected direction (choosing unhealthier food), while in the money allocation task only 31% show present-biased behavior (allocating more money to the sooner payment date). While the reported result considers the quota of fruits and vegetables, the findings for the remaining criteria are similar in direction (57% for calories, 53% for fat and 54% for nutrient profile scores). These differences are significant applying two-sample z-tests: $z = 1.73$ with $p = 0.08$ for the quota of fruits and vegetables, $z = 3.29$ with $p = 0.00$ for calories, $z = 2.76$ with $p = 0.01$ for saturated fats and $z = 2.93$ with $p = 0.00$ for nutrient profile scores.

In an alternative specification, we define the dynamic inconsistency dummy from the food consumption task to take the value 1 only if the individual estimate lies strictly below -0.01. In this case, 40% of individuals show dynamic inconsistency in the expected direction when considering the quota of fruits and vegetables (47% for calories, 43% for fat and 40% for nutrient profile scores). Applying two-sample z-tests, these differences between the food consumption and money allocation task are not significant anymore: $z = 1.22$ with $p = 0.22$ for the quota of fruits and vegetables, $z = 2.07$ with $p = 0.04$ for calories, $z = 1.56$ with $p = 0.12$ for saturated fats and $z = 1.22$ with $p = 0.22$ for nutrient profile scores.

We now look at the correlation between individual estimates. As the linear estimation in Figure 1.6 (lower part) reveals, there is no significant correlation between the money allocation and food consumption task. The coefficient from a linear regression is -0.07 ($p = 0.93$). The estimated Spearman's correlation coefficient for the quota of fruits and vegetables is $\rho = -0.15$ with $p = 0.20$. The corresponding correlation coefficients for the remaining nutrients are: $\rho = 0.19$ ($p = 0.11$) for calories, $\rho = 0.06$ ($p = 0.60$) for saturated fats and $\rho = 0.18$ ($p = 0.13$) for nutrient profile scores. Note that while correlation coefficients for calories and nutrient profile scores seem to be only marginally insignificant, this is mainly driven by one very high observation for money present bias (β_i=2.45). In a 97% sub sample (additionally excluding this observation), the correlation coefficients move away from marginal significance: $\rho = 0.16$ ($p = 0.18$) for calories and $\rho = 0.15$ ($p = 0.21$) for nutrient profile scores. A graphical representation of linear regression results for the three remaining criteria are shown in the lower part of Figures 1.A.2, 1.A.3 and 1.A.4 in the Appendix. Note that the significant correlation for calories is again driven by the highest individual estimate for money present bias (β_i=2.45). When excluding this observation (97% sample), the correlation turns insignificant with a slope of 0.08 ($p = 0.24$). For saturated fats and nutrient profile scores, the slopes are not statistically different from zero.

When looking at the correlation between the two binary measures, a comparable picture emerges. For the quota of fruits and vegetables, we estimate a correlation coefficient of $\rho = -0.169$ ($p = 0.16$). The corresponding correlation coefficients for the remaining nutrients are: $\rho = 0.03$ ($p = 0.81$) for calories, $\rho = 0.02$ ($p = 0.84$) for saturated fats and $\rho = 0.07$ ($p = 0.58$) for nutrient profile scores. With the alternative specification for the inconsistency dummy over food choices (threshold -0.01), results are qualitatively similar: $\rho = -0.11$ ($p = 0.34$) for the quota of fruits and vegetables, $\rho = -0.02$ ($p = 0.84$) for calories, $\rho = 0.09$ ($p = 0.44$) for saturated fats and $\rho = 0.01$ ($p = 0.94$) for nutrient profile scores.

We conclude from this exercise that within-individual behavior over both tasks does not seem to be correlated. Our results are in line with Augenblick et al. (2015) who find no correlation between an effort and money allocation task and a much more dispersed distribution for the effort task.

1.3.2.4 Money Choices and Food Commitment

We now turn to the question whether the use of the commitment device in the food consumption task is informative for behavior in the money allocation task. To investigate this topic, we estimate two interval censored Tobit regressions with maximum likelihood at the aggregate level: one for individuals choosing to commit in the food task and one for non-committers. Table 1.8 summarises the results of this exercise. Column 1 reports utility parameter estimates for non-committing individuals, column 2 for committing individuals. Because 38 individuals choose the commitment device in the food consumption task, the specification in column 2 is based on 38 individuals x 4 CTB sets x 7 interest rates = 1064 observations. The estimation in column 1 is based on 35 x 4 x 7 = 980 observations. Standard errors are clustered at individual level.

Table 1.8: *Money Present Bias and Food Commitment*

	Committer=0	Committer=1
	(1)	(2)
Utility parameters		
Present bias parameter ($\hat{\beta}$)	0.994	1.032
	(0.023)	(0.026)
Discount factor ($\hat{\delta}$)	1.028	1.020
	(0.007)	(0.006)
Curvature ($\hat{\alpha}$)	0.797	0.833
	(0.050)	(0.038)
# Observations	980	1064
# Clusters	35	38
$H_0 : \hat{\beta} = 1$	$\chi^2(1) = 0.06$	$\chi^2(1) = 1.59$
	$p = 0.809$	$p = 0.208$
$H_0 : \hat{\beta}(Col.1) = \hat{\beta}(Col.2)$	$\chi^2(1) = 1.23$	
	$p = 0.268$	

Note: The table shows results from an interval-censored Tobit regression split by whether individuals choose the commitment device offered in the food consumption task. The structural estimation considers a minimum amount of background consumption given by the show-up fee paid at the end of each experimental session. Models are estimated with maximum likelihood using the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm. Parameters are computed as nonlinear combinations of regression coefficients. Standard errors are clustered at individual level, recovered via the delta method. For each column, results of a Wald-test are reported. The underlying hypothesis H_0 is: $\hat{\beta} = 1$. To test for equality between present bias parameter estimates for committing and non-committing individuals, we apply a seemingly unrelated estimation framework. Parameters are again computed as nonlinear combinations of regression coefficients with standard errors clustered at individual level.

As Table 1.8 reveals, committing individuals appear to have a slightly higher present bias parameter estimate ($\hat{\beta} = 1.032$) than non-committing individuals ($\hat{\beta} = 0.994$). Both parameters are not distinguishable from 1: Wald tests reveal that the null hypothesis cannot be rejected in both columns. To test for the difference between estimated parameters, we apply a seemingly unrelated estimation framework and test the null $H_0 : \hat{\beta}(Col.1) = \hat{\beta}(Col.2)$. As Table 1.8 shows, the difference is not statistically significant ($p = 0.268$). While non-committing individuals appear to behave rather present-biased at the food dish level in the food consumption task, they do not show more present-biased behavior in the money allocation task. Looking at the 99% subsample does not change the results: we estimate $\hat{\beta} = 1.023$ for committing and $\hat{\beta} = 0.994$ for non-committing subjects. This difference is statistically not significant ($\chi^2 = 0.78$, $p = 0.38$). Our results are in line with Augenblick et al. (2015) who do not find a significant difference in money allocation behavior over time between committing and non-committing individuals when commitment is offered in an effort task.

1.3.3 Robustness Tests

In our food choice analysis, we interpret dynamically inconsistent behavior as evidence for dynamically inconsistent preferences. We apply random utility techniques to examine the possibility that inconsistent behavior is observed given consistent preferences. While the model explicitly considers random shocks to utility, it imposes structural assumptions on the formation of utility, especially with respect to potential utility drivers. In this subsection, we provide further evidence supporting the notion that behavioral patterns reveal information about preferences rather than noise, changes in the decision environment or in arbitrage opportunities.

1.3.3.1 Subjective Healthiness Perception

During the experiment we do not inform subjects about the nutritional content of dishes. One concern might be that subjects have deviating beliefs about the overall healthiness of canteen food items. To alleviate this concern, we provide the following information supporting the view that subjects are experienced and informed canteen consumers: First, we ask subjects how often they ate lunch at the canteen within the last week before a session took place. Subjects stated to visit the canteen on average 1.8 times a week. This implies that subjects chose to eat a canteen lunch on over one third of all possible five opening days. Additionally, lunch menus at the canteen are very standardized: During regular weeks, as main dish options the canteen offers at least one vegetarian and two non-vegetarian main dishes, the possibility to serve a big salad bowl and a vegetarian soup bowl. As side dish options, there is always one type of vegetable and a constant variety of small salads, different sorts of buns, a small vegetarian soup bowl as well as at least one hot side dish such as noodles, rice, potatoes or fries. As dessert options, the canteen always offers pudding, mousse and fruit quark with different flavors, yoghurt and a fruit.

Second, we can look at the correlation between individual healthiness perception and nutrients: We elicit subjective beliefs about the healthiness of all food item on an 11-point Likert-scale ranging from 0 (very unhealthy) to 10 (very healthy) that we call a subjective health score. We observe a statistically highly significant correlation between this score and nutrients. For the quota of fruits and vegetables, the correlation coefficient is $\rho = 0.66$ with ($p < 0.00$), for calories the correlation is $\rho = -0.40$ with ($p < 0.00$), for fat the correlation is $\rho = -0.25$ with ($p < 0.00$) and for nutrient profile scores we observe $\rho = -0.52$ with ($p < 0.00$).

Third, we re-run the random utility analysis from Section 1.3.1.2 by applying the subjective health score and report the results in Table 1.9. As before, the first three output columns show results from a rank-order Logit regression for the three dish categories (main dishes, side dishes, desserts) separately for individuals choosing the commitment device in session 2. The latter three columns depict results for non-committing individuals. We again focus on the comparison of advance and immediate choices before the commitment device was offered in session 2. As Table 1.9 reveals, in advance choice committing individuals choose unhealthier main dishes while non-committing individuals choose healthier desserts. In immediate choice, committing individuals choose healthier desserts while non-committing subjects show a tendency to include unhealthier main dishes into their food bundles. While the coefficients are less precisely estimated, they show a comparable picture to the results reported in Table 1.4: non-committing individuals behave rather present-biased over main dishes in immediate choice while committing individuals seem to balance food bundle healthiness between main and side dishes on the one hand and desserts on the other hand. These individuals include healthier desserts but unhealthier main dishes (although this effect is imprecisely estimated).

We also repeat the analysis from Section 1.3.1.3 and focus on second round choices for non-committing individuals. We report results in Table 1.A.3 in the Appendix. The results are very comparable to the estimates reported in Table 1.5 and suggest that for non-committing individuals show present-biased behavior over desserts in second round

Table 1.9: *Robustness: Utility Weight Estimates and Commitment Demand*

	Committer=1			Committer=0		
	Main dish	Side dish	Dessert	Main dish	Side dish	Dessert
Subjective Health Score ($\hat{\phi}_A$)	-0.177***	-0.071	0.070	-0.005	0.036	0.176***
	(0.067)	(0.054)	(0.057)	(0.063)	(0.085)	(0.068)
Immediate choice ×	-0.038	-0.009	0.137**	-0.057	-0.008	-0.088
Subjective Health Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.035)	(0.038)	(0.062)	(0.042)	(0.082)	(0.096)
Log-likelihood	-173.783	-337.568	-122.148	-166.455	-308.116	-123.429
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 1$	$\chi^2(1) = 1.177$	$\chi^2(1) = 0.053$	$\chi^2(1) = 4.901$	$\chi^2(1) = 1.847$	$\chi^2(1) = 0.008$	$\chi^2(1) = 0.853$
	($p = 0.278$)	($p = 0.818$)	($p = 0.027$)	($p = 0.174$)	($p = 0.927$)	($p = 0.356$)
# Observations	380	934	450	350	846	414
# Clusters	76	76	76	70	70	70

Note: The table presents results from rank-ordered Logit regressions applying a random utility model. We report results for the subjective health score that is a subjective healthiness measure on an 11-point Likert scale ranging from 0 (very unhealthy) to 10 (very healthy). We elicit scores after making advance food choices in session 1 and report results for committing and non-committing individuals separately. We regress an "Is chosen" dummy equalling 1 if a food item is chosen by an individual and an interaction term with choice perspective (immediate vs. advance) on the utility driver. In each panel, the first coefficient represents the utility weight given to food items in advance choice. The interaction term indicates a utility weight change from advance to immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to advance choice (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

choices leading to parts of food bundles to become unhealthier.

1.3.3.2 Decision Environment

To check whether changes in the decision environment might influence food choices over time, we take additional exercises and investigate systematic correlations between our structural dynamic inconsistency measures and environmental factors. First, differences in the level of hunger might influence food choices over time: Subjects might become more hungry over time resulting in unhealthier food consumption in immediate compared to advance choice. To mitigate this effect beforehand, we require subjects to not eat at least two hours before the start of each session and remind subjects in an email one the day before each session. We additionally ask subjects in every session to rate their hunger level on an 11-point Likert scale ranging from 0 (not at all hungry) to 10 (very hungry). The correlation between changing the reported hunger level to "very hungry" (hunger level of 8, 9 or 10) from a lower hunger level and dynamic inconsistency is $\rho = -0.16$ ($p = 0.18$) for the quota of fruits and vegetables, $\rho = -0.03$ ($p = 0.80$) for calories, $\rho = -0.11$ ($p = 0.34$) for saturated fats and $\rho = -0.13$ ($p = 0.26$) for nutrient profile scores.[6]

Second, subjects might adapt their food choice behavior depending on whether they inspect the dishes in the canteen on session day. Logistically, subjects can enter the lane to pick up food items without actually purchasing lunch before coming to the experimental booth in the dining hall. While food items are on display for the current day, there is no possibility to inspect next week's offers. Since food items in the canteen are standardized, uncertainty about the actual dish behind a dish label should be relatively low. To test for a potential influence of resolution of uncertainty, we ask subjects in each session whether they inspected the dishes in the canteen on that day. 54 out of 73 (74%) do not indicate any behavioral changes over time. The correlation between observing dishes in immediate choice but not in advance choice and dynamic inconsistency is $\rho = 0.12$ ($p = 0.29$) for the quota of fruits and vegetables, $\rho = 0.04$ ($p = 0.77$) for calories, $\rho = -0.03$ ($p = 0.81$) for fat and $\rho = -0.05$ ($p = 0.68$) for nutrient profile scores.

Third, the frequency of canteen lunch purchases on days prior to an experimental session might influence food choice behavior. We ask subjects for the number of canteen lunch purchases within seven days prior to a session and again relate this number to individual estimates of dynamic inconsistency. The correlation between changing the number of lunch purchases and dynamic inconsistency is $\rho = -0.03$ ($p = 0.0.81$) for the quota of fruits and vegetables, $\rho = -0.05$ ($p = 0.69$) for calories, $\rho = -0.03$ ($p = 0.83$) for fat and $\rho = -0.07$ ($p = 0.53$) for nutrient profile scores.

Fourth, food choices might be influenced by day-specific outdoor temperatures. Given that the experiment was conducted in Germany between October and December, food consumption might become more energy-dense (unhealthier) as temperatures drop. To investigate this correlation, we collect city-day-specific temperature information from an online weather platform. The correlation between temperatures becoming lower and dynamic inconsistency is $\rho = -0.02$ with $p = 0.85$ for the quota of fruits and vegetables, $\rho = -0.06$ ($p = 0.63$) for calories, $\rho = -0.05$ ($p = 0.65$) for saturated fats and $\rho = -0.08$ ($p = 0.52$) for nutrient profile scores. As temperatures might capture raw weather conditions only partially, we additionally look at the amount of rainfall. Correlation

[6] Throughout the robustness tests, we continue multiplying food inconsistency measures based on calories, saturated fats and nutrient profile scores with -1 to make results comparable to the money allocation task. After this conversion, for all inconsistency measures a negative value indicates choices to become unhealthier or present-biased, respectively.

coefficients and significance levels do not change.

A final potential change to the decision environment is the amount of financial resources available to subjects: Food choices might be influenced by differences in disposable income over time. We ask subjects in every session whether they were expecting an income inflow during the seven days preceding the session day. We assume that if, for instance, a subject was expecting income within the last seven days in session 2, the individual has a relatively lower income level while making food choices in session 1. We compute correlations between differences in expecting income over time (proxy for relative income level over time) and dynamic inconsistency. If anything, we would expect a positive correlation: a relatively lower (within-individual) income level in session 2 should result in unhealthier food consumption choices (maximizing energy intake per Euro). We observe no correlation between our proxy for income deviations over time and dynamic inconsistency: $\rho = -0.02$ ($p = 0.89$) for the quota of fruits and vegetables, $\rho = -0.15$ ($p = 0.20$) for calories, $\rho = -0.17$ ($p = 0.33$) for saturated fats and $\rho = -0.15$ ($p = 0.20$) for nutrient profile scores. Taken all tests in this subsection together, the evidence suggests that observed inconsistencies in food choices are unlikely driven by observable changes to the decision environment.

1.3.3.3 Arbitrage Opportunities

One common concern about monetary allocation experiments is the high fungibility of money allowing to easily exchange it outside the experiment. Money allocation choices made in the experiment might then only mirror one's lending and borrowing opportunities outside the lab (Cubitt & Read, 2007). This can be one reason for observing time consistent behavior in money allocation over time (Augenblick et al., 2015). A consequence of arbitrage opportunities in food choices would be that subjects' choices do not reflect their true preferences but rather their opportunities to trade food items more advantageously outside the experiment. Imagine for example an individual who can trade salad for fries to better conditions outside an experimental session. This individual should choose only salad and after receiving the tray, she would trade salad to receive fries. In our food setting, arbitrage opportunities are rather unlikely to exist: First, food item prices and sizes in the experiment are identical to regular canteen prices and sizes. Second, food items are perishable putting a tight time constraint on trades.

Third, it is practically difficult to find individuals interested in food trades, not least because every member of the college community can purchase food at the canteen, and no quantity restrictions in canteen purchases exist.

Although trade opportunities are unlikely to exist during an experimental session, the natural problem of arbitrage might still exist if subjects substitute healthier eating during a session with unhealthier eating after a session. A substitution would confound our dynamic inconsistency measure and present-biased behavior could only be observed when substitution rates change over time. We provide several reasons speaking against the existence of large extra-lab smoothing opportunities for food consumption choices: First, the average selected meal during the experiment has around 1,200 kilo calories. The recommended daily calorie need is 2,000 for women and 2,500 for men. These numbers suggest that subjects cover 50-60% of their daily calorie need by making lunch choices during an experimental session. For comparison, consider a setting where subjects choose between healthy and unhealthy snacks. Even if consumption would happen immediately, the snack choice would only cover 4-5% if a fruit is chosen ($\approx$ 100 calories) and 10-12% if a chocolate bar is chosen ($\approx$ 240 calories). As our subjects take high-stake (nutrient) decisions, they should reliably choose according to their true preferences.

To approach this topic in a more data-driven manner, we additionally collect data on subjects' on-campus food transactions. More precisely, we can observe all of subjects' food purchases using subjects' unique campus card numbers. Campus cards are the only eligible payment method on campus (at both the canteen and cafeteria). On all days of session 1 and 2, we observe 15 out of 73 (21%) subjects making 23 on-campus food transactions.[7] We collect nutritional information for all food items bought on-campus and calculate the correlation between purchasing food items on session days outside the experiment (dummy) and nutrients chosen during a session: $\rho = 0.03$ ($p = 0.66$) for the quota of fruits and vegetables, $\rho = 0.00$ ($p = 0.96$) for calories, $\rho = 0.02$ ($p = 0.72$) for saturated fats and $\rho = 0.02$ ($p = 0.75$) for nutrient profile scores. We also look at nutrients purchased outside the lab on session days. The correlation is $\rho = 0.01$ ($p = 0.93$) for the quota of fruits and vegetables, $\rho = -0.00$ ($p = 0.99$) for calories, $\rho = 0.02$ ($p = 0.78$) for saturated fats and $\rho = 0.03$ ($p = 0.66$) for nutrient profile scores. Summarizing this evidence, we observe no correlation between making healthier food choices during a session and buying unhealthier food items on campus outside the

[7] Additionally considering session 3 days, we observe 23 (32%) individuals making 40 food transactions on campus.

experiment on session days. This finding suggests that at least with respect to on-campus food consumption, extra-lab substitution possibilities are unlikely to confound our measure of dynamic inconsistency over food choices.

1.4 Discussion and Conclusion

We implement a longitudinal, framed field experiment to examine dynamically inconsistent preferences for a continuous convex non-monetary budget in an entirely natural environment: College students repeatedly make lunch choices over time in the college canteen that are immediately consumed on receipt in the dining hall. We document the following findings: First, we show evidence that subjects treat food categories differently, and that they balance food healthiness over different food categories. Due to this balancing, we observe dynamically consistent behavior when we look at overall meal choices. This result suggests that more complex behavioral patters are navigating human decision making in a true natural consumption task.

Second, over half of subjects choose to restrain themselves voluntarily when a commitment device is offered. We examine control mechanisms for committing and non-committing subjects and document behavioral patterns suggesting a negative relation between self-control problems and beliefs thereof: Subjects choosing our (external) commitment device seem to already enforce internal self-control before commitment is offered. Non-committing subjects show present-biased behavior over single food categories when commitment is not available. These results suggest that non-committing subjects are at least partially naive about their self-control problem while subjects demanding commitment show dynamically consistent behavior. This finding suggests that internal and external commitment strategies are substitutes; and that committing individuals actively enforce internal self-control when external commitment is absent. Substituting internal with external control is also rationally consistent with the view of Hofmann et al. (2008) that internal self-control is costly because it depletes psychological resources while, at least in our design, external commitment has a price of 0.

Our results provide new perspectives in the evaluation of recent changes in public food policies. One prominent example is the large-scale roll-out of an online purchasing pilot program by the US Department of Agriculture that allows online pre-ordering under the Supplemental Nutrition Assistance Program (SNAP).[8] The aim of this recent policy change targeted at low-income communities is to foster healthier nutrition by committing individuals to their advance food choices. Our findings suggest only limited effects of these types of commitment offers for individuals with self-control problems: Those individuals that would benefit the most do not take up the commitment device. Those individuals that do take it up would apply other self-control strategies also in the absence of this commitment offer.

Third, we contrast within-individual food consumption and money allocation choices to examine the fundamental question whether dynamic inconsistencies in real consumption choices are reflected in intertemporal behavior derived from monetary rewards. We find that the distributions of food inconsistency measures are much more dispersed compared to the inconsistency distribution of money; the latter is more tightly centered around consistency. We also observe no significant correlation in behavior between the money allocation and food consumption task. These findings suggest only a limited applicability of monetary reward studies to actual behavior in the field.

Our results point to future research avenues. First, by comparing money and food choices, we also compare a more informed with a relatively less informed criterion. This difference is a result of choosing the most suited elicitation technique in each domain. To align the two while eliciting preferences over a true consumption task with consumption on receipt in a natural setting remains a challenge that needs to be addressed in future research. Second, we collect data on on-campus food purchases to check for substitution of observed food consumption behavior during the experiment with out-of-experiment consumption. While subjects make high-stake choices, and while our data speak against this substitution behavior, we cannot completely rule it out. If subjects systematically substitute eating healthier during the experiment with eating unhealthier at home, our results in the food consumption task would be biased towards time consistency. Hence, our results should still be considered as lower bound estimates for the true extent of dynamic inconsistency in food consumption.

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

1.5 Appendix A

Figure 1.A.1: *Full Example Food Choice Task*

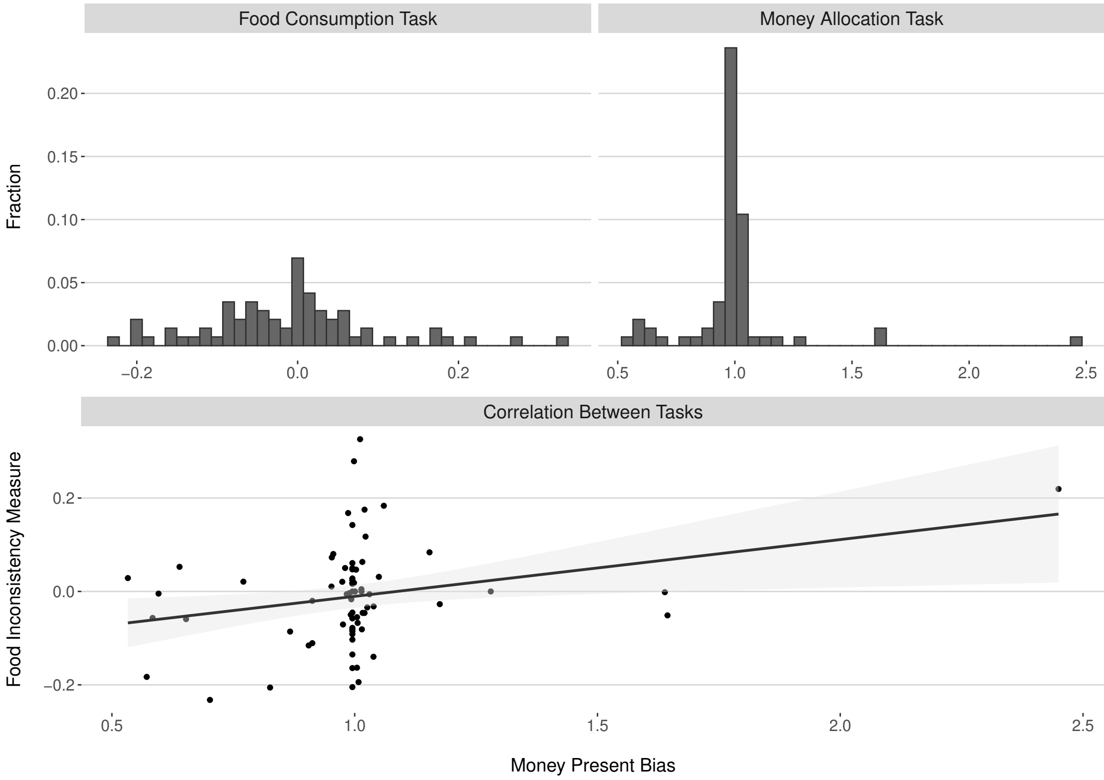
Select the dishes for your canteen lunch that you will receive at the end of the second session on [*date of 'today in one week'*] with a probability of 25%. Your seleced items must not exceed the total value of €4.00. Your chosen budget is indicated below the canteen menu. Click on the plus or minus sign to add an item, discard an item or change the amount.

Note: A large mixed salad has approximately 260 grams. If a dish is offered in the self-serving area, the plate will be fully filled by eye. The portion sizes of all other dishes are set by the canteen operator.

Main Dishes	€	Amount	Side Dishes	€	Amount	Desserts	€	Amount	Sides	€	Amount
Vegan Thai noodle vegetable pan with peanuts in coconut sauce	1.92	0	Rice	0.70	0	Fresh Fruit	0.50	0	Mayonnaise	0.20	0
Chicken breast with onion cream sauce	2.35	0	Green leaf salad	0.70	0	Fruit quark	0.70	0	Ketchup	0.20	0
Alaska pollock fillet in batter with tomato sauce and rice	2.81	0	Cucumber salad	0.70	0	Natural yogurt with muesli	0.70	0			
Vegetarian soup of the day large with roll	1.20	0	Spaetzle	0.70	0	Pudding	0.80	0			
Large mixed salad (green leaf lettuce, carrots, tomatoes, cucumber) with dressing	2.21	0	Carotts	0.70	0	Mousse/ Creme	1.10	0			
			Potatos	0.90	0	Sweetened yogurt with muesli	0.70	0			
			Bell pepper salad	0.70	0						
			Potato salad	0.90	0						
			Whole wheat roll	0.55	0						
			Tomato salad	0.70	0						
			Colorful mixed salad	0.70	0						
			Vegetarian soup of the day small	0.60	0						
			Pretzel/ Lye bar	0.60	0						
			Kaiser bun	0.35	0						

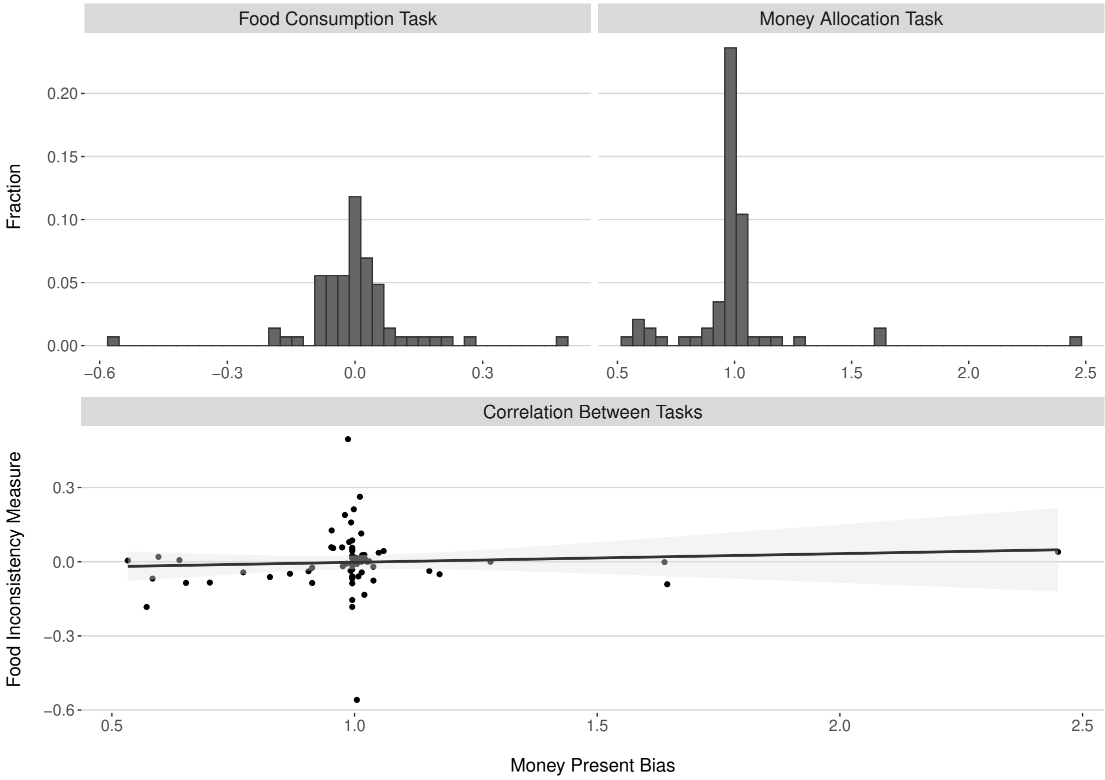
Note: The figure shows a full example screen in the food choice task (translated from German). Students can click on the green plus or the red minus button to select or discard a food item. Items are categorized into food categories: main dishes, side dishes, desserts and sides. There are no restrictions posed on participants' choices except for the budget condition. Participants make two food choices: for a 4 € and a 5 € budget.

Figure 1.A.2: *Individual Estimates: Calories*



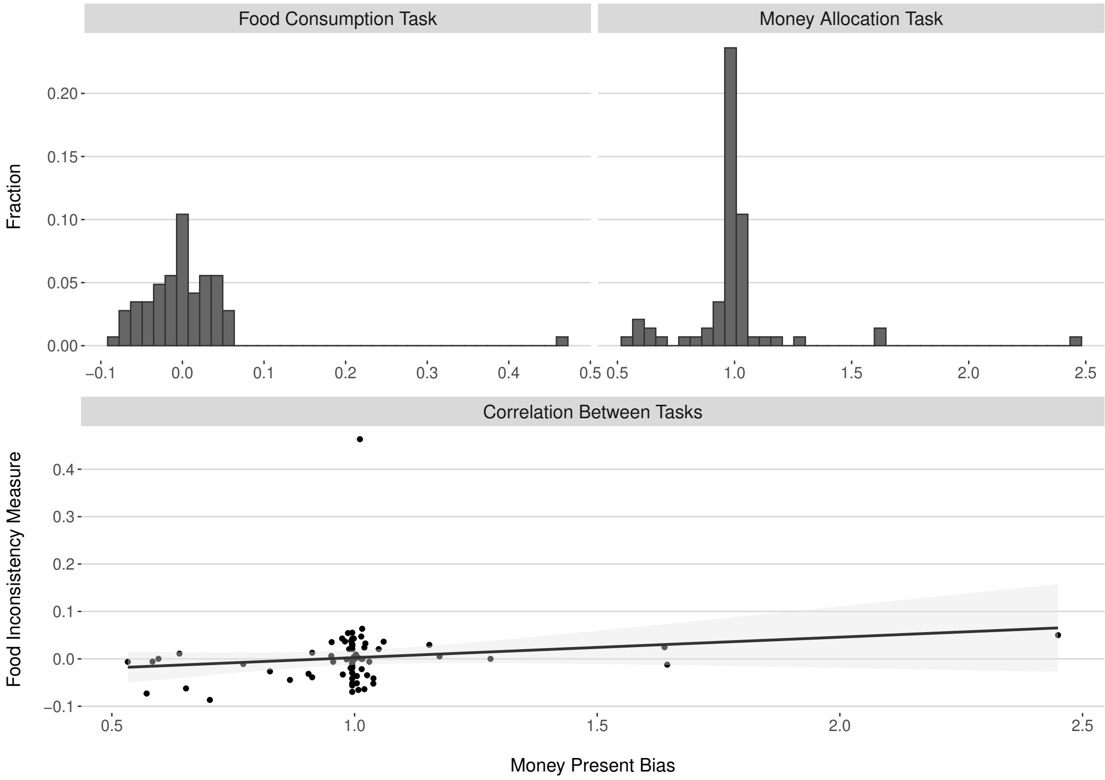
Note: The figure summarises estimates of dynamic inconsistency at individual level for a 99% sub-sample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming calories as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Figure 1.A.3: *Individual Estimates: Fat*



Note: The figure summarises estimates of dynamic inconsistency at individual level for a 99% subsample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming saturated fats as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Figure 1.A.4: *Individual Estimates: Nutrient Profile Score*



Note: The figure summarises estimates of dynamic inconsistency at individual level for a 99% sub-sample with 72 individuals. The upper left panel shows the distribution of the inconsistency measure for the food consumption task assuming nutrient profile scores as utility driver. The upper right panel shows the distribution of the present bias parameter for the money allocation task. Inconsistency estimates from the food consumption task are more dispersed while estimates of the present bias parameter from the money task are more centered around 1 (time consistency). The lower panel depicts the regression line assuming a linear relation between inconsistency measures.

Table 1.A.1: *Summary of Nutrients: Food Items*

Food Category	Food Label	Nutrient Profile Score	Calories (Kcal)	Sugar (g)	Saturated Fats (g)	Proteins (g)	Salt (Sodium in mg)	Veg Quota (%)	Item Size (g)	Price
	Panel A: average weight (in g)									
Main dishes	Main dish heavy	24.9	828.02	16.80	11.97	39.21	2351.46	22.08	477.44	3.05
	Main dish light	17.9	583.01	7.72	7.71	37.56	1568.99	21.18	359.34	2.62
	Main dish veg	19.1	690.52	17.74	7.84	20.46	1479.14	44.52	449.49	2.23
	Big salad veg	-9.0	92.35	6.88	0.45	3.23	174.00	96.15	260.00	2.21
	Big soup bowl veg	7.0	201.89	5.47	7.49	6.62	345.60	44.00	288.00	1.20
Side dishes	Bun "kaiser"	1.00	131.39	1.58	0.20	4.59	367.20	0	51.00	0.35
	Pretzel	3.00	327.93	0.68	1.02	7.74	510.00	0	85.00	0.60
	Wholegrain bun	-4.00	174.12	0.63	0.11	6.27	319.20	0	57.00	0.55
	Fries	25.00	1135.80	4.40	17.42	7.16	1575.60	0	196.00	1.00
	Rice	2.00	50.17	0.04	0.04	1.07	205.24	0	39.47	0.70
	Potatoes	-6.00	258.28	2.22	0.00	6.35	0.00	0	317.30	0.90
	Vegetable	-10.31	105.76	8.78	0.40	7.71	81.09	100	225.97	0.70
	Small salad veg	-6.4	66.03	4.51	0.35	1.42	135.6	91.34	143	0.7
	Small soup bowl veg	-1.00	101.64	2.76	3.77	3.34	174.0	53.00	145	0.6
Desserts	Fruit	-3	106.72	19.44	0.07	0.95	0.00	100	135	0.5
	Fruit quark	15	243.65	28.67	5.83	10.63	96.80	0	220	0.7
	Yoghurt with cereals	7	234.00	15.70	5.38	10.32	152.00	0	200	0.7
	Yoghurt w. cereals (sugared)	15	366.30	23.40	12.98	8.52	120.00	0	200	0.7
	Mousse	17	266.69	27.90	7.33	6.59	107.52	0	128	1.1
	Pudding	5	267.00	12.65	2.04	3.64	179.52	0	136	0.8
	Panel B: per 100g									
Main dishes	Main dish heavy	3.94	174.41	3.60	2.67	8.81	496.13	22.08	100	0.67
	Main dish light	2.03	161.07	2.10	2.22	11.16	455.82	21.18	100	0.78
	Main dish veg	0.39	161.98	4.10	1.72	4.61	355.15	44.52	100	0.54
	Big salad	-7.00	35.52	2.65	0.17	1.24	66.92	96.15	100	0.85
	Big soup bowl	-1.00	70.10	1.90	2.60	2.30	120.00	44.00	100	0.42
Side dishes	Bun "kaiser"	1.00	257.62	3.10	0.40	9.00	720.00	0	100	0.69
	Pretzel	7.00	385.80	0.80	1.20	9.10	600.00	0	100	0.71
	Wholegrain bun	-1.00	305.48	1.10	0.20	11.00	560.00	0	100	0.96
	Fries	21.00	579.49	2.24	8.89	3.65	803.88	0	100	0.51
	Rice	4.00	127.10	0.10	0.10	2.70	519.99	0	100	1.77
	Potatoes	-3.00	81.40	0.70	0.00	2.00	0.00	0	100	0.28
	Vegetable	-10.16	46.80	3.85	0.18	3.44	34.65	100	100	0.31
	Small salad	-5.8	46.27	3.02	0.25	1.02	98.24	91.34	100	0.51
	Small soup bowl	-1.0	70.10	1.90	2.60	2.30	120.00	53.00	100	0.41
Desserts	Fruit	-4	79.05	14.40	0.05	0.70	0	100	100	0.37
	Fruit quark	2	110.75	13.03	2.65	4.83	44	0	100	0.32
	Yoghurt with cereals	-1	117.00	7.85	2.69	5.16	76	0	100	0.35
	Yoghurt w. cereals (sugared)	3	183.15	11.70	6.49	4.26	60	0	100	0.35
	Mousse	11	208.35	21.80	5.73	5.15	84	0	100	0.86
	Pudding	5	196.32	9.30	1.50	2.68	132	0	100	0.59

Note: The table summarizes nutrients for a subset of food items that is regularly offered in the college canteen. Nutrient profile scores range from -15 (most healthy) to +40 (most unhealthy). Panel A summarizes nutrient information per dish size, panel B shows information per 100 grams of a food item. For heavy, light and vegetarian main dishes, as well as soup bowls and vegetables, we calculate nutrients as average over different dishes since the actual dish changes on a daily basis. For small salads, we report averages over different types that are constantly offered every day. For desserts, we report nutrient information at category level. The actual dish within a subcategory (pudding, mousse, fruit quark) changes on a daily basis with only minor variation (vanilla vs. chocolate pudding).

Table 1.A.2: *Individual Parameter Estimates*

	Median	5th Perc.	25th Perc.	75th Perc.	95th Perc.
Money Allocation Task					
Present bias parameter ($\hat{\beta}_i$)	0.995	0.622	0.980	1.015	1.424
Discount factor ($\hat{\delta}_i$)	1.000	0.991	0.998	1.016	1.140
Curvature ($\hat{\alpha}_i$)	0.991	-0.099	0.861	0.996	0.996
Food Consumption Task					
Inconsistency measure ($\hat{\phi}_I - \hat{\phi}_A$):					
Quota of Fruits and Vegetables	0.018	-2.87	-0.736	0.693	2.29
Calories ($\times -1$)	-0.005	-0.187	-0.071	0.047	0.179
Fats ($\times -1$)	0	-0.142	-0.049	0.036	0.177
Nutrient Profile Scores ($\times -1$)	0	-0.065	-0.03	0.029	0.053

Notes: Table shows descriptive statistics for all utility parameters structurally estimated from the money allocation and food consumption task. We estimate parameters for the full sample of 73 individuals. To facilitate comparison, we convert the utility drivers calories, fat and nutrient profile scores by multiplying with -1: the lower a value is, the unhealthier the choice becomes. Estimates are reported for the median, 5th percentile, 25th percentile, 75th percentile and 95th percentile.

Table 1.A.3: *Utility Weight Estimates: Second Round Choices (Subjective Score)*

	Main dish	Side dish	Dessert
Subjective Health Score ($\hat{\phi}_A$)	-0.088	-0.028	0.174***
	(0.066)	(0.049)	(0.057)
Immediate choice $\times$	0.047	0.006	-0.120***
Subjective Health Score ($\hat{\phi}_I - \hat{\phi}_A$)	(0.042)	(0.047)	(0.044)
Log-likelihood	-151.529	-350.993	-135.610
$H_0 : (\hat{\phi}_I - \hat{\phi}_A) = 0$	$\chi^2(1) = 1.259$	$\chi^2(1) = 0.016$	$\chi^2(1) = 7.464$
	($p = 0.262$)	($p = 0.900$)	($p = 0.006$)
# Observations	354	908	420
# Rankings	70	70	70
# Clusters	35	35	35

Notes: The table presents results from rank-ordered Logit regressions for non-committing subjects after commitment was offered (and not taken). We report results for the subjective health score that is a subjective healthiness measure on an 11-point Likert scale ranging from 0 (very unhealthy) to 10 (very healthy). We elicit scores after making advance food choices in session 2. We regress an "Is chosen" dummy that equals 1 if a food item is chosen by an individual on the subjective health score and an interaction term between health score and immediate choice dummy. The advance choice coefficient in each panel represents the utility weight in advance choice. The interaction term coefficient indicates a utility weight change in immediate choice. The null hypothesis tests whether the utility weight is different in immediate choice (ϕ_I) compared to the utility weight from the advance choice perspective (ϕ_A). Results are reported for three food categories: main dishes, side dishes and desserts. Standard errors are clustered at individual level. Levels of significance: *0.10, **0.05, ***0.01

1.6 Appendix B

Experimental instructions before selecting food items for lunch in one week (displayed to subjects in session 1). To facilitate understanding and reduce complexity, all lunch choices are assigned an alphabetic letter starting from A for choices made in session 1 for session 1 in the low budget condition (t_1t_1, 4 €) to J for immediate lunch choices made in session 3 in the high budget condition (t_3t_3, 5 €). Before making lunch choices, subjects were always informed about the contextual details.

> Your canteen menu in one week:
>
> On the following pages, you will make decisions and set options C and D. In doing so, you will consider the canteen menu that will be in effect one week from today on [date of 'today in one week']. For both options, you will choose today the components for your canteen menu that you would like to receive on [date of 'today in one week']. You may choose from a variety of components - there will be a variety of main dishes, side dishes, desserts and add-ons. For Option C, the chosen components must not exceed the total value of 4 €, for Option D they must not exceed the total value of 5 €. For each option, you may select menu components more than once or not at all. You may select the same or different menu components for both options. You alone decide which components you select.
>
> At the next meeting on [date of 'today in one week'], you will again select the menu components for the canteen meal on [date of 'today in one week'] to determine options E and F. Thus, at the end of the next session on [date of 'today in one week'], you will have determined 4 options - you will determine options C and D today, and you will determine options E and F a week from today. For all 4 options, you can choose the same or different components for your canteen meal.
>
> You will receive one of the 4 options for free at the end of the next session. Which option you will get is randomly determined by the computer. All options are equally likely, that is, the probability of receiving option C, D, E or F for actual consumption is 25% each. Thus, it is in your interest to set

each option as if it were the one that will be chosen.

Experimental instructions before allocating money over time:

On the following pages we ask you to choose between different amounts of money. You will make 14 choices about how to divide money between an earlier time (e.g. today) and a later time (e.g. in two weeks). One of these 14 decisions will certainly be paid out to you in cash at the end of the first, second or third session by the experiment leader. The payout of the selected decision is guaranteed to you by the Chair of Microeconomics of the Catholic University of Eichstaett-Ingolstadt.

In which session the payout will be made depends on your decisions. All decisions you make in this part of the session are treated by the computer as completely independent decisions. This means that all decisions you will make now will be paid out independently of all previous decisions. Consequently, when the computer selects a decision, it does not matter what components you have previously selected for food options A, B, C, and D.

Which decision is paid out to you is determined randomly by the computer. All decisions can be chosen with the same probability. You are informed about the decision that is chosen at the end of the session.

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

2.1 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 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

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

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 2.2 describes the conceptual framework. Section 2.3 provides information on the data set used in this study, and gives a detailed description of outcome, explanatory and control variables. Section 2.4 provides reduced form results, explores mechanisms and implements robustness checks before Section 2.5 concludes.

2.2 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 2.1:

$$U(c_t, c_{t+k}) = \beta\delta c_t + \beta\delta^2 c_{t+k} \geq 0. \tag{2.1}$$

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 2.1 can be simplified to equation 2.2:

$$c_t + \delta c_{t+k} \geq 0. \tag{2.2}$$

Equation 2.2 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 $1.5 > 0$.

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 2.3:

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

$$c_t + \beta\delta c_{t+k} \geq 0. \tag{2.3}$$

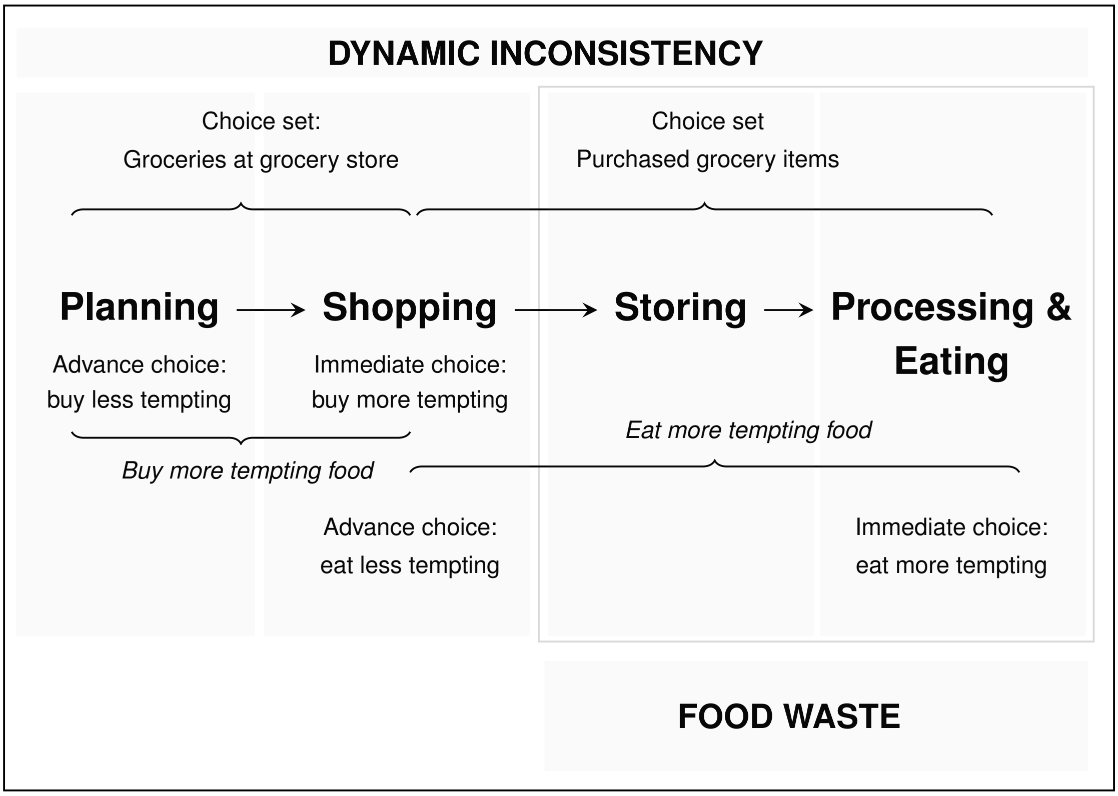
Since the present bias parameter β refers to all payoffs received in the future, the individual is overly discounting c_{t+k} if $\beta < 1$. A present-biased individual consumes too much of the relatively more tempting food and too little of the less tempting food item because $\beta\delta c_{t+k} < \delta c_{t+k}$. Coming back to the example, assume $\beta = 0.65$. Equation 2.3 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 2.1. 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.

As Figure 2.1 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.

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

Figure 2.1: *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.

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 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

[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.

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.

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.

[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.

[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.

2.3 Empirical Strategy

2.3.1 Data Set

While the focus of Section 2.2 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.

2.3.1.1 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.

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

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

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 2.A.1 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.

2.3.1.2 Summary Statistics

The encompassing data set allows me to construct a detailed set of control variables that is summarized in Table 2.1. An overview of each variable can be found in Table 2.A.2 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 2.1 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 2.1 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.

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..

Table 2.1: *Summary Statistics: Outcome and Control Variables*

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.

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 2.1 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.

2.3.1.3 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 2.2 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 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.

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.

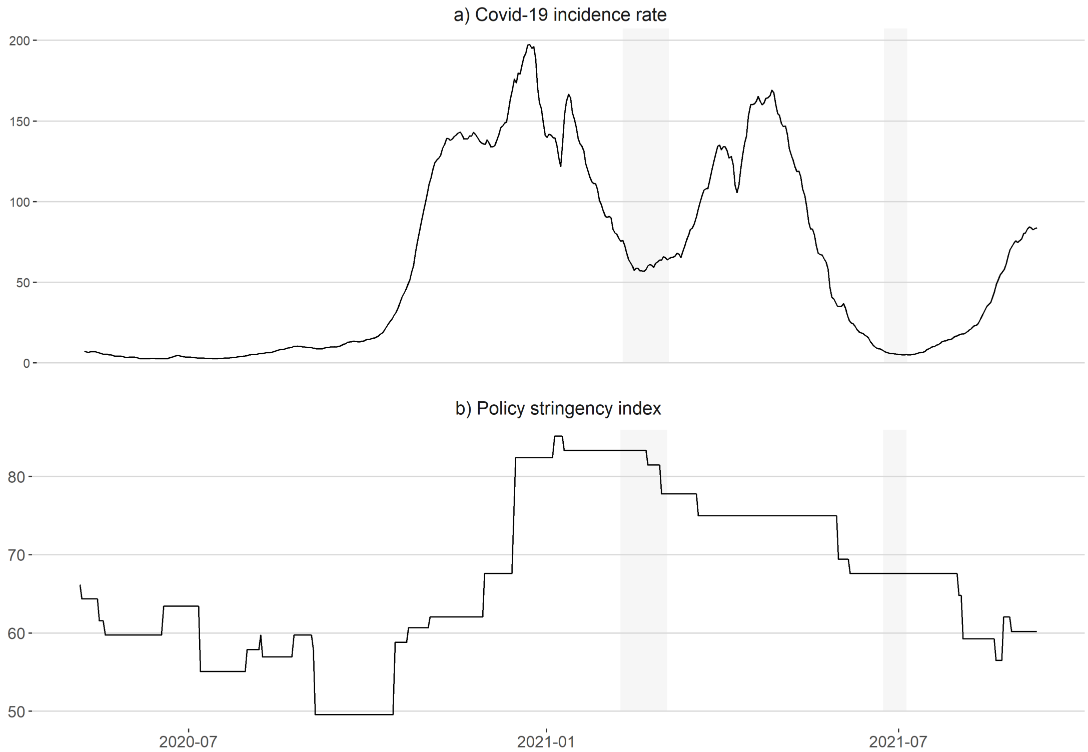
[9] Daycare facilities and schools were closed, and many workplaces except for essential goods and services were shut down. Also private gatherings were restricted to a small number of people and public events were canceled. An international travel ban was introduced and internal movements were limited.

[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.

Figure 2.2: *Covid-19 Incidence Rates and Policy Stringency 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 time periods of data collection. Wave 1 was implemented from February to March 2021, followed by wave 2 from June to early July 2021.

Until wave 2, stringency decreases to a level of 67 but remains at a relatively high level compared to 2020 index values. Figure 2.2 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 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

[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...".

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 2.1). In wave 2, the mean is significantly lower at 1.7 days ($p < 0.01$).

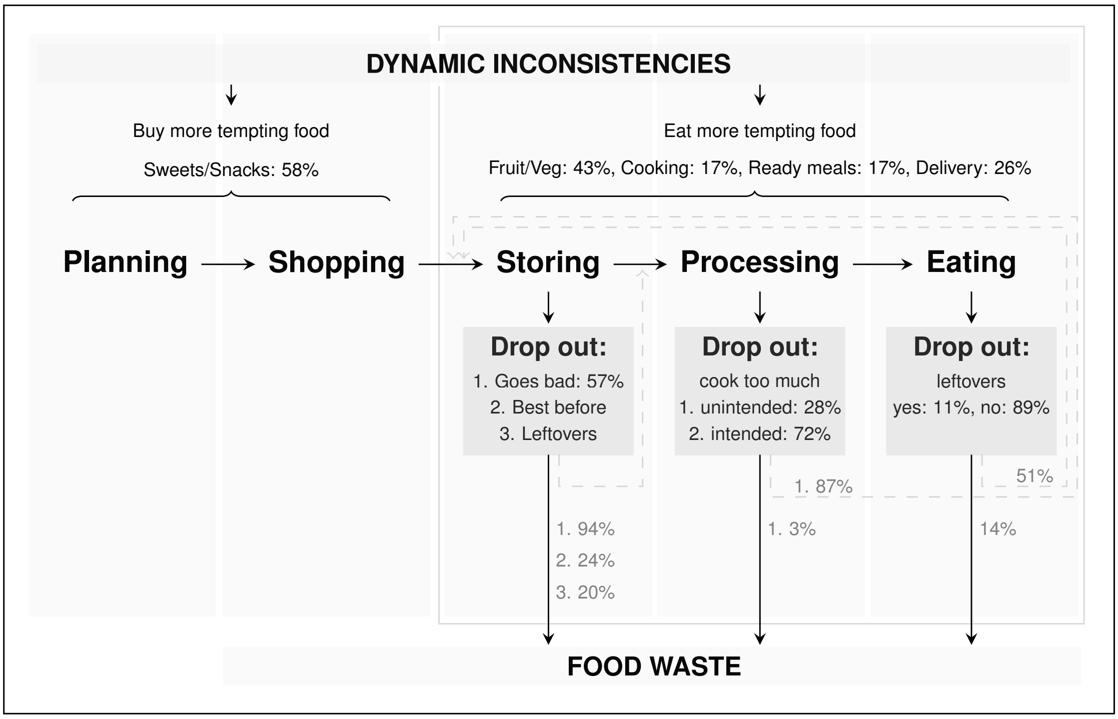
[14] https://www.gesetze-im-internet.de/ifsg/IfSG.pdf

[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.

2.3.2 Food Waste Metrics

In Section 2.2, 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 2.3 depicts the food consumption process and summarizes descriptive statistics for the different food waste measures.

Figure 2.3: *Dynamic Inconsistency and Food Waste*



Note: The figure depicts the food consumption chain and summarizes statistics 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). Numbers 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.

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 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 2.1 reports summary statistics for all food waste variables. The mean value for the food going bad index is 1.22. As Figure 2.3 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 2.3, 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 2.1).

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 2.1, 20% of respondents indicate to have thrown away leftovers within the last seven days in wave1, and 22% in wave 2.

Figure 2.3 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.

2.3.3 Dynamic Inconsistency Measure

Based on the (β, δ) model introduced in Section 2.2, 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:

$$DF1 = \frac{1,000}{(1,000 + amount1)}. \tag{2.4}$$

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 <u>a month</u> to claim the prize. If you wait, you will receive <u>more</u> than 1000 €. What is the <u>smallest</u> amount of money you would need to receive <u>in addition</u> to the 1000 € in <u>one month</u> to convince you to wait instead of claiming the prize now? Enter this <u>additional</u> 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:

$$DF2 = \left[\frac{1,000}{(1,000 + amount2)}\right]^{12}. \tag{2.5}$$

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:

$$\beta\delta = \frac{1,000}{(1,000 + amount1)} \tag{2.6}$$

and

$$\beta\delta^{\frac{1}{12}} = \frac{1,000}{(1,000 + amount2)}. \tag{2.7}$$

Solving for β and δ, this leads to

$$\beta = \frac{1,000}{[\delta(1,000 + amount1)]} \tag{2.8}$$

and

$$\delta = \left[\frac{(1,000 + amount2)}{(1,000 + amount1)}\right]^{\frac{12}{11}}. \tag{2.9}$$

Summary statistics for the two time preference parameters as well as the two discount factors are shown in Table 2.2. 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.

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 2.4 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

Table 2.2: *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: The table reports summary statistics for variables measuring patience and dynamic inconsistency. The parameters β and δ are calculated based on two questions eliciting the amount of money needed to be willing to delay the payment by one year/one month. The measures for procrastination and patience are take from the GSOEP and measure patience and procrastination on an 11-point Likert scale from 0 (lowest level) to 10 (highest level). 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.

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.

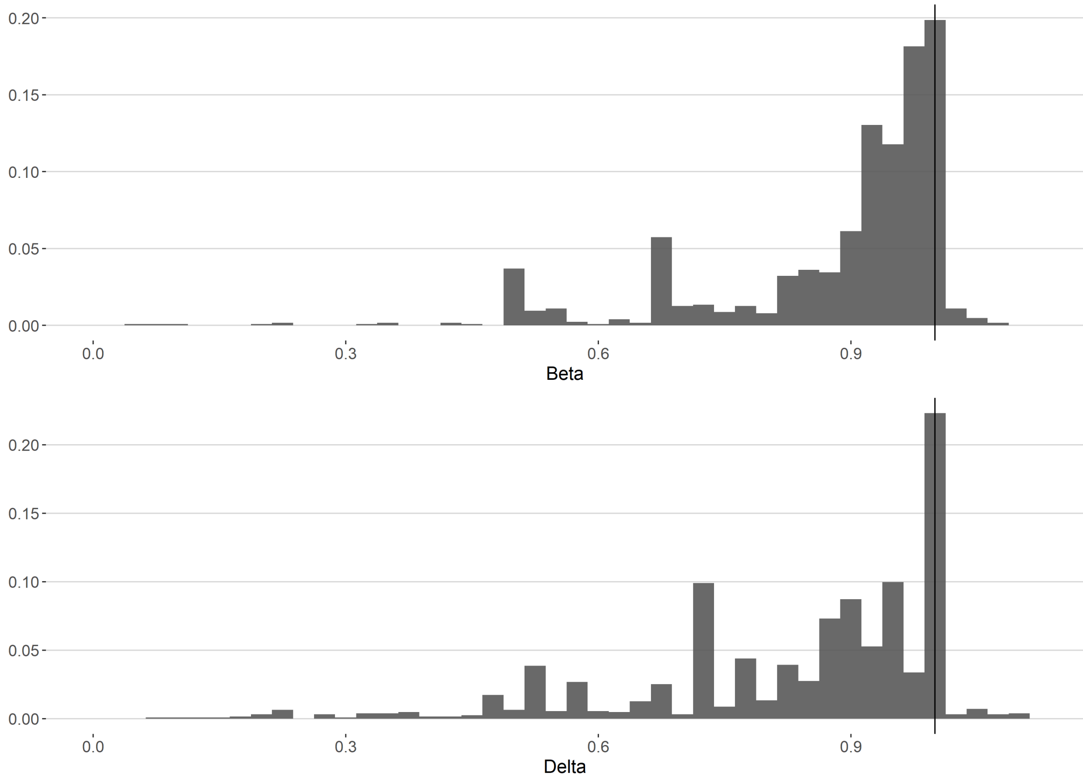
2.3.4 Econometric Specification

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

$$\text{Food waste}_i = \alpha_0 + \alpha_1 \beta_i + \mathbf{X}_i \alpha_2 + \epsilon_i, \tag{2.10}$$

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 2.3.2: 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

Figure 2.4: *Distribution of Time Preference Parameters*



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 (β) or full patience (δ), respectively.

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 2.3 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 2.3 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.

Table 2.3: *Correlation of Time Preference Parameters 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 2.3 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 2.3 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]

2.4 Results

2.4.1 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 2.4 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.

[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.

Table 2.4: *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 OLS 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 indicates 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

As Table 2.4 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 2.2, 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.

Table 2.5 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 2.4. 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.

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

[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 $0.1/5 = 0.02$.

[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%.

Table 2.5: *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 OLS 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 indicates 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

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 2.A.3 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 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 2.5 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 2.2, 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 2.6 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.

2.4.2 Mechanism Exploration

The goal of Section 2.4 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 2.5 to a more holistic testing of the mechanisms suggested in Section 2.2. 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

[20] Figure 2.3 summarizes the reasoning graphically.

Table 2.6: *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 OLS 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 indicates 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

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 2.7 provides evidence that dynamically inconsistent individuals are not different in their planning behavior than dynamically consistent individuals. For this analysis, I regress the three 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 2.7 are not sensitive at all to the threshold specification.[22]

Focusing on the first outcome variable (fridge checking dummy) in Table 2.7, 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

[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.

Table 2.7: *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 OLS 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 indicates 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

significant and the present bias dummy specification in column 6 again suggests that there is no effect.[23] Table 2.A.4 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.
>
> **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 2.3 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

[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.

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 2.8, 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 2.3.1. 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 2.8 suggests that, indeed, individuals with higher dynamic inconsistencies deviate more from their consumption plans at home. Table 2.A.5 in the Appendix provides an overview of coefficient estimates for all control variables.

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 2.9 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).

[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%.

Table 2.8: *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 OLS 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 indicates 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

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 2.5, there is no systematic effect of long-run patience δ on food waste measures, and risk seeking individuals waste more food. Table 2.A.6 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 2.2.

Table 2.9: *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 OLS 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 indicates 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

2.4.3 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 2.5. In the second part of this subsection, I will provide empirical evidence for the assumption that dynamic inconsistency stays constant over time.

2.4.3.1 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 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 2.5 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

[25] See Subsection 2.4.1 for the exact wording.
[26] See Subsection 2.4.1 for the calculation of β.

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 2.5. 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 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 2.10.

Columns 1-3 again refer to food waste measures from wave 1 while columns 4-6 report results for wave 2 outcomes. Table 2.10 shows that the procrastination coefficient is

Table 2.10: *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 OLS 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 indicates 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

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 2.5, 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 2.A.7 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.

2.4.3.2 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 2.10 but now use the wave-specific measure of procrastination to test whether estimates over time are significantly different from each other. Table 2.11 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.

Table 2.11: *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 OLS 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 indicates 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

2.5 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.

2.6 Appendix

Table 2.A.1: *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 socio-economic and household characteristics. Levels of significance: *0.10, **0.05, ***0.01

Table 2.A.2: *Description of Variables*

Variable	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.

Variable	Definition
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.

Variable	Definition
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 GSOEP.
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 GSOEP.
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 GSOEP.
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.

Variable	Definition
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.

Variable	Definition
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 2.A.3: *Food Waste Behavior and Dynamic Inconsistency: All Controls*

	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 OLS 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 indicates 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 2.A.4: *Consumption Planning Behavior: All Controls*

	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 OLS 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 indicates 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 2.A.5: *Deviating from Intentions at Home: All Controls*

	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 OLS 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 indicates 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 2.A.6: *Deviating from Intentions and Food Waste Behavior: All Controls*

	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 OLS 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 indicates 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 2.A.7: *Procrastination and Food Waste Behavior: All Controls*

	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 OLS 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 indicates 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

3 Economic Behavior under Containment: How do People Respond to Covid-19 Restrictions?

3.1 Introduction

Many challenges for a society necessitate behavioral changes of its members: For instance, climate change probably requires a complete overhaul of established consumption patterns, and digitization requires new ways to manage data. Yet, little is known about how societies can accomplish such alterations. One possibility is that individuals change their behavior intrinsically; alternatively, governments can regulate behavior extrinsically through policies such as taxation, restrictions, or bans. Understanding the importance of external drivers of behavioral change is relevant for public policy since it sheds light on the efficacy of policies. Furthermore, a better understanding of the drivers of behavior allows for an improved assessment of the costs accruing to different economic agents.

This paper assesses the importance of extrinsic regulation for behavioral changes in people's everyday lives to overcome and mitigate the risks and potential social costs of a global health crisis. To do so, we exploit an episode of fundamental state intervention: The Covid-19 pandemic. Using novel nationally representative longitudinal survey data from Germany, a country with substantial spatial and temporal variation in Covid-19 containment measures, the paper assesses behavioral changes in three economic domains: the labor market domain (i.e., workplace and childcare behavior), the shopping domain (i.e., food purchasing behavior), and the consumption domain (i.e., risky or dietary behavior). We pick these three domains since Germany's Covid-19 regulations prevented or inhibited economic activities in many markets: In large parts of Germany, restaurants were closed, retail trade was forbidden (except for essential goods), and most market-based leisure activities were shut down (e.g., cinemas, concert houses, sports facilities) during substantial parts of our observation period.

The data were collected in the year 2021 in February/March (wave 1) and June/July (wave 2). Covid-19 incidence rates in Germany were slowly increasing after a nadir during wave 1 and falling during wave 2. Variation across German federal states was substantial throughout the entire pandemic, leading to regionally dispersed Covid-19 containment measures. Establishing a causal link between individual behavior and those measures is challenging: Many other pandemic indicators potentially relevant for individual actions, e.g. Covid-19 incidence rates, number of deaths or testing strategies for Covid-19 are highly correlated and also determine Covid-19 restrictions. To account for potential endogeneity problems that might be caused by omitted variables, reverse causality, or a bad control problem regarding pandemic indicators, we instrument policy stringency with the duration to the next state election exploiting exogenous variation through pre-determined election cycles.

Before applying a Two-Stages Least Squares (2SLS) approach, the paper first documents behavioral changes by regressing economic behaviors on policy stringency while using simple OLS. Our estimation model utilizes state fixed effects to control for time-invariant unobserved heterogeneity between regions. We proxy extrinsic regulation through regional governmental Covid-19 containment policies by computing a state-level version of the Oxford Covid-19 policy stringency index (Hale et al., 2020) for Germany. We demonstrate the plausibility of this measure: Increases of the policy stringency index (i.e., stronger Covid-19 regulations on individual behavior) are associated with respondents' perception of living through an exceptional period of life.

We find that extrinsically induced policy regulation significantly changes economic behavior in the workplace and in household childcare, in food purchasing decisions, (reported) risk preferences, fear of Covid-19 but seems to have no systematic impact on consumption or health behavior. The OLS and IV results are qualitatively almost indistinguishable with small differences regarding their quantitative interpretation. Overall, stricter policy regulations induced individuals to work from home and care for kids at home more often. While labor market outcomes respond partly mechanically to containment measures since some workplaces and childcare facilities were shut down, individuals also respond to stricter measures by adapting their consumption behavior: They reduce the number of grocery shopping trips. We also observe a significant effect on self-reported risk preferences and fear of Covid-19: Individuals in the sample show a lower willingness to take risks and are more afraid of Covid-19 as government regulations become stricter. With respect to consumption and health behaviors, we do not observe a significant effect on the frequency of alcohol consumption or diet healthiness.

We contribute to the literature in three ways: First, we investigate the effects of extrinsic regulation in a real live setting and assess economic behavior across different economic domains. While a large literature has emerged on the impact of the pandemic on the labor market (Adams-Prassl et al., 2020; Albanesi & Kim, 2021; Aum et al., 2021; Béland et al., 2020; Koczan, 2022), or on the within household division of labor (Del Boca et al., 2021), much of the literature focuses on single economic or health outcomes (Adams-Prassl et al., 2022; Brodeur et al., 2021; Giuntella et al., 2021). Capitalizing on a rich data set, we are able to compare effect sizes across different markets. Specifically, the assessment of grocery shopping behavior is complementary to the existing literature. Second, we add to an understanding of the role of election cycles in explaining policy stringency. To the best of our knowledge, there is only a small amount of empirical evidence regarding non-pandemic factors that determine governmental responses to the spread of Covid-19: For example, Pulejo and Querubin (2021) analyze cross-country data and find that incumbent political leaders implement less stringent Covid-19 restrictions when the election is closer in time. Gonzalez-Eiras and Niepelt (2022) analyze US state level data and find the opposite effect: An upcoming election causes stricter regulations. Chen et al. (2022) focus on local leaders in China and find evidence for a negative relation between promotion incentives and policy stringency. We provide a further perspective by analyzing within-country data in a multi-party system over time. Additionally, this paper is among the first to shed light on this relation in a mid-pandemic time period. All mentioned papers focus on the first months of the pandemic where political agendas and actions are likely to be driven by very different motives compared to a more settled time. Finally, this study contributes to an understanding of the stability of reported economic preferences by investigating the effect of regulatory stringency on selected economic and psychological outcomes. We add to a small list of studies focusing on the relation between policy stringency and risk preferences (Shachat et al., 2021), social preferences and trust (Casoria et al., 2023), and also fear (Fetzer et al., 2021).

The remainder of the paper is structured as follows: Section 3.2 describes the theoretical and institutional background. Section 3.3 is devoted to the newly collected data set.

Section 3.4 presents the empirical analysis with Subsection 3.4.1 containing the empirical model, Subsection 3.4.3 showing regression results, and Subsection 3.4.4 presenting a number of robustness tests. Section 3.5 concludes.

3.2 Institutional Background

Even in democratic societies with widely accepted civil rights, governments sometimes restrict free choices during incisive and socially challenging situations like wars, natural disasters, terror attacks or public health emergencies. Under such emergency states, civil liberties are restricted and defiance can entail legal penalties. During the Covid-19 pandemic many governments restricted or closed transportation, educational facilities, workplaces or shops, among others. Governments justify such regulation either with attempts to suppress externalities (i.e., inhibit the spread of Covid-19 in the population) or to correct behavioral biases (i.e., prevent people from making errors and infect themselves).

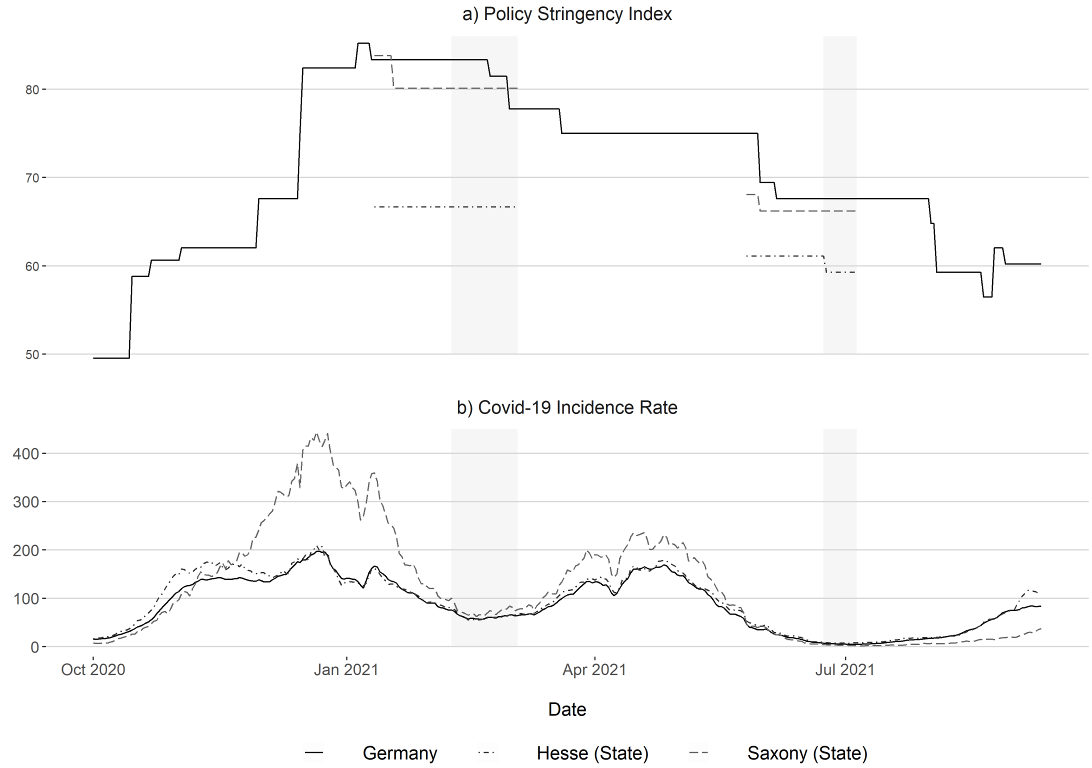
Governmental regulations to mitigate the spread of Covid-19 in Germany in 2021 affected many areas of private and public life: schools at all levels were closed and many workplaces with customer interaction were shut down (except for essential goods and services). Private gatherings were restricted to a limited number of people, public events were canceled and facial covering was required in public spaces. An international travel ban was introduced and internal movements were restricted. Covid-19 regulations differed across the 16 federal states whose governments implemented different sets of policies, even conditional on similar Covid-19 incidence rates.

Figure 3.1, panel a) depicts the development of regulatory stringency between October 2020 and October 2021. We hand collect information from state-level ordinances on protection measures against Covid-19 for all 16 federal states of Germany and measure the stringency of governmental regulations according to the methodology developed by the Oxford Policy Stringency Index (Hale et al., 2020).[1] The index constitutes a composite measure based on nine different indicators including school closures, workplace closures,

[1] Details on the differences in implementation and strictness of Covid-19 containment measures across the 16 federal states are discussed in connection with the instrumental variable strategy in Section 3.4.2.

travel controls and public information campaigns among others.[2] It can take on values between 0 (no measures) and 100 (most strict measures) with higher values indicating a stricter policy response.

Figure 3.1: *Development of Policy Stringency in Germany*



Notes: The figure depicts the stringency of political containment measures due to Covid-19 (panel a) and Covid-19 incidence rates (panel b) over time and for Germany as a whole and two federal states: Hesse and Saxony. The grey shaded areas mark the two time periods the survey data were collected in. For their calculations of the stringency index at federal level, Hale et al. (2020) use the strictest state-level value for each sub-index (panel a)). For our calculations we use the actual stringency levels for each sub-index within each state. This computational difference may lead to deviations to our stringency measure. Thus, even the strictest measure on the state level as of February 2021 (Saxony) tends to be slightly lower than at the federal level.

We plot the policy stringency index for the whole of Germany, and for the two federal states disposing of the lowest and highest Covid-19 policy stringency indices as of February 2021, Hesse and Saxony.[3] The grey shaded areas highlight the data collection periods of the survey. Policy stringency is high during survey wave 1 with index

[2]Oxford Covid-19 Government Response Tracker: https://covidtracker.bsg.ox.ac.uk/.
[3]Policy stringency data at the state level were only hand collected from four weeks preceding each survey wave until the end of each wave.

values ranging between 77 and 83 for Germany as a whole. Until wave 2, stringency decreased to a level of 67. Differences in policy stringency occur not only over time, but also between federal states: While the federal state Hesse implemented less strict regulations, Saxony followed a stricter plan over time. Figure 3.1 also reveals differences between the strictest value in a state and Germany as a whole. The reason stems from a computational difference: The index for Germany as computed by Hale et al. (2020) always adapts the strictest state stringency level to Germany as a whole. If one state is strictest in school closures while a different state is strictest on internal movement, by computation the maximum values from both states will flow in the calculation of the overall index. As a consequence, policy stringency values for Germany as a whole might overestimate the true stringency at state levels.[4]

Panel b) of Figure 3.1 plots corresponding Covid-19 incidence rates, an official measure of the number of individuals diagnosed with Covid-19 per 100,000 inhabitants within the last seven days. 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. Both survey waves were conducted during periods of rather low incidence rates: During the implementation of wave 1, the average incidence rate for Germany as a whole ranges between 50 and 70. During wave 2, the incidence rate falls below 30. Heterogeneity between the two federal states is especially pronounced during the high-incidence period from November 2020 until February 2021.

3.3 Data

Our analysis exploits a unique data set, specifically collected to investigate the impact of Covid-19 containment regulations on behavioral change. The longitudinal data are nationally representative for Germany and comprise two interviews per respondent: Wave 1 of the survey was implemented in February to March 2021, followed by wave 2 in June to early July 2021. Respondi, an established market research company with a representative pool of respondents in Germany, conducted the survey online and applied stratified random sampling of individuals by gender, age and state of residency for the

[4]Details addressing the calculation of the policy stringency index at state level are provided in Section 3.3.

first survey wave. The attrition rate from wave 1 to wave 2 is 31%. After carefully cleaning the data, we have information on a balanced sample of 851 individuals across Germany. Survey respondents were between 18 and 72 years old; based on their age, almost no participants of our panel were eligible for vaccination in the first wave.

The survey contains questions about demographic and household characteristics, economic preferences, labor market outcomes, as well as shopping and health behavior. We also include survey questions regarding respondents' fear of Covid-19, a question specifically designed for the purpose of our research. Importantly, respondents' place of residence can be geocoded according to their postal catchment area. The surveys take about 20 minutes to respond, for each wave.

Extrinsic regulation is captured by the governmental Covid-19 policy stringency index. Importantly, the 16 regional governments of the German federal states were responsible for formulating most of the policy responses to Covid-19, with substantial policy heterogeneity. We therefore collect data and calculate the stringency index at the state level by applying the Oxford policy stringency index methodology to the German setting. More precisely, we consider the following containment and closure policies in the stringency index: 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. We adapt the calculation of the stringency index at the state level to better capture the heterogeneity in governmental regulations across federal states: Referring to school closures, stay at home requirements, and restrictions on internal movement we distinguish between closures that are dependent or independent of the local incidence rate. Referring to public gathering restrictions, we distinguish between restrictions with and without a maximum number of people, specifically applied to public political protests.[5]

In our analysis, we exploit two sources of heterogeneity: We use differences in policy stringency between federal states and within states over time. The average policy stringency in the sample is 67, with a decline of about 10 points between waves 1 and 2. We link the geocoded survey data with our self-computed stringency data to establish a link between the regional policy stringency and behavioral changes. Owing to a staggered

[5] At the state level there was substantial variation in admitting public assemblies for political protests, especially regarding numerical limits to participation. Private gatherings in public or at home were more or less subject to the same rules across states. Therefore we base this sub-index on public political gatherings.

roll-out of the survey, we observe variation in policy stringency within the same region.

Table 3.1 shows summary statistics for all outcome and control variables. Summarizing our outcome variables, individuals in the sample work on average 1.9 days remotely from home and take personally care of their children on 2.3 days per week (excluding weekends). On average survey respondents go grocery shopping 2.6 times a week including online purchases and 2.3 times when excluding online purchases. We measure risk preference by applying the standard 11-point Likert scale measure of self-assessed general willingness to take risks used in the German Socio-Economic Panel (GSOEP). A value of 0 indicates no willingness to take risks, while a value of 10 indicates the highest level of risk seeking. The mean value in the sample is 4.4. Corona fear is a newly developed survey measure capturing the fear of Covid-19: We ask respondents to assess how anxious they personally are in the light of the novel Corona virus (leading to Covid-19) on a 11-point Likert scale. A value of 0 means being not anxious at all while a value of 10 means being extremely anxious. The sample average is 4.7. Frequency of alcohol consumption is measured in five categories, with a mean value of 1.14 reflecting drinking alcohol on approximately one day per week. The variable health of diet is a self-assessed measure capturing how healthy respondents perceive their diet. It is measured in six categories ranging from 'not at all healthy' (0) to 'very healthy' (5). The average category in our sample is "quite healthy" (3).

As Table 3.1 reveals in terms of socio-demographic variables, 49% of respondents are female and 40% of individuals hold a tertiary education degree. Respondents are on average 47 years old and live in a two-person household. Fifteen percent of individuals have at least one child aged 11 or younger, and 43% live together with a partner. The average net household income lies at almost 2650 €; for the regression analysis we use the natural log of household income. We also include indicators of labor market participation. Forty-five percent of individuals in the sample work full time while 20% work part-time. Exactly 30% of respondents are not working. Comparably small shares of individuals indicate to be on furlough (3%) or in apprenticeship (2%).

The last category of control variables captures political party shares in federal state parliaments. As summarized in Table 3.1, we include the share of AfD, an extreme right-wing party entirely refusing Covid-19 containment measures, and the share of FDP, the liberal democratic party favoring low levels of restrictions on civil liberties. We include these parties since party supporters were systematically less satisfied with the crisis

Table 3.1: *Summary Statistics*

	Mean	*SD*	*Min*	*Max*	*Obs.*
Outcomes:					
Days remote work (week)	1.87	2.10	0	5	1128
Days childcare at home (week)	2.26	2.22	0	5	314
No. grocery shopping (week)	2.61	2.24	0	20	1690
No. grocery shopping excl. online (week)	2.26	1.87	0	11	1690
Risk preferences	4.39	2.41	0	10	1702
Corona fear	4.68	2.91	0	10	1702
Freq. alcohol week	1.14	1.20	0	4	1702
Healthiness of diet	3.06	0.87	0	5	1702
Main regressors:					
Pol. stringency	66.9	6.10	59.3	80.1	1702
Weeks to election	98.7	71.8	2	259	1702
Controls:					
Female	0.49	0.50	0	1	1702
Age	47.2	13.7	18	72	1702
Tertiary education	0.40	0.49	0	1	1702
Full time	0.45	0.50	0	1	1702
Apprenticeship	0.020	0.14	0	1	1702
Furlough	0.032	0.18	0	1	1702
Not working	0.30	0.46	0	1	1702
Part time	0.20	0.40	0	1	1702
Household size	2.04	1.42	1	11	1702
Household net income (in €)	2646.4	1591.6	10.0	9750.5	1702
Child below 12	0.15	0.35	0	1	1702
Partner	0.43	0.50	0	1	1702
Political controls:					
AfD (%)	10.7	6.86	0	27.5	1702
FDP (%)	7.53	3.12	3	12.6	1702
Voter turnout prev. election (%)	66.5	3.64	51.2	72.3	1702
Robustness:					
Farming	1.36	1.47	0.033	8.71	1702
Manufacturing (no constr.)	18.1	8.15	3.43	50.0	1702
Constructions	5.92	2.19	1.91	12.7	1702
TTHITC (serv.)	25.7	3.78	15.9	48.0	1702
FIFR (serv.)	17.0	5.74	6.59	34.1	1702
Public & Others (serv.)	31.9	5.91	17.8	50.6	1702
Female labor part. (15-64 Y)	72.8	2.91	67.6	77.5	1702
Weeks since peak (inc.)	8.56	1.62	3	15	1702
Pol. stringency (SV)	48.4	10.7	35.4	74.0	1702

Note: This table provides summary statistics for outcome and main regressor variables as well as control and robustness variables. It shows the mean, standard deviation (SD), minimum (Min) and maximum (Max) value as well as the number of observations. A detailed description for each variable is provided in Table 3.A.1 in the Appendix.

management of state and federal governments, and criticised containment measures as too strict. The average AfD share is around 11% while the liberals have on average almost 8% of seats in state parliaments. The voter turnout in the previous elections of the 16 federal states ranges between 51% and 72% with an average of 66.5%. A detailed description of each variable and the relevant outcome categories can be found in Table 3.A.1 in the Appendix.

3.4 Empirical Analysis

This section first describes the econometric approach that we apply to establish a causal effect of policy stringency on our outcome measures in different economic domains. We will then focus on the instrument (weeks to election) applied in a 2SLS framework and contextualize the meaning of weeks until the next federal state election with respect to the strictness of Covid-19 containment measures at the state level. In the subsequent regression analysis, we provide results of Ordinary Least Squares (OLS) and Instrumental Variable (IV) regressions and implement several robustness checks that support our findings.

3.4.1 Econometric Approach

Our empirical strategy is based on a state fixed effects model. By exploiting regional variation in policy stringency at the state level within and across the two survey waves, the regression equation can be formalized as:

$$Y_{ist} = \beta \text{Stringency}_{st} + X'_{ist}\gamma + \lambda_s + \tau_s t + \epsilon_{ist}, \tag{3.1}$$

where i indexes individuals, s federal states and t date of interview. Y_{ist} reflects one of the eight outcomes of interest in Table 3.1. Our main coefficient of interest β captures the effect of policy stringency in state s at time t. X'_{ist} is a vector of controls including the socio-demographic characteristics age[6], gender, tertiary education and log of net monthly household income. We also control for individual labor market participation and measure whether an individual works full time, part time, is on furlough or doing an apprenticeship (reference category: not working). Vector X'_{ist} further includes the household characteristics household size, a dummy for a co-residing child aged 11 or below, and a partner dummy. It finally contains voter turnout in the previous federal state election and party shares for AfD and FDP at state level parliaments. The term λ_s captures state fixed effects and τ a state specific linear time trend measuring weeks since the last peak in incidence rates. Standard errors ϵ_{ist} are clustered at the calendar week $\times$ state level.

In the presence of reverse causality or omitted variables bias, the OLS specification of equation 3.1 does not necessarily result in the estimation of causal effects. Omitted variable bias can plague OLS if some unobservable factor is not only related to Y_{ist} but also to $Stringency_{st}$. For instance, the regional level of conservatism might influence Covid-19 containment rules and at the same time relate to the extent of childcare provided at home. In this case, OLS estimates would underestimate the true effect of policy stringency. For the number of days worked remotely from home, the opposite might be true: conservatism in society reduces the acceptance of working from home and results in OLS estimates being too high. Reverse causality implies that policy stringency affects behavioral outcomes while outcome variables influence policy stringency. This might be plausible if individuals being more afraid of Covid-19 put more pressure on politicians to implement stricter rules. Policy stringency is also a response to Covid-19 incidence and death rates, and simultaneously political leaders seek to reduce incidence and death rates by enacting stricter containment measures. In this paper, we are interested in that part of the effect of stringency on individual behavior that is driven by political considerations and not epidemiological aspects that might also directly influence behavior. To isolate this effect, we propose an IV approach by exploiting pre-determined election cycles that generate exogenous variation in policy stringency and vary across states. The election cycle was first exploited as instrumental variable in Levitt (1997). Regression equation 3.2 shows the first stage of the IV estimation:

$$\text{Stringency}_{ist} = \alpha \text{Weeks}_{st} + X'_{ist}\delta + \sigma_s + \rho_s t + \epsilon_{ist}. \tag{3.2}$$

[6] We form four age groups to include them into the regression. The reference category is 18-35Y. The other three categories are 36-49Y, 50-59Y and 60-72Y.

The variable Weeks_{st} measures the duration to the next state election in weeks. The vector X'_{ist} is identical to the one in equation 3.1. The term σ_s captures state fixed effects and ρ a state-specific linear time trend measuring weeks since the last peak in incidence rates. Standard errors ϵ_{ist} are clustered at the calendar week $\times$ state level. Using only the exogenous variation in policy stringency determined by the distance to the next election, equation 3.3 formulates the second stage of the IV estimation:

$$Y_{ist} = \beta \widehat{\text{Stringency}}_{ist} + X'_{ist}\gamma + \lambda_s + \tau_s t + \epsilon_{ist}. \tag{3.3}$$

Different to the OLS specification in equation 3.1, $\widehat{\text{Stringency}}_{ist}$ captures only the exogenous portion of policy stringency at state level s and time t. The identification is based on the following assumptions: First, the instrument is relevant. This assumption implies that the duration to the next election has an influence on policy stringency. Results of Chen et al. (2022), Gonzalez-Eiras and Niepelt (2022), and Pulejo and Querubin (2021) provide evidence for the existence of this link for the first month of the pandemic. We report the results of the first stage in Table 3.2 for our mid-pandemic observation period. Column 1 shows first stage results for the first outcome variable 'days remote work', column 2 reports the coefficient for the second outcome measure 'days childcare at home'. Column 3 refers to first stage results for the outcome 'grocery shopping' including and excluding online shopping while column 4 states first stage results for all remaining outcome variables (risk preferences, corona fear, frequency alcohol and health of diet). As summarized in Table 3.2, duration to the next election (measured in weeks) has a highly significant effect on policy stringency - irrespective of the sample of the respective outcome. The further away an election is, the stricter are Covid-19 containment regulations. In each column, the reported F-statistic is large and far above the threshold value of 10. The results are robust to additionally including individual fixed effects reported in Table 3.A.2 in the Appendix.

Of the 16 federal states in Germany, six states experienced a state election in 2021.[7] As Table 3.1 indicates, the average time period to the next state election is 99 weeks or 1.9 years. One might worry that this time period is too long to influence policy stringency already during our observation period. We provide the following arguments to alleviate

[7] Note that for Thuringia, the election was scheduled for September 2021 but cancelled in late July 2021 after the second survey period ended.

Table 3.2: *First Stage IV Estimation*

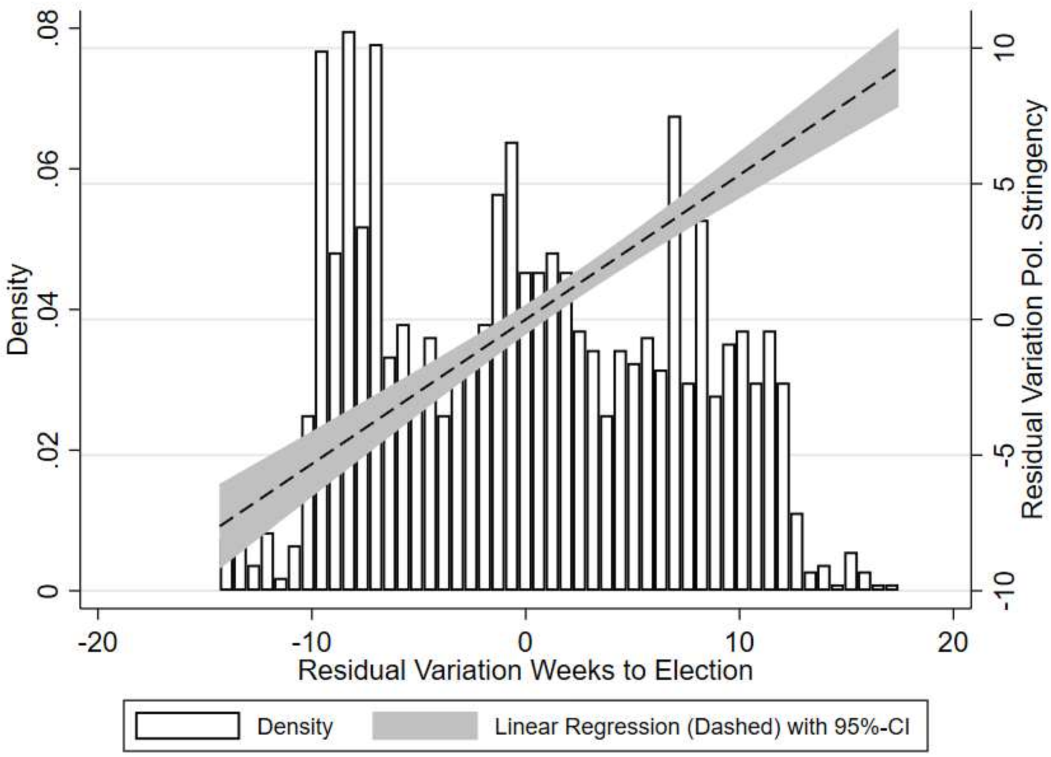
	(1) Pol. Stringency	(2) Pol. Stringency	(3) Pol. Stringency	(4) Pol. Stringency
Weeks to election	0.5390***	0.5180***	0.5309***	0.5328***
	(0.0452)	(0.0471)	(0.0455)	(0.0453)
Obs.	1,128	314	1,690	1,702
State FE	X	X	X	X
F-Stat	142	121	136	138

Notes: The table shows coefficient estimates from the first stage of the IV estimation. Standard errors in parentheses are clustered at federal state-calendar week level. Column (1) depicts the first stage for days remote work (week), column (2) for days childcare at home (week), column (3) for no. grocery shopping including and excluding online shopping (week), and column (4) for all remaining outcomes. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

this concern. First, the study of Gonzalez-Eiras and Niepelt (2022) suggests that state governors in the US start political campaigning after half of an electoral term is over (usually lasting five years in Germany). The study of Iaryczower et al. (2022) shows that the majority of US senators is willing to make relatively large policy concessions in order to increase chances of re-election. These findings provide first evidence that incumbent policy makers might start campaigning already two years before an election is up. Second, due to lockdown and containment measures during the pandemic, people cannot be reached by traditional campaigning methods such as house campaigns, on-site events at the town hall square or other campaign events. This has likely shifted the campaigning start forward in time. We further provide robustness tests by splitting the sample depending on whether an election occurred in 2021. The results are robust and discussed in Section 3.4.4.

Figure 3.2 provides graphical evidence supporting our hypothesis that closer elections lead to lower levels of policy stringency. The dashed line in Figure 3.2 graphically depicts the relationship between weeks to election and policy stringency conditional on the controls and state fixed effects from equation 3.2 in the full sample. Accordingly, residual variation originates from regressions of the respective variable on state fixed effects, a peak trend, individual specific, and state-level political controls. The histogram shows the distribution of our identifying variation in weeks to election along the left y-axis. Focusing on residual variation, Figure 3.2 shows that there is a highly significant, positive (almost linear) relation between distance to next state election and the state-level stringency index which we will exploit as first stage in the analysis in Section 3.4.3.

Figure 3.2: *First Stage Identifying Variation*



Notes: The histogram shows the density of residuals in weeks to election along the left y-axis (while excluding the top and bottom 2%). Residual variation of policy stringency is depicted along the right y-axis and residual variation of weeks to election along the x-axis. The dashed line depicts a linear regression of residuals in policy stringency on residuals in weeks to election while the grey area shows 95% confidence intervals for this regression (standard errors are clustered at the federal state-calendar week level). Residual variation stems from regressions of the respective variable on state fixed effects, a peak trend, individual specific and state-level political controls. Graph design originates from Dahl et al. (2014) and Bhuller et al. (2020).

The second assumption is that the instrument only affects the outcomes through its effect on policy stringency without any direct influence. We consider this assumption to hold in our context since weeks to the next federal state election are unlikely to influence everyday economic, consumption or health behaviors involving daily routine activities.

3.4.2 State Elections, Election Proximity and Policy Stringency

State elections in Germany's 16 federal states are fully decentralized.[8] The respective 16 individual constitutions regulate the election system and process. In general, all states follow variants of the proportional representation system. Smaller differences exist with respect to the electoral terms, mostly lasting five years (except for the city state of Bremen with a four year electoral term), and the lower age limit of the electorate (16 or 18 years). Stronger differences exist with respect to the allocation of parliamentary seats. For subsequent elections, the approximate election periods are fixed (i.e., year and quarter according to the electoral term), while the government proposes an exact election date roughly one year in advance. Elections in Germany always take place on Sundays.

The federal states nowadays feature a multi-party system with mostly five to six parties represented in parliament. Consequently, state governments normally comprise a coalition of two to three parties. These governments are usually led by the largest party, which also provides the state prime minister. The most commonly represented parties are the conservative party union (CDU/CSU), the social democrats (SPD), the environmentalist Green party (Buendnis 90/Die Gruenen), the liberals (FDP), the left-wing party (Die Linke), and the extreme right-wing populist party (AfD). The governments of the federal states are led by the SPD (8), CDU/CSU (6), the Green party (1) and the Linke (1).

The Covid-19 pandemic forced politicians to make fundamental decisions affecting all areas of life. To coordinate containment measures, the 16 prime ministers and the German chancellor accompanied by other officials of the German state government irregularly met at a newly established federal-state conference taking place on March 12, 2020 for the first time. As a result, the agreements of this conference were implemented in the Infection Protection Act (IfSG, 2000)[9]. This enabled the federal states to enact Covid-19 restrictions since the detailed design of disaster control and public health regulation mainly belongs to the political responsibility of state governments (IfSG, §32 & §54). Consequently, the exact implementation differed and thus induced sufficient variation in policy stringency across states.

[8] Federal Returning Officer (2023). Elections to the Länder Parliaments, https://www.bundeswahlleiter.de/en/service/landtagswahlen.html

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

Since the onset of the Covid-19 Pandemic in 2020, political debates evolved around the question how to best contain the spread of the virus. During the first couple of months, most German politicians and parties favored a very strict policy of reducing social contacts in most domains except for the labor market. This was implemented through school (and even playground) closures, the restriction to meet only limited numbers of people in the public space and the closure of all but the most essential retail shops. With the progression of the pandemic in later waves, and especially the onset of vaccine developments, the political positions diverged substantially between the parties strongly opposing containment policies (especially the liberal party FDP and the extreme right-wing populist party AfD) and those strongly favoring lockdowns (in parts most of the remaining parties). Interestingly, even state governments of the same party membership had diverging preferences with respect to the strictness of containment policies.

The existing literature documents a link between upcoming elections and the strictness of Covid-19 containment policies for the first pandemic months in 2020. Gonzalez-Eiras and Niepelt (2022) and Pulejo and Querubin (2021) reveal differences in response behavior by incumbent policy makers who could run for re-election suggesting that policy makers not only considered the epidemiological, but also economic and politico-economic consequences of their actions. Restrictions were not implemented by a hypothetical social planner, but by self-interested politicians who sought to run for another term in office (Gonzalez-Eiras & Niepelt, 2022). For this very early pandemic period the link between election proximity and policy stringency is not entirely clear. Focusing on within-country variation in the US, Gonzalez-Eiras and Niepelt (2022) find evidence suggesting a positive relation between election proximity and policy stringency: As an election comes closer, policy stringency increases. The authors explain this finding with career concerns of incumbent politicians who wanted to demonstrate competence in this new and confusing situation. In contrast, Pulejo and Querubin (2021) find a negative relationship in a cross-country set-up: As elections come nearer, policy stringency decreases. The authors suggest an economic motive to drive this observation: Countermeasures with negative economic consequences were watered down.

The trade-off between reducing health risks and allowing social and economic activity arguably changed during the different pandemic time periods: While the pandemic situation was entirely new to German citizens and policy makers at the onset of the Covid-19 crisis, the situation started to change as treatment methods and hospital procedures became more effective, and first Covid-19 vaccines were approved by the European Medicines Agency (EMA) in December 2020.[10] The German federal government officially started the nationwide vaccination campaign on December 27, 2020 with offering vaccinations to individuals with highest priority[11]. As a consequence, the health risk for the most vulnerable parts of the population decreased substantially. This first round was completed in March 2021, followed by two more rounds offering vaccinations to individuals with high and heightened priority.[12] This priority setting ended in July 2021. At the beginning of June 2021, 45% of the German population were vaccinated once and 20% were fully vaccinated.

Throughout 2020, policy makers in Germany justified harsh containment rules and lockdowns - among others- with the lack of effective vaccines against Covid-19. As three different vaccines received approval until January 2021, incumbent policy makers came under pressure to relax containment measures to not loose credibility. In the upcoming elections in 2021, our survey year, the treatment of the pandemic became a politically more and more contested topic: People were tired of Covid-19 containment measures and it didn't seem to be beneficial anymore for political careers to call for more stringent measures. Figure 3.3 shows the development of pandemic fatigue, a psychological measure developed by Lilleholt et al. (2020). At the beginning of 2021, people clearly became more fatigued. This trend continues throughout the years 2021 and 2022, and is first reversed in August 2022. Anecdotal evidence from newspaper articles listed in the Appendix (3.7) suggests that those state prime ministers facing a re-election in the near future strongly favored policies to re-open the country. In some cases, politicians were even accused of explicitly favoring less stringent containment policies for the sake of their personal election success. Some politicians even seem to have suddenly changed their mind about containment policies around election dates. This reasoning suggests that for later pandemic periods, incumbent policy makers favored less harsh containment measures as state elections approached.

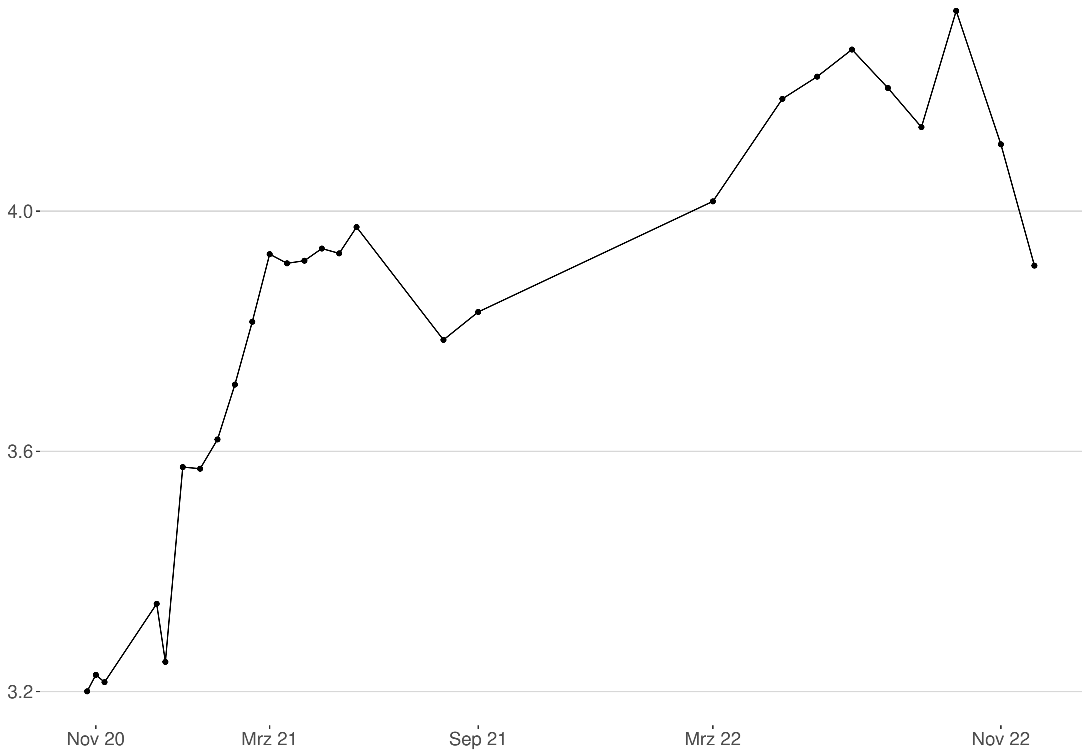
Overall, our analysis of state level containment policies confirms that those states facing a near election favored less stringent restrictions. In order for the first stage relation to be

[10]The EMA is responsible for coordinating the centralized approval procedure for vaccines in Europe.

[11]Individuals with highest priority were defined as individuals being above the age of 80, individuals living or working in care facilities, intensive care unit, emergency unit and ambulance staff and selected personnel in medical facilities.

[12]The Covid-19 vaccination prioritization was regulated in the Coronavirus Vaccination Ordinance, §§1-4, https://www.bundesgesundheitsministerium.de/fileadmin/Dateien/3_Downloads/C/Coronavirus/Verordnungen/CoronaImpfV_BAnz_AT_08.02.2021_V1.pdf.

Figure 3.3: *Development of Pandemic Fatigue*



Notes: The figure depicts the development of pandemic fatigue in Germany between October 2020 and November 2022. Pandemic fatigue is a psychological scale developed by Lilleholt et al. (2020). The measure is composed of six different items that are measured on a 7-point Likert scale ranging from 1 (do not agree at all) to 7 (fully agree). Pandemic fatigue is the mean taking over the six items. The six survey items are the following: 1. I am tired of all the Covid-19 discussions in TV shows, newspapers, and radio programs, etc., 2. I am sick of hearing about Covid-19., 3. When friends or family members talk about Covid-19, I try to change the subject because I do not want to talk about it anymore., 4. I feel strained from following all of the behavioral regulations and recommendations around Covid-19., 5. I am tired of restraining myself to save those who are most vulnerable to COVID- 19., 6. I am losing my spirit to fight against Covid-19. Survey data are taken from Covid-19 Snapshot Monitoring (COSMO), https://projekte.uni-erfurt.de/cosmo2020/web/explorer/. COSMO is a joint project by Erfurt University, Bernhard Nocht Institute for Tropical Medicine, Robert Koch Institute, the Federal Centre for Health Education, Leibniz Institute for Psychology and Science Media Center. It publishes representative results stratified by gender, age and state of residence from repeated cross-sectional survey waves.

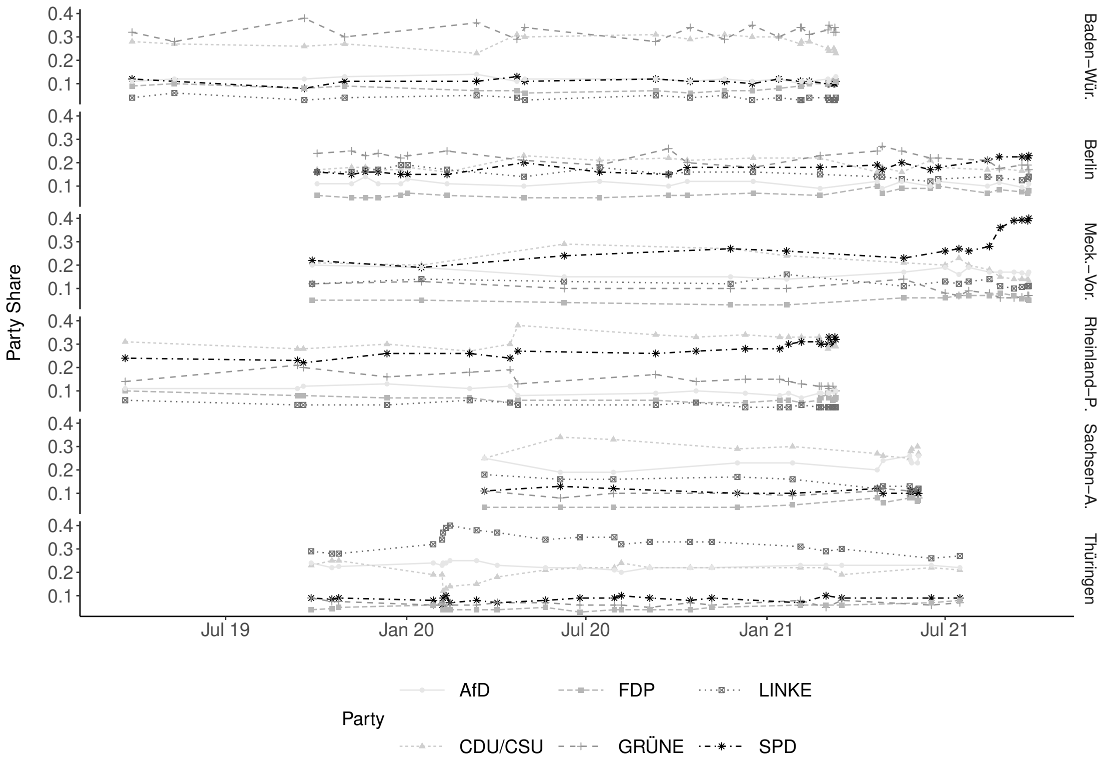
qualitatively powerful, we assume that governments in power were sufficiently likely to win the re-election (ultimately, all of them did). Figure 3.4 provides empirical evidence that incumbent parties could expect to be re-elected in the upcoming state elections: Ruling parties experienced solid voter shares in the election forecasts up to 24 months prior to 2021 state elections. In Baden-Württemberg for example, the two government parties the Greens (Grüne) and conservative Union (CDU/CSU) led the polls. In Berlin, after the last state election in 2016, a coalition of social democrats (SPD), the green party and the left-wing party (Linke) was in power. As Figure 3.4 shows, all three parties had stable shares 24 months prior to election in 2021. In Mecklenburg-Vorpommern, the two coalition parties SPD and CDU/CSU also had stable election forecasts. We observe a similar development for the other three states: government parties experienced stable election forecasts for the 24 months prior to elections in 2021. We secondly assume that the election was sufficiently important to the electorate. This assumption likely holds, given that the voter turnout across states in our sample ranges between 51% and 72%.

3.4.3 Policy Stringency and Economic Behavior

In this section, we present the results from the OLS and IV specification. Table 3.3 reports regression estimates for the OLS model while Table 3.4 summarizes effects based on the IV second stage. To improve comparability across our estimates, all dependent variables are standardized with mean zero and a standard deviation of one.

Columns 1 and 2 of Table 3.3 show a significant and positive effect of policy stringency on the weekly number of days worked at home for those being employed ($p < 0.05$) as well as on the weekly number of days parents give care to their children at home ($p < 0.01$). Columns 3 and 4 investigate the effect of the policy stringency measure on individual grocery shopping behavior. Higher levels of policy stringency significantly reduce the total number of grocery shopping trips, and remains significant when excluding online purchases ($p < 0.01$ in both instances). Columns 5 through 8 show results on the impact of policy stringency that go beyond market behavior in the previously discussed domains. Column 5 suggests that being subject to higher policy stringency measures marginally significantly reduces the reported willingness to take risks ($p < 0.10$). Moreover, individual assessments of fear of Covid-19 are positively and significantly ($p < 0.01$) associated with policy stringency (column 6). Even though we do not find any significant effect of

Figure 3.4: *State Election Forecasts 2021*



Notes: The figure shows election forecasts for the 24 months prior to election for all states that had a state election in 2021. For Thuringia (Thüringen), the election was scheduled but cancelled at the end of July in 2021 (after the second survey wave). Note that while the populist right-wing party AfD is expected to receive quite many votes in some states during the observation period, the other parties are constantly refusing to build a coalition since AfD party formation.

policy stringency on alcohol consumption or dietary behavior, both coefficients exhibit a negative coefficient . All regression results are robust to state fixed effects and including the time-varying control variables introduced in Section 3.4.1.

Table 3.3: *Market Behavior, Preferences, and Health (OLS)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0126**	0.0588***	-0.0266***	-0.0220***
	(0.0055)	(0.0147)	(0.0038)	(0.0040)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X

	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0093*	0.0154***	-0.0048	-0.0082
	(0.0049)	(0.0058)	(0.0046)	(0.0054)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X

Notes: The table shows coefficient estimates from OLS regressions of the eight different outcome variables on the state level policy stringency index and control variables. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

In terms of effect sizes, reported coefficients in Table 3.3 refer to a one unit increase in policy stringency. To assess the economic relevance of our results, we consider an increase in the policy stringency measure by ten units since this roughly reflects the average change in stringency from survey wave 1 to 2. An increase of policy stringency by ten units yields the following effects expressed in standard deviations of the respective outcome: Looking at Table 3.3, days of working from home increase by 0.3. This is equivalent to an increase in 13% of one standard deviation. For childcare provided at home, the effect is 1.3 days or 59% of one standard deviation. The number of grocery shopping trips decreases by 0.6 or 27% of one standard deviation. Excluding online shopping, the effect changes only marginally (decrease by 0.4 or 22% of one standard deviation). Individuals become more risk averse: the willingness to take risks decreases by 0.2 or 10% of one standard deviation. Fear of Covid-19 increases by 0.5 equivalent to 16% of one standard deviation. Policy stringency has no significant effect on the frequency of alcohol consumption and healthiness of the diet. The results are robust to additionally including individual fixed effects reported in Table 3.A.3 in the Appendix.

Table 3.4 reports coefficients from the IV estimation using 'weeks to next state election' as instrument. Columns 1-8 again show our eight outcome variables. In terms of effect sizes, almost all coefficients increase in absolute terms except for grocery shopping (excluding online) in column 4 and diet healthiness in column 8. We find significant effects of policy stringency for Columns 1-6, where results in columns 1 through 4 and column 6 are significant at the 1%-level and the remaining column 5 at the 10%-level. Coefficients for the frequency of drinking alcohol and healthiness of the diet remain insignificant. An increase of (instrumented) policy stringency by ten units yields the following effects expressed in standard deviations of the respective outcome: the number of days worked remotely from home increases by 15% of one standard deviation. The number of days on which childcare is provided at home increases by 82% of one standard deviation. On average, individuals in the sample decrease the number of grocery shopping trips by 28% (column 3) or 23% (column 4), respectively. Respondents become more risk averse: the willingness to take risks decreases by 11% of one standard deviation. They become more afraid of Covid-19: Corona fear increases by 22% of a standard deviation. In Section 3.4.4, we demonstrate that the results from the IV estimation remain robust against alternative assumptions concerning the structure of the error term. The effects are also robust against including individual fixed effects. Results of this exercise are reported in Table 3.A.4 in the Appendix.

Table 3.4: *Market Behavior, Preferences, and Health (IV)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0148***	0.0815***	-0.0283***	-0.0232***
	(0.0054)	(0.0197)	(0.0040)	(0.0047)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
F-Stat (1^{st} stage)	142	121	136	136
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0109*	0.0221***	-0.0070	-0.0076
	(0.0059)	(0.0065)	(0.0055)	(0.0059)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X
F-Stat (1^{st} stage)	138	138	138	138

Notes: The table shows coefficient estimates from IV regressions of the eight different outcome variables on the instrumented state level policy stringency index and control variables. The instrument is weeks to next federal state election. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Comparing results from the OLS and IV estimation, effect sizes increase in absolute terms for almost all outcomes in the IV estimation, but the increase for most outcomes is small. This finding speaks against a severe endogeneity problem in the OLS specification. The largest difference in effect size can be observed for the number of days childcare is provided by parents at home (column 2): The coefficient increases by almost 20 percentage points in absolute terms. To further investigate an omitted variable bias, we rerun the OLS specification in equation 3.1 and add additional controls. First, we control for female labor participation at the district level taking data from Eurostat[13]. If there were an omitted variable bias due to unobserved conservatism in society, including labor market participation of women as a proxy should affect the OLS estimates. Results of this exercise are reported in Table 3.5. The coefficient for the number of days childcare is provided at home does not change. Also the other seven coefficients are -if anything- only marginally affected by including labor market participation of women in the regression. The results provided in Table 3.5 do not support this type of bias.

Table 3.5: *OLS: Female Labor Participation (15-64Y)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0126**	0.0588***	-0.0265***	-0.0218***
	(0.0055)	(0.0147)	(0.0038)	(0.0040)
Female labor part. (15-64 Y)	-0.0088	0.0129	0.0543***	0.0421***
	(0.0186)	(0.0381)	(0.0161)	(0.0150)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X

	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0093*	0.0153***	-0.0047	-0.0083
	(0.0049)	(0.0058)	(0.0046)	(0.0055)
Female labor part. (15-64 Y)	0.0043	-0.0103	0.0333**	-0.0480**
	(0.0191)	(0.0248)	(0.0157)	(0.0205)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X

Notes: The table shows coefficient estimates from OLS regressions of the eight outcome variables on the state policy stringency index and an additional control measuring female labor market participation at district level. Female labor market participation is measured on the district level. Standard errors in parentheses are clustered at federal state-calendar week level. Further controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Second, we include variables describing the industry structure at the county level and use data from the Federal Statistical Office and Statistical Offices of the federal states in

[13] https://ec.europa.eu/eurostat/databrowser/view/lfst_r_lfe2emprt/default/table?lang=de

Germany.[14] Local industry structure might lead to an omitted variable bias due different sectors varying in capability of offering working from home jobs to their employees. This might affect the policy stringency, and at the same time determine the number of days that are worked remotely from home. Table 3.6 reports OLS results when including control variables representing local industry structure. Industry structure shares are measured in percent ranging from 0 to 100. Farming is the reference category. The service sector is measured with the following variables: TTHITC refers to trade, traffic, hospitality, information and communication technology industry services and FIFR indicates the finance, insurance, firms, real estate and housing industry services sector. Controlling for local industry structure does not change the OLS results suggesting that the proposed type of bias is not a serious concern.

3.4.4 Robustness

We run several robustness tests to back our results: We vary the clustering of standard errors, restrict the number of sub-indices used for policy stringency, run a placebo test for only one sub-index, allow for a different functional form of the instrument, and compare results for states with and without elections in 2021. First, we test four additional specifications of clustered standard errors. Since the effect of policy stringency varies across states, and the number of 16 clusters is small, our preferred specification includes clusters formed by grouping states and calendar weeks. This is possible due to the staggered implementation of the survey within states in survey wave 1. Thus, we test two different state level clusters either grouped by calendar months or survey waves. Additionally, standard errors are clustered at the individual and the county level. Each panel of Figure 3.5 depicts the second stage IV policy stringency coefficients for our eight different outcomes. The error bars present estimates of the respective 95%-confidence intervals for the five differently specified clustered standard errors. In comparison to state-week level clustering, results remain robust across different cluster specifications.

Second, we apply an alternative specification to calculate the policy stringency index at the federal state level by only including sub-indices that vary at the state level during the observation period. This alternative stringency index includes school closings, stay-at-home requirements, restrictions on internal movements, and restrictions on public

[14] https://www.statistik.rlp.de/fileadmin/dokumente/gemeinschaftsveroeff/etr/ETR_R2B1_2019_hj.pdf

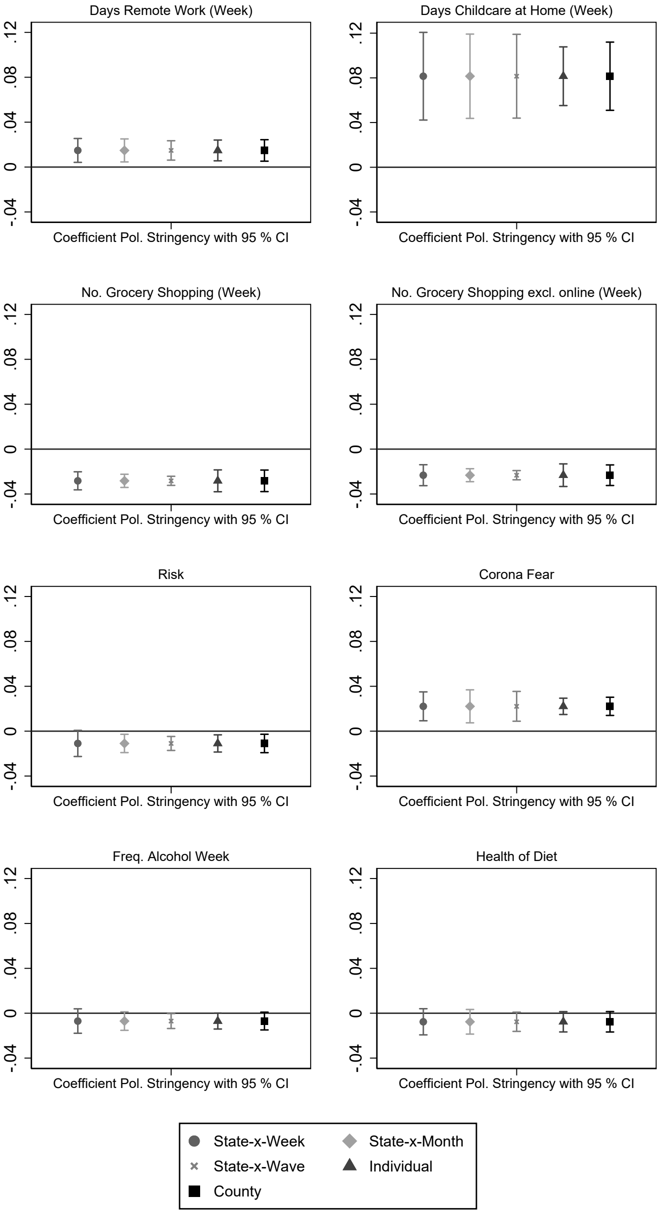
Table 3.6: *OLS: Industry Structure*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0127**	0.0585***	-0.0266***	-0.0219***
	(0.0056)	(0.0149)	(0.0039)	(0.0040)
Manufacturing (no constr.)	-0.0377	0.0009	-0.0207	-0.0027
	(0.0334)	(0.0553)	(0.0279)	(0.0273)
Constructions	-0.0549	-0.0322	-0.0099	0.0183
	(0.0485)	(0.0826)	(0.0434)	(0.0409)
TTHITC (serv.)	-0.0314	0.0159	-0.0213	-0.0048
	(0.0336)	(0.0562)	(0.0286)	(0.0281)
FIFR (serv.)	-0.0337	-0.0054	-0.0141	0.0047
	(0.0318)	(0.0556)	(0.0280)	(0.0266)
Public & Others (serv.)	-0.0375	-0.0043	-0.0180	0.0026
	(0.0328)	(0.0546)	(0.0289)	(0.0279)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X

	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0093*	0.0156***	-0.0043	-0.0083
	(0.0048)	(0.0057)	(0.0047)	(0.0054)
Manufacturing (no constr.)	-0.0276	0.0452	0.0179	0.0162
	(0.0295)	(0.0298)	(0.0203)	(0.0245)
Constructions	-0.0223	0.0965**	0.0847***	0.0018
	(0.0443)	(0.0396)	(0.0290)	(0.0384)
TTHITC (serv.)	-0.0253	0.0477	0.0327	0.0038
	(0.0306)	(0.0293)	(0.0197)	(0.0247)
FIFR (serv.)	-0.0243	0.0461*	0.0409**	0.0254
	(0.0300)	(0.0277)	(0.0187)	(0.0239)
Public & Others (serv.)	-0.0322	0.0563*	0.0274	0.0165
	(0.0284)	(0.0290)	(0.0198)	(0.0250)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X

Notes: The table shows coefficient estimates from OLS regressions of the eight outcome variables on the state policy stringency index and additional controls measuring industry structure shares at county level. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Figure 3.5: *Coefficient Estimates and Varying Standard Errors*



Notes: This figure plots point estimates of policy stringency from IV regressions according to Table 3.4 and corresponding 95%-confidence intervals for the eight outcomes of interest: days worked remotely from home during a working week, days childcare was provided at home during a working week, number of online and on-site grocery purchases a week, number of on-site grocery purchases a week, risk preference, corona fear, frequency of drinking alcohol during a week and health of diet. The varying confidence intervals stem from IV-regressions applying distinct clustering of the standard errors at: state × week level, state × month level, state × wave level, individual level and county level.

political gatherings. This addresses a potential concern that our results are driven by sub-indices varying over time but not across states. Results of this exercise for the IV specification are reported in Table 3.7. Compared to Table 3.4 that is based on the full policy stringency measure, we observe a moderate decline in absolute effect size for all outcome variables. But coefficients remain highly significant at the 1% level (5% level for working from home and 10% for risk preferences). The first stage F-statistic is still above the critical value of 10; results are reported in the Appendix in Table 3.A.5. As before, coefficients from the second stage IV estimation increase in size compared to OLS coefficients based on the sub-index reported in Table 3.A.6 in the Appendix. In comparison to the OLS specification with the full policy stringency measure, absolute coefficient sizes of OLS estimates in Table 3.A.6 reduce but most estimates remain significant at previous levels, except for working from home (10%) and Corona fear (5%).

Table 3.7: *Robustness IV: State-Varying Sub-Indices*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency (SV)	0.0109**	0.0611***	-0.0209***	-0.0172***
	(0.0041)	(0.0176)	(0.0033)	(0.0036)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
F-Stat (1^{st} stage)	53	44	50	50
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency (SV)	-0.0081*	0.0163***	-0.0051	-0.0056
	(0.0043)	(0.0054)	(0.0040)	(0.0044)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X
F-Stat (1^{st} stage)	51	51	51	51

Notes: The table shows IV regression results of the eight outcome variables on an instrumented alternative state policy stringency index. The alternative policy stringency measure only includes four state-varying sub-indices instead of all nine. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Third, we suggest a falsification exercise by only applying restrictions on public political gatherings as one sub-index instead of using the general policy stringency measure in the standard OLS specification based on equation 3.1. Since this sub-index measures the maximum number of people allowed to assemble for political protests or gatherings (e.g. maximum of 10, 100, 1000 or more individuals), it should not independently have a significant impact on our eight outcomes of interest. For example, this restriction should not affect an individual's reported number of days working from home or the decision to go grocery shopping. Results from Table 3.8 provide evidence in favor of this claim: Restrictions on public political gatherings do not have a significant effect on any of our outcomes, and coefficients are considerably smaller in size in comparison to the general OLS estimates reported in Table 3.3. These results partially alleviate the concern that our main estimates are simply driven by chance.

Table 3.8: *Falsification: Public Political Gatherings (OLS)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Restr. pol. gath.	0.0018	0.0112	-0.0054	-0.0057
	(0.0039)	(0.0078)	(0.0046)	(0.0051)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Restr. pol. gath.	-0.0009	0.0008	-0.0028	-0.0039
	(0.0047)	(0.0029)	(0.0038)	(0.0044)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X

Notes: The table shows OLS regression results of the eight outcome variables on a sub-index of the original stringency index only containing restrictions on public political gatherings. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Fourth, since our main analysis investigates the effect of policy stringency on eight different outcomes, this involves testing eight distinct hypotheses. To account for multiple hypothesis testing, we calculate adjusted p-values using the Romano-Wolf procedure with 1,000 bootstraps proposed in Clarke et al. (2020) and apply it to the IV-specification introduced in equation 3.3. The results of this exercise and the corresponding significance levels are summarized in Table 3.9. Coefficient sizes and standard errors are identical to IV estimates reported in Table 3.4. In Table 3.9, we additionally report standard p-values in brackets and adjusted p-values in braces. After the adjustment, p-values are generally larger than standard ones (with one exception for health of diet). All of our previous results, however, remain statistically significant at conventional levels. Only the coefficient for the effect of policy stringency on working from home switches its significance level from 1% to 5%.

Table 3.9: *Robustness IV: Multiple Hypothesis Testing*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0148**	0.0815***	-0.0283***	-0.0232***
	(0.0054)	(0.0197)	(0.0040)	(0.0047)
	[0.0068]	[0.0001]	[0.0000]	[0.0000]
	{0.0120}	{0.0010}	{0.0010}	{0.0010}
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
F-Stat (1^{st} stage)	142	121	136	136
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0109*	0.0221***	-0.0070	-0.0076
	(0.0059)	(0.0065)	(0.0055)	(0.0059)
	[0.0655]	[0.0009]	[0.2063]	[0.1971]
	{0.0789}	{0.0020}	{0.2258}	{0.2258}
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X
F-Stat (1^{st} stage)	138	138	138	138

Notes: The table shows OLS regression results of the eight outcome variables on state policy stringency index when correcting for multiple hypothesis testing. Brackets contain the original p-values, and braces the p-values adjusted for multiple hypothesis testing. For adjustments we use the Romano-Wolf procedure with 1000 bootstraps. Significance levels refer to adjusted p-values. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

In a fifth check, we focus on the assumption made for the previous analyses that there is a linear relation between weeks to election and policy stringency. This linearity assumption might raise the concern that the estimation specification is too restrictive. One could for example argue that the relation should rather follow an inverted U-shape: The positive effect of weeks to election on policy stringency becomes weaker as elections are sufficiently far away because politicians do not consider Covid-19 restrictions as a strategically relevant component for their policy decisions. To model an inverted U-shape relation, we square the instrument weeks to election and additionally include this term in the first stage. Table 3.10 present the results of this exercise: The coefficient of weeks to election remains positive and statistically significant while the same holds for the coefficient of the squared term. The results reported in Table 3.10 do not provide evidence for an inverted U-shaped relation between election proximity and policy stringency. If anything, our first stage results become even slightly stronger due to a higher F-statistic, and suggest a slight convex relation.[15] Second stage results reported in Table 3.A.7 remain qualitatively identical, with effect sizes becoming slightly smaller compared to those from the main specification.

Table 3.10: *Robustness First Stage: Weeks to Election Squared*

	(1) Pol. Stringency	(2) Pol. Stringency	(3) Pol. Stringency	(4) Pol. Stringency
Weeks to election	0.3742***	0.3374***	0.3595***	0.3644***
	(0.0756)	(0.0782)	(0.0731)	(0.0732)
Weeks to election x Weeks to election	0.0009***	0.0010***	0.0010***	0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Obs.	1,128	314	1,690	1,702
State FE	X	X	X	X
F-Stat	145	129	154	155

Notes: The table shows coefficient estimates from first stage IV regressions of state policy stringency on weeks to next state election and weeks to next state election squared. Standard errors in parentheses are clustered at federal state-calendar week level. Column (1) depicts the first stage for days remote work (week), column (2) for days childcare at home (week), column (3) for no. grocery shopping including and excluding online shopping (week), and column (4) for all remaining outcomes. . Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

In a final step, we analyse whether first stage results are solely driven by very close elections or the three elections that actually take place between survey waves 1 and 2 in March and June 2021. Hence, we split our sample in six election states (with elections in 2021) and ten non-election states (without elections in 2021), and re-run

[15] We also allow for higher degree polynomials and the relation remains almost linear. Results are available upon request.

the IV estimation for both samples separately. Results of this exercise are reported in Table 3.11. Comparing the upper four columns (election states) with the lower four columns (non-election states), the positive and statistically significant relation between election proximity and policy stringency holds in both sub-samples. As one might expect, coefficients and the F-statistic are larger for the election sample. This alleviates the concern that our results are solely driven by election states. In addition, the second stage results remain qualitatively similar compared to the full sample. Second stage results are reported in Table 3.A.8 for election states and Table 3.A.9 for non-election states in the Appendix.

Table 3.11: *Robustness First Stage: Election and Non-Election States 2021*

	(1) Pol. Stringency	(2) Pol. Stringency	(3) Pol. Stringency	(4) Pol. Stringency
Weeks to election	0.6482***	0.6036***	0.6197***	0.6215***
	(0.0307)	(0.0698)	(0.0393)	(0.0382)
Obs.	328	64	497	503
State FE	X	X	X	X
F-Stat	447	75	249	265
	(5) Pol. Stringency	(6) Pol. Stringency	(7) Pol. Stringency	(8) Pol. Stringency
Weeks to election	0.4963***	0.4864***	0.4933***	0.4939***
	(0.0471)	(0.0488)	(0.0482)	(0.0481)
Obs.	800	250	1,193	1,199
State FE	X	X	X	X
F-Stat	111	100	105	105

Notes: The table shows first stage IV results for federal states with elections and without elections in 2021. The upper 4 columns show results for election states whereas the bottom row refers to non-election states. Standard errors in parentheses are clustered at federal state-calendar week level. Columns (1) and (5) depict the first stage for days remote work (week), columns (2) and (6) for days childcare at home (week), columns (3) and (7) for no. grocery shopping including and excluding online shopping (week), and columns (4) and (8) for all remaining outcomes. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

3.5 Conclusion

This paper analyzes the effect of external regulation on individual decision-making across a number of economic domains. Exploiting variation in the policy stringency of Covid-19 containment policies across German federal states and over time, we show that many economic behaviors, such as working from home, caring for children at home and grocery shopping are strongly influenced by the strictness of Covid-19 containment measures. This link, however, does not exist for consumption behavior (alcohol consumption and health of diet). We estimate causal effects of government regulations on individual behavior by applying an instrumental variable approach that relies on exogenously determined state level election cycles. Using weeks to an upcoming federal state election as an instrument, we show that Covid-19 containment policies become less strict with elections moving closer in time. Besides effects of government regulations on economic behavior, we also observe individuals to become less willing to take risks and are more afraid of Covid-19 as a result of government regulations becoming stricter. All effects are robust to several robustness tests and variations in the econometric specification. Yet, the question remains how long these effects will prevail after regulations are lifted. This question provides an avenue for future research.

3.6 Appendix A

Table 3.A.1: *Description of Variables*

Variable	Definition
Outcomes:	
Days remote work (week)	Number of days working remotely per week (average past 2 weeks).
Days childcare (week)	Number of days taking care of children per week (average past 2 weeks).
No. grocery shopping (week)	Total number of grocery purchases including online purchases per week (average past 4 weeks).
No. grocery shopping excl. online	Total number of grocery purchases excluding online purchases per week (average past 4 weeks). Online Purchases are measured on the household level, total grocery purchases on the individual level. Therefore, before deduction total online purchases are divided by the number of adult household members. After deduction negative values are replaced with zero.
Risk pref.	Personal willingness to take risks. Measured on 11-point Likert scale from 0 to 10. 0 indicates "not at all willing" and 10 indicates "very willing"
Corona fear	Personal level of fear of Covid-19. Measured on 11-point Likert scale from 0 to 10. 0 indicates "not at all anxious" and 10 indicates "very anxious".
Freq. alcohol week	Weekly alcohol consumption (average past 4 weeks) : 0: never, 1: one day 2: two to three days, 3: four to six days, 4: every day.
Health of diet	Individually assessed health of diet 0 : Very unhealthy, 1: Unhealthy, 2: Quite unhealthy, 3: Quite healthy, 4: Healthy, 5: Very Healthy.
Main regressors:	
Pol. stringency	Generated Policy Stringency Index at the state level. Calculations based on the Oxford Stringency Index.

Variable	Definition
Weeks to election	Duration until the next election in a respondent's residential federal state measured in weeks.
Controls:	
Female	Dummy equal to 1 if individual is female and zero if male.
Age & Age groups	Individual age in years. Age groups include 18-35 years, 36-49 years, 50-59 years, and 60-72 years.
Tertiary education	Dummy equal to 1 if individual has a tertiary education degree (Abitur) and 0 otherwise.
Net income (€)	Personal monthly net income measured in Euros. Since income is observed as categorical variable, we calculate the mean for all categories and treat it as numeric information.
Full time	Dummy equal to 1 if individual works full time and 0 otherwise.
Apprenticeship	Dummy equal to 1 if individual currently completes an apprenticeship and 0 otherwise.
Furlough	Dummy equal to 1 if individual works in furlough and 0 otherwise.
Not working	Dummy equal to 1 if individual does not work currently and 0 otherwise.
Part time	Dummy equal to 1 if individual works part time and 0 otherwise.
Household size	Size of own household.
Child12	Dummy equal to 1 if children aged 12 or younger live in the household and 0 otherwise.
Partner	Dummy equal to 1 if individual lives with a partner and 0 otherwise.
Political controls:	
AfD(%)	Vote-share in percent of the political party AfD in a respondent's residential federal state.

Variable	Definition
FDP(%)	Vote-share in percent of the political party FDP in a respondent's residential federal state.
Voter turnout prev. election (%)	Voter turnout in percent of the last election in a respondent's residential federal state.
Robustness:	
Farming	Share of employed individuals working in the agricultural sector measured on the county level in 2019.
Manufacturing (no constr.)	Share of employed individuals working in manufacturing (excl. constructions) measured on the county level in 2019.
Constructions	Share of employed individuals working in constructions measured on the county level in 2019.
TTHITC (serv.)	Share of employed individuals working in trade, traffic, hospitality, and information and communication technology industry services measured on the county level in 2019.
FIFR (serv.)	Share of employed individuals working in finance, insurance, firms, real estate and housing industry services measured on the county level in 2019.
Public & Others (serv.)	Share of employed individuals working in public and remaining industry services measured on the county level in 2019.
Female labor part. (15-64 Y)	Share of employed women in the working population measured on the district level in 2019.
Weeks since peak (inc.)	Time since last peak in incidence rates in the residential federal state. Reference point for survey wave 2 is time between wave 1 and wave 2.
Pol. stringency (SV)	Alternative policy stringency measure only using state-varying sub-indices. These include school closings, stay-at-home requirements, restrictions on internal movement, and restrictions on public political gatherings.

Table 3.A.2: *First Stage IV Estimation (incl. ind. FE)*

	(1) Pol. Stringency	(2) Pol. Stringency	(3) Pol. Stringency	(4) Pol. Stringency
Weeks to election	0.5300***	0.5026***	0.5225***	0.5247***
	(0.0637)	(0.0668)	(0.0641)	(0.0641)
Obs.	1,128	314	1,690	1,702
Indiv. FE	X	X	X	X
State FE	X	X	X	X
F-Stat	69	57	66	67

Notes: The table shows coefficient estimates from the first stage of the IV estimation including individual fixed effects. Standard errors in parentheses are clustered at federal state-calendar week level. Column (1) depicts the first stage for days remote work (week), column (2) for days childcare at home (week), column (3) for no. grocery shopping including and excluding online shopping (week), and column (4) for all remaining outcomes. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.3: *Market Behavior, Preferences, and Health (OLS incl. ind. FE)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0125***	0.0612***	-0.0253***	-0.0233***
	(0.0034)	(0.0168)	(0.0034)	(0.0035)
Obs.	1,128	314	1,690	1,690
Indiv. FE	X	X	X	X
State FE	X	X	X	X
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0091**	0.0191***	-0.0084***	-0.0059*
	(0.0041)	(0.0038)	(0.0028)	(0.0035)
Obs.	1,702	1,702	1,702	1,702
Indiv. FE	X	X	X	X
State FE	X	X	X	X

Notes: The table shows coefficient estimates from OLS regressions of the eight outcome variables on state policy stringency additionally including individual fixed effects. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.4: *Market Behavior, Preferences, and Health (IV incl. ind. FE)*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0156***	0.0868***	-0.0280***	-0.0248***
	(0.0045)	(0.0251)	(0.0039)	(0.0044)
Obs.	1,128	314	1,690	1,690
Indiv. FE	X	X	X	X
State FE	X	X	X	X
F-Stat (1^{st} stage)	69	57	66	66
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0110**	0.0253***	-0.0101***	-0.0069
	(0.0045)	(0.0061)	(0.0033)	(0.0042)
Obs.	1,702	1,702	1,702	1,702
Indiv. FE	X	X	X	X
State FE	X	X	X	X
F-Stat (1^{st} stage)	67	67	67	67

Notes: The table shows IV coefficient estimates from regressions of the eight outcome variables on instrumented state policy stringency additionally including individual fixed effects. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.5: *Robustness First Stage: State-Varying Sub-Indices*

	(1) Pol. Stringency (SV)	(2) Pol. Stringency (SV)	(3) Pol. Stringency (SV)	(4) Pol. Stringency (SV)
Weeks to election	0.7362***	0.6908***	0.7187***	0.7229***
	(0.1008)	(0.1043)	(0.1011)	(0.1009)
Obs.	1,128	314	1,690	1,702
State FE	X	X	X	X
F-Stat	53	44	50	51

Notes: The table shows first stage IV regression results applying an alternative policy stringency measure only including four state-varying sub-indices instead of all nine. Standard errors in parentheses are clustered at federal state-calendar week level. Column (1) depicts the first stage for days remote work (week), column (2) for days childcare at home (week), column (3) for no. grocery shopping including and excluding online shopping (week), and column (4) for all remaining outcomes. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.6: *Robustness OLS: State-Varying Sub-Indices*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency (SV)	0.0071*	0.0313***	-0.0165***	-0.0138***
	(0.0037)	(0.0086)	(0.0026)	(0.0027)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency (SV)	-0.0054*	0.0080**	-0.0026	-0.0051
	(0.0032)	(0.0036)	(0.0029)	(0.0036)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X

Notes: The table shows coefficient estimates from OLS regressions of the eight outcome variables on an alternative policy stringency measure only including four state-varying sub-indices instead of all nine. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.7: *Robustness IV: Weeks to Election Squared*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0138**	0.0768***	-0.0277***	-0.0223***
	(0.0057)	(0.0185)	(0.0041)	(0.0045)
Obs.	1,128	314	1,690	1,690
State FE	X	X	X	X
F-Stat (1^{st} stage)	145	129	154	154
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0113*	0.0202***	-0.0068	-0.0065
	(0.0058)	(0.0067)	(0.0054)	(0.0060)
Obs.	1,702	1,702	1,702	1,702
State FE	X	X	X	X
F-Stat (1^{st} stage)	155	155	155	155

Notes: The table shows coefficient estimates of IV regressions of the eight outcome variables on instrumented policy stringency. The instrument is weeks to election and weeks to election squared. Standard errors in parentheses are clustered at federal state-calendar week level. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.8: *Robustness IV: Election States 2021*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0145*	0.0834**	-0.0286***	-0.0266**
	(0.0077)	(0.0312)	(0.0093)	(0.0101)
Obs.	328	64	497	497
State FE	X	X	X	X
F-Stat (1^{st} stage)	447	75	249	249
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0111*	0.0183**	-0.0030	-0.0039
	(0.0057)	(0.0074)	(0.0104)	(0.0091)
Obs.	503	503	503	503
State FE	X	X	X	X
F-Stat (1^{st} stage)	265	265	265	265

Notes: The table shows coefficient estimates of IV regressions of the eight outcome variables on instrumented policy stringency only for states with a 2021 election. Standard errors in parentheses are clustered at federal state-calendar week level. Regressions only contain federal states with elections in 2021. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

Table 3.A.9: *Robustness IV: Non-Election States 2021*

	(1) Days Remote Work (Week)	(2) Days Childcare at Home (Week)	(3) No. Grocery Shopping (Week)	(4) No. Grocery Shopping excl. Online (Week)
Pol. stringency	0.0180**	0.0856***	-0.0289***	-0.0214***
	(0.0069)	(0.0243)	(0.0051)	(0.0057)
Obs.	800	250	1,193	1,193
State FE	X	X	X	X
F-Stat (1^{st} stage)	111	100	105	105
	(5) Risk Preferences	(6) Corona Fear	(7) Freq. Alcohol (Week)	(8) Health of Diet
Pol. stringency	-0.0139*	0.0233**	-0.0092	-0.0128*
	(0.0074)	(0.0089)	(0.0070)	(0.0064)
Obs.	1,199	1,199	1,199	1,199
State FE	X	X	X	X
F-Stat (1^{st} stage)	105	105	105	105

Notes: The table shows coefficient estimates of IV regressions of the eight outcome variables on instrumented policy stringency only for states without a 2021 election. Standard errors in parentheses are clustered at federal state-calendar week level. Regressions only contain federal states without elections in 2021. Controls include age categories including 18-35 Y (reference category), 36-49 Y, 50-59 Y, 60-72 Y, a gender dummy, a tertiary education dummy, logarithmized income, a dummy whether children with 12 years of age or younger live in the household, employment status, a dummy indicating whether the respondent lives with a partner, household-size, voter turnout in the previous election, and AfD and FDP vote-share of the residential federal state. All regressions contain a linear time trend measuring weeks passed since the last peak in incidence rates in a given federal state. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: ELKiD Panel 2021.

3.7 Appendix B

> Amtskollegin Dreyer aus Mainz meint hingegen: Bis Ende des Monats müsse es "sehr klare Vorschläge" geben, wie es im Februar weitergehen solle. Sie plädierte für eine schrittweise Rückkehr in ein öffentlicheres Leben. Schließlich sei nicht vorstellbar, "dass wir dauerhaft in einer solchen Shutdown-Situation bleiben".

Example from 01/05/2021 by Prime Minister Dreyer (Rhineland-Palatinate with elections on 03/14/2021). Approximately translated:
Dreyer demands concise suggestions for a return to public life. It is unimaginable to permanently live under such circumstances.
Source: tagesschau.de, 01/05/2021.
https://www.tagesschau.de/inland/gesellschaft/corona-gipfel-streitpunkte-101.html. Last visited: 02/13/2023.

> Die rheinland-pfälzische Ministerpräsidentin Malu Dreyer fordert, bei den nächsten Corona-Beratungen von Bund und Ländern einen Plan für Öffnungen vorzulegen. Man brauche „klare Aussichten für die Menschen, wie es weitergeht",

Example from 02/20/2021 by Prime Minister Dreyer (Rhineland-Palatinate with elections on 03/14/2021). Approximately translated:
Dreyer demands a clear plan for re-openings and relaxations with respect to Covid-19 regulations in the next meeting of prime ministers and the overall state government.
Source: Rheinpfalz, 02/27/2021.
https://www.rheinpfalz.de/lokal/pfalz-ticker_artikel,-dreyer-fordert-%C3%B6ffnungsperspektive-und-beratergremium-_arid,5171145.html. Last visited: 02/13/2023.

> Ich will den Beratungen am 3. März jetzt nicht vorgreifen. Ich habe klare Vorstellungen davon, dass wir Perspektiven aufzeigen müssen. Wir brauchen Lösungen für den Einzelhandel, für Kultur, für die Außengastronomie, für körpernahe Dienstleistungen. Aber auch für Hotels und Ferienwohnungen. Ich bin auch dafür, die privaten Kontaktbeschränkungen zu lockern.
>
> eine andere Aktivität als Spazierengehen gibt. Aus meiner Sicht wäre es sehr sinnvoll, wenn man wieder auf diese etwas weitere Kontaktbeschränkung geht, die immer noch sehr streng ist: Zwei Haushalte mit maximal fünf Personen, die Kinder nicht mitgezählt.

Example from 02/27/2021 by Prime Minister Dreyer (Rhineland-Palatinate with elections on 03/14/2021). Approximately translated:
Dreyer speaks about the next meeting with prime ministers. She demands solutions for the retail sector, outdoor gastronomy, close-up services, and hotels. Additionally, she demands less strict rules with respect to meeting other people.
Source: tagesspiegel, 02/27/2021.
https://www.tagesspiegel.de/politik/ein-bussgeld-fur-impfdrangler-ist-angemessen-5391499.html. Last visited: 02/13/2023.

Stuttgart - Es ist ein bemerkenswerter Kurswechsel: Auch **Baden-Württemberg**s Ministerpräsident **Winfried Kretschmann** (Grüne) will den monatelangen **Lockdown** nun **trotz der Gefahr einer dritten Corona-Welle schrittweise lockern**. Gelingen soll das mit Hilfe von Schnell- und Selbsttests, die bald

Example from 02/26/2021 by Prime Minister Kretschmann (Baden-Wurttemberg with elections on 03/14/2021). Approximately translated:
Kretschmann wants to relax the current lockdown even though there is a risk of a third wave of infections. This is supposed to be achieved with the help of Covid-19 rapid and self-tests.
Source: Stuttgarter Zeitung, 02/26/2021.
https://www.stuttgarter-zeitung.de/inhalt.coronalockdown-in-baden-wuerttemberg-so-realistisch-ist-winfried-kretschmanns-oeffnungskurs.30a3ad6a-45e3-4c9f-91bb-220e0ec42ddb.html. Last visited: 02/13/2023.

Schulwesen. Aber man spürt jetzt, dass die Leute einfach genug von den Einschränkungen haben. Vielleicht führt das auch dazu, dass wir den Geschmack von Freiheit wieder richtig zu schätzen wissen, wenn wir sehen, was uns im Alltag plötzlich fehlt durch ein fieses Virus. Vielleicht ist das ein Kollateralnutzen.

Example from 03/02/2021 by Prime Minister Kretschmann (Baden-Wurttemberg with elections on 03/14/2021). Approximately translated:
Kretschmann acknowledges that people by now are exhausted by the restrictions and beliefs that people might value freedom even more now.
Source: taz.de, 03/02/2021.
https://taz.de/Winfried-Kretschmann-ueber-Wahlkampf/!5754351/. Last visited: 02/13/2023.

Es ist ein ungewöhnlicher Schritt: In einem gemeinsamen Brief an ihre 14 Ministerpräsidenten-Kolleginnen und -Kollegen fordern Markus Söder (CSU) und Winfried Kretschmann (Grüne) eine strikte Anti-Corona-Politik.

Example from 03/31/2021 by Prime Minister Kretschmann (Baden-Wurttemberg with elections on 03/14/2021). Approximately translated:
Kretschmann and his Bavarian counterpart are writing an open letter to the other prime ministers demanding stricter Covid-19 regulations.
Source: focus.de, 03/31/2021.
https://www.focus.de/politik/deutschland/appell-an-ministerpraesidenten-soeder-und-kretschmann-verlangen-in-brief-konsequentere-corona-politik-von-kollegen_id_13149810.html. Last visited: 02/13/2023.

Die Entscheidung der Bundeskanzlerin Angela Merkel (CDU), von einer erweiterten Ruhezeit zu Ostern abzusehen, bezeichnete Haseloff als richtigen Schritt. «Eine Osterruh hätte einen zusätzlichen Beitrag zur Reduzierung der Corona-Fallzahlen leisten können. Allerdings müssen wir auch immer im Auge behalten, was theoretisch denkbar und was praktisch umsetzbar ist.» Auf diese Probleme habe Sachsen-Anhalt in der Ministerpräsidentenkonferenz hingewiesen.

Ministerpräsident Reiner Haseloff (CDU) hatte zudem eine Experimentierklausel angekündigt, nach der Modellprojekte etwa in der Gastronomie, im Sport und in der Kultur möglich sein sollen. Auch dabei

Example from 03/24/2021 by Prime Minister Reiner Haseloff (Saxony-Anhalt with elections on 06/06/2021). Approximately translated:
Haseloff reports his support for the cancellation of a planned shutdown during easter and stresses that he was concerned about the practical implementation. Haseloff also announced the plan to allow for testing certain models of reopening gastronomy, sports or cultural events.
Source: zeit.de, 03/31/2021.
https://www.zeit.de/news/2021-03/24/sachsen-anhalt-bleibt-auf-corona-kurs-osterruhe-entfaellt. Last visited: 02/13/2023.

Dabei kritisierte er vor allem das Gesetz zur so genannten „Bundes-Notbremse“, einer Ergänzung des Infektionsschutzgesetzes, die mit deutschlandweiten Regelungen die Corona-Pandemie eindämmen sollte. Diese habe „sicher ungewollt den rechten Extremisten in die Hände gespielt“, behauptete Haseloff gegenüber der Tageszeitung. „Politisch war

Example from 05/30/2021 by Prime Minister Reiner Haseloff (Saxony-Anhalt with elections on 06/06/2021). Approximately translated:
Haseloff criticized the rules allowing the enforcement of stricter regulation after certain incidence levels are surpassed in a county (“Bundes-Notbremse”). This could have pushed voters to the far-right political spectrum.
Source: Frankfurter Rundschau, 05/30/2021.
https://www.fr.de/politik/landtagswahl-sachsen-anhalt-cdu-haseloff-kritisiert-bundespolitik-rechtspopulisten-bundesnotbremse-corona-90780886.html. Last visited: 02/13/2023.

> Magdeburg (dpa/sa) - Die angekündigten Lockerungen der Corona-Regeln in Sachsen-Anhalt haben laut Ministerpräsident Reiner Haseloff (CDU) nichts mit der bevorstehenden Landtagswahl am kommenden Sonntag zutun. Die Landesregierung werde die Vorschriften am Dienstag nicht aus taktischen Gründen, sondern wegen der geringen Infektionswerte lockern, sagte Haseloff am Montag in der "MDR-Wahl-Arena".

Example from 05/31/2021 by Prime Minister Reiner Haseloff (Saxony-Anhalt with elections on 06/06/2021). Approximately translated:
According to Haseloff the announced relaxations in Covid-19 containment measures have nothing to do with tactical considerations in the light of the upcoming federal state elections. This was supposedly only due to lower infection rates.
Source: Zeit.de, 05/31/2021.
https://www.zeit.de/news/2021-05/31/mdr-wahl-arena-koalition-verteidigt-corona-politik. Last visited: 02/13/2023.

Bibliography

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, *189*.

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2022). The impact of the coronavirus lockdown on mental health: Evidence from the United States. *Economic Policy*, *37*(109), 139–155.

Akerlof, G. A. (1991). Procrastination and obedience. *American Economic Review*, *81*(2), 1–19.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., & Zarate, P. (2023). Time savings when working from home. *NBER Working Paper*.

Alan, S., & Ertac, S. (2015). Patience, self-control and the demand for commitment: Evidence from a large-scale field experiment. *Journal of Economic Behavior & Organization*, *115*, 111–122.

Albanesi, S., & Kim, J. (2021). Effects of the Covid-19 recession on the US labor market: Occupation, family, and gender. *Journal of Economic Perspectives*, *35*(3), 3–24.

Allison, P. D., & Christakis, N. A. (1994). Logit models for sets of ranked items. *Sociological Methodology*, 199–228.

Andreoni, J., Callen, M., Hussain, K., Khan, M. Y., & Sprenger, C. (2022). Using preference estimates to customize incentives: An application to polio vaccination drives in Pakistan. *Journal of the European Economic Association*, *00*(0), 1–50.

Andreoni, J., Kuhn, M. A., & Sprenger, C. (2015). Measuring time preferences: A comparison of experimental methods. *Journal of Economic Behavior & Organization*, *116*, 451–464.

Andreoni, J., & Sprenger, C. (2012a). Estimating time preferences from convex budgets. *American Economic Review*, *102*(7), 3333–3356.

Andreoni, J., & Sprenger, C. (2012b). Risk preferences are not time preferences. *American Economic Review*, *102*(7), 3357–76.

Arambepola, C., Scarborough, P., & Rayner, M. (2008). Validating a nutrient profile model. *Public Health Nutrition*, *11*(4), 371–378.

Ashraf, N., Karlan, D., & Yin, W. (2006). Tying odysseus to the mast: Evidence from a commitment savings product in the Philippines. *Quarterly Journal of Economics*, *121*(2), 635–672.

Augenblick, N. (2018). Short-term time discounting of unpleasant tasks. *Unpublished Manuscript*.

Augenblick, N., Niederle, M., & Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *Quarterly Journal of Economics*, *130*(3), 1067–1115.

Aum, S., Lee, S. Y., & Shin, Y. (2021). Inequality of fear and self-quarantine: Is there a trade-off between gdp and public health? *Journal of Public Economics*, *194*.

Avery, M., Giuntella, O., & Jiao, P. (2022). Why don't we sleep enough? A field experiment among college students. *Review of Economics and Statistics*, 1–45.

Bai, L., Handel, B., Miguel, E., & Rao, G. (2021). Self-control and demand for preventive health: Evidence from hypertension in India. *Review of Economics and Statistics*, *103*(5), 835–856.

Balakrishnan, U., Haushofer, J., & Jakiela, P. (2020). How soon is now? evidence of present bias from convex time budget experiments. *Experimental Economics*, *23*(2), 294–321.

Barrero, J. M., Bloom, N., & Davis, S. J. (2021). Why working from home will stick. *NBER Working Paper*.

Becker, G. S. (1965). A theory of the allocation of time. *Economic Journal*, *75*(299), 493–517.

Beggs, S., Cardell, S., & Hausman, J. (1981). Assessing the potential demand for electric cars. *Journal of Econometrics*, *17*(1), 1–19.

Béland, L.-P., Brodeur, A., & Wright, T. (2020). The short-term economic consequences of Covid-19: Exposure to disease, remote work and government response. *IZA Discussion Paper*.

Belot, M., Berlin, N., James, J., & Skafida, V. (2018). The formation and malleability of dietary habits: A field experiment with low income families. *IZA Discussion Paper*.

Belot, M., & James, J. (2011). Healthy school meals and educational outcomes. *Journal of Health Economics*, *30*(3), 489–504.

Benhabib, J., & Bisin, A. (2005). Modeling internal commitment mechanisms and self-control: A neuroeconomics approach to consumption–saving decisions. *Games and Economic Behavior*, *52*(2), 460–492.

Bhuller, M., Dahl, G. B., Løken, K. V., & Mogstad, M. (2020). Incarceration, recidivism, and employment. *Journal of Political Economy*, *128*(4), 1269–1324.

Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2021). Covid-19, lockdowns and well-being: Evidence from Google trends. *Journal of Public Economics*, *193*.

Bublitz, M. G., Peracchio, L. A., & Block, L. G. (2010). Why did I eat that? Perspectives on food decision making and dietary restraint. *Journal of Consumer Psychology*, *20*(3), 239–258.

Bucher, T., Müller, B., & Siegrist, M. (2015). What is healthy food? Objective nutrient profile scores and subjective lay evaluations in comparison. *Appetite*, *95*, 408–414.

Bütikofer, A., Mølland, E., & Salvanes, K. G. (2018). Childhood nutrition and labor market outcomes: Evidence from a school breakfast program. *Journal of Public Economics*, *168*, 62–80.

Buzby, J. C., Guthrie, J. J. F., Assistance, F., et al. (2002). Plate waste in school nutrition programs: Final report to congress. *Economic Research Service, US Dept. of Agriculture*.

Buzby, J. C., Hyman, J., Stewart, H., & Wells, H. F. (2011). The value of retail-and consumer-level fruit and vegetable losses in the United States. *Journal of Consumer Affairs*, *45* (3), 492–515.

Casoria, F., Galeotti, F., & Villeval, M. C. (2023). Trust and social preferences in times of acute health crisis. *IZA Discussion Paper*.

Cheema, A., & Soman, D. (2006). Malleable mental accounting: The effect of flexibility on the justification of attractive spending and consumption decisions. *Journal of Consumer Psychology*, *16* (1), 33–44.

Chen, D., Schonger, M., & Wickens, C. (2016). Otree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

Chen, Q., Huang, Q., Liu, C., & Wang, P. (2022). Career incentives of local leaders and crisis response: A case study of Covid-19 lockdowns in China. *European Journal of Political Economy*.

Cherchye, L., De Rock, B., Griffith, R., O'Connell, M., Smith, K., & Vermeulen, F. (2020). A new year, a new you? Within-individual variation in food purchases. *European Economic Review*, *127*.

Cheung, S. L., Tymula, A., & Wang, X. (2022). Present bias for monetary and dietary rewards. *Experimental Economics*, 1–32.

Clarke, D., Romano, J. P., & Wolf, M. (2020). The Romano–Wolf multiple-hypothesis correction in Stata. *Stata Journal*, *20* (4), 812–843.

Cohen, J., Ericson, K. M., Laibson, D., & White, J. M. (2020). Measuring time preferences. *Journal of Economic Literature*, *58* (2), 299–347.

Cornsweet, T. N. (1962). The staircase-method in psychophysics. *American Journal of Psychology*, *75* (3), 485–491.

Courtemanche, C., Heutel, G., & McAlvanah, P. (2015). Impatience, incentives and obesity. *Economic Journal*, *125* (582), 1–31.

Cubitt, R. P., & Read, D. (2007). Can intertemporal choice experiments elicit time preferences for consumption? *Experimental Economics*, *10* (4), 369–389.

Cutler, D. M., Glaeser, E. L., & Shapiro, J. M. (2003). Why have Americans become more obese? *Journal of Economic Perspectives*, *17* (3), 93–118.

Dahl, G. B., Løken, K. V., & Mogstad, M. (2014). Peer effects in program participation. *American Economic Review*, *104* (7), 2049–2074.

Danzer, A., Holzmann, M., & Zeidler, H. (2023). Economic behavior under containment: How do people respond to Covid-19 restrictions? *Unpublished Manuscript*.

Danzer, A., & Zeidler, H. (2023). Present bias in choices over food and money: Evidence from a framed field experiment. *Unpublished Manuscript*.

Del Boca, D., Oggero, N., Profeta, P., & Rossi, M. C. (2021). Household division of labor during two waves of Covid-19 in Italy. *Covid Economics*, *60*.

Delgado, L., Schuster, M., & Torero, M. (2021). Quantity and quality food losses across the value chain: A comparative analysis. *Food Policy*, *98*.

Della Vigna, S., & Malmendier, U. (2006). Paying not to go to the gym. *American Economic Review*, *96*(3), 694–719.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature*, *47*(2), 315–72.

EAT-Lancet Commission. (2019). EAT-Lancet Commission summary report: Healthy diets from sustainable food systems. https://eatforum.org/content/uploads/2019/07/EAT-Lancet_Commission_Summary_Report.pdf

Efron, B. (1977). The efficiency of Cox's likelihood function for censored data. *Journal of the American Statistical Association*, *72*(359), 557–565.

Ellison, B., & Kalaitzandonakes, M. (2020). Food waste and Covid-19: Impacts along the supply chain. *Farmdoc Daily*, *10*, 164.

Ellison, B., & Lusk, J. L. (2018). Examining household food waste decisions: A vignette approach. *Applied Economic Perspectives and Policy*, *40*(4), 613–631.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., & Sunde, U. (2018). Global evidence on economic preferences. *Quarterly Journal of Economics*, *133*(4), 1645–1692.

FAO. (2019). The state of the world's biodiversity for food and agriculture. In J. Bélanger & D. Pilling (Eds.), *FAO Commission on Genetic Resources for Food and Agriculture Assessments*. Rome. https://www.fao.org/documents/card/en/c/ca3129en/

Fetzer, T., Hensel, L., Hermle, J., & Roth, C. (2021). Coronavirus perceptions and economic anxiety. *Review of Economics and Statistics*, *103*(5), 968–978.

Finkelstein, E. A., Trogdon, J. G., Cohen, J. W., & Dietz, W. (2009). Annual medical spending attributable to obesity: Payer-and service-specific estimates: Amid calls for health reform, real cost savings are more likely to be achieved through reducing obesity and related risk factors. *Health Affairs*, *28*(1), 822–831.

Flores, D., Reimann, M., Castaño, R., & Lopez, A. (2019). If I indulge first, I will eat less overall: The unexpected interaction effect of indulgence and presentation order on consumption. *Journal of Experimental Psychology: Applied*, *25*(2), 162.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351–401.

Giuntella, O., Hyde, K., Saccardo, S., & Sadoff, S. (2021). Lifestyle and mental health disruptions during Covid-19. *Proceedings of the National Academy of Sciences*, *118*(9).

Gonzalez-Eiras, M., & Niepelt, D. (2022). The political economy of early Covid-19 interventions in US states. *Journal of Economic Dynamics and Control*.

Grainger, M. J., Aramyan, L., Piras, S., Quested, T. E., Righi, S., Setti, M., Vittuari, M., & Stewart, G. B. (2018). Model selection and averaging in the assessment of the drivers of household food waste to reduce the probability of false positives. *PloS One*, *13*(2).

Griffin, M., Sobal, J., & Lyson, T. A. (2009). An analysis of a community food waste stream. *Agriculture and Human Values*, *26*(1), 67–81.

Gustavsson, J., Cederberg, C., Sonesson, U., Van Otterdijk, R., & Meybeck, A. (2011). Global food losses and food waste - Extent, causes and prevention. https://www.fao.org/3/i2697e/i2697e.pdf

Hale, T., Webster, S., Petherick, A., Phillips, T., & Kira, B. (2020). Oxford Covid-19 government response tracker. https://www.bsg.ox.ac.uk/research/covid-19-government-response-tracker

Halevy, Y. (2015). Time consistency: Stationarity and time invariance. *Econometrica*, *83*(1), 335–352.

Hall, K. D., Guo, J., Dore, M., & Chow, C. C. (2009). The progressive increase of food waste in America and its environmental impact. *PloS One*, *4*(11).

Hamilton, S. F., & Richards, T. J. (2019). Food policy and household food waste. *American Journal of Agricultural Economics*, *101*(2), 600–614.

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic Literature*, *42*(4), 1009–1055.

Hofmann, W., Strack, F., & Deutsch, R. (2008). Free to buy? Explaining self-control and impulse in consumer behavior. *Journal of Consumer Psychology*, *18*(1), 22–26.

Huebener, M., Hape, A., Danzer, N., Spiess, C. K., Siegel, N. A., & Wagner, G. G. (2022). Cracking under pressure? Gender role attitudes toward maternal employment during Covid-19. *BiB Working Paper*, *4*.

Iaryczower, M., Lopez-Moctezuma, G., & Meirowitz, A. (2022). Career concerns and the dynamics of electoral accountability. *American Journal of Political Science*, *00*(00), 1–18.

Imai, T., Rutter, T. A., & Camerer, C. F. (2021). Meta-analysis of present-bias estimation using convex time budgets. *Economic Journal*, *131*(636), 1788–1814.

IPBES. (2019). Global assessment report on biodiversity and ecosystem services of the intergovernmental science-policy platform on biodiversity and ecosystem services. https://www.ipbes.net/sites/default/files/ipbes_global_assessment_report_summary_for_policymakers.pdf

Jörissen, J., Priefer, C., & Bräutigam, K.-R. (2015). Food waste generation at household level: Results of a survey among employees of two European research centers in Italy and Germany. *Sustainability*, *7*(3), 2695–2715.

Katare, B., Serebrennikov, D., Wang, H. H., & Wetzstein, M. (2017). Social-optimal household food waste: Taxes and government incentives. *American Journal of Agricultural Economics*, *99*(2), 499–509.

Kaur, S., Kremer, M., & Mullainathan, S. (2015). Self-control at work. *Journal of Political Economy*, *123*(6), 1227–1277.

Khare, A., & Inman, J. J. (2006). Habitual behavior in American eating patterns: The role of meal occasions. *Journal of Consumer Research*, *32*(4), 567–575.

Knight, L. J., & Boland, F. J. (1989). Restrained eating: An experimental disentanglement of the disinhibiting variables of perceived calories and food type. *Journal of Psychopathology and Clinical Science*, *98*(4), 412.

Koch, A. K., & Nafziger, J. (2016). Goals and bracketing under mental accounting. *Journal of Economic Theory*, *162*, 305–351.

Koczan, Z. (2022). Not all in this together? Early estimates of the unequal labour market effects of Covid-19. *Applied Economics*, *0*(0), 1–14.

Koivupuro, H.-K., Hartikainen, H., Silvennoinen, K., Katajajuuri, J.-M., Heikintalo, N., Reinikainen, A., & Jalkanen, L. (2012). Influence of socio-demographical, behavioural and attitudinal factors on the amount of avoidable food waste generated in Finnish households. *International Journal of Consumer Studies*, *36*(2), 183–191.

Lades, L. K., Laffan, K., & Weber, T. O. (2021). Do economic preferences predict pro-environmental behaviour? *Ecological Economics*, *183*.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, *112*(2), 443–478.

Laibson, D. (2015). Why don't present-biased agents make commitments? *American Economic Review*, *105*(5), 267–272.

Landry, C. E., & Smith, T. A. (2019). Demand for household food waste. *Applied Economic Perspectives and Policy*, *41*(1), 20–36.

Lebersorger, S., & Schneider, F. (2011). Discussion on the methodology for determining food waste in household waste composition studies. *Waste Management*, *31*(9-10), 1924–1933.

Levitt, S. (1997). Using electoral cycles in police hiring to estimate the effect of police on crime. *American Economic Review*, *87*, 270–90.

Lilleholt, L., Zettler, I., Betsch, C., & Böhm, R. (2020). Pandemic fatigue: Measurement, correlates, and consequences. *PsyArXiv*.

Loewenstein, G. (1988). Frames of mind in intertemporal choice. *Management Science*, *34*(2), 200–214.

Loewenstein, G., & Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation. *Quarterly Journal of Economics*, *107*(2), 573–597.

Loewenstein, G., & Thaler, R. H. (1989). Anomalies: Intertemporal choice. *Journal of Economic perspectives*, *3*(4), 181–193.

Lührmann, M., Serra-Garcia, M., & Winter, J. (2018). The impact of financial education on adolescents' intertemporal choices. *American Economic Journal: Economic Policy*, *10*(3), 309–32.

Lusk, J. L., & Ellison, B. (2017). A note on modelling household food waste behaviour. *Applied Economics Letters*, *24*(16), 1199–1202.

Lusk, J. L., & Ellison, B. (2020). Economics of household food waste. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *68*(4), 379–386.

Masotti, M., van der Haar, S., Janssen, A., Iori, E., Zeinstra, G., Bos-Brouwers, H., & Vittuari, M. (2022). Food waste in time of Covid-19: The heterogeneous effects on consumer groups in Italy and the Netherlands. *Appetite*.

Mbow, C., Rosenzweig, C., Barioni, L., Benton, T., Herrero, M., Krishnapillai, M., Liwenga, E., Pradhan, P., Rivera-Ferre, M., Sapkota, T., Tubiello, F., & Xu, Y. (2019). Food security. In *Climate change and land: An IPCC special report on* *climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. In press. https://www.ipcc.ch/site/assets/uploads/2019/11/08_Chapter-5.pdf

McAlvanah, P. (2010). Subadditivity, patience, and utility: The effects of dividing time intervals. *Journal of Economic Behavior & Organization*, *76*(2), 325–337.

McClure, S. M., Ericson, K. M., Laibson, D. I., Loewenstein, G., & Cohen, J. D. (2007). Time discounting for primary rewards. *Journal of Neuroscience*, *27*(21), 5796–5804.

Meier, S., & Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, *2*(1), 193–210.

Morris, G. E., & Holthausen Jr, D. M. (1994). The economics of household solid waste generation and disposal. *Journal of Environmental Economics and Management*, *26*(3), 215–234.

Neff, R. A., Spiker, M. L., & Truant, P. L. (2015). Wasted food: US consumers' reported awareness, attitudes, and behaviors. *PloS One*, *10*(6), e0127881.

O'Donoghue, T., & Rabin, M. (1999). Doing it now or later. *American Economic Review*, *89*(1), 103–124.

O'Donoghue, T., & Rabin, M. (2001). Choice and procrastination. *Quarterly Journal of Economics*, *116*(1), 121–160.

Phelps, E. S., & Pollak, R. A. (1968). On second-best national saving and game-equilibrium growth. *Review of Economic Studies*, *35*(2), 185–199.

Piras, S., Pancotto, F., Righi, S., Vittuari, M., & Setti, M. (2021). Community social capital and status: The social dilemma of food waste. *Ecological Economics*, *183*, 106954.

Pulejo, M., & Querubin, P. (2021). Electoral concerns reduce restrictive measures during the Covid-19 pandemic. *Journal of Public Economics*, *198*.

Quested, T., & Johnson, H. (2009). Household food and drink waste in the UK. https://wrap.org.uk/sites/default/files/2020-12/Household-Food-and-Drink-Waste-in-the-UK-2009.pdf

Quested, T., Marsh, E., Stunell, D., & Parry, A. (2013). Spaghetti soup: The complex world of food waste behaviours. *Resources, Conservation and Recycling*, *79*, 43–51.

Quested, T., Parry, A., Easteal, S., & Swannell, R. (2011). Food and drink waste from households in the UK. *Nutrition Bulletin*, *36*(4), 460–467.

Rayner, M., Scarborough, P., Boxer, A., & Stockley, L. (2005). Nutrient profiles: Development of final model. https://www.researchgate.net/profile/Peter-Scarborough/publication/266447771_Nutrient_profiles_Development_of_Final_Model_Final_Report/links/5440d4fe0cf218719077d82d/Nutrient-profiles-Development-of-Final-Model-Final-Report.pdf

Rayner, M., Scarborough, P., & Lobstein, T. (2009). The UK Ofcom Nutrient Profiling Model: Defining 'healthy'and 'unhealthy' foods and drinks for TV advertising to children. https://www.ndph.ox.ac.uk/food-ncd/files/about/uk-ofcom-nutrient-profile-model.pdf

Read, D., Loewenstein, G., & Kalyanaraman, S. (1999). Mixing virtue and vice: Combining the immediacy effect and the diversification heuristic. *Journal of Behavioral Decision Making*, *12*(4), 257–273.

Read, D., & Van Leeuwen, B. (1998). Predicting hunger: The effects of appetite and delay on choice. *Organizational Behavior and Human Decision Processes*, *76*(2), 189–205.

Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F. S., Lambin, E. F., Lenton, T. M., Scheffer, M., Folke, C., Schellnhuber, H. J., et al. (2009). A safe operating space for humanity. *Nature*, *461*(7263), 472–475.

Roe, B. E., Bender, K., & Qi, D. (2021). The impact of Covid-19 on consumer food waste. *Applied Economic Perspectives and Policy*, *43*(1), 401–411.

Royer, H., Stehr, M., & Sydnor, J. (2015). Incentives, commitments, and habit formation in exercise: Evidence from a field experiment with workers at a fortune-500 company. *American Economic Journal: Applied Economics*, *7*(3), 51–84.

Sadoff, S., Samek, A., & Sprenger, C. (2020). Dynamic inconsistency in food choice: Experimental evidence from two food deserts. *Review of Economic Studies*, *87*(4), 1954–1988.

Samuelson, P. A. (1937). A note on measurement of utility. *Review of Economic Studies*, *4*(2), 155–161.

Scarborough, P., Boxer, A., Rayner, M., & Stockley, L. (2007). Testing nutrient profile models using data from a survey of nutrition professionals. *Public Health Nutrition*, *10*(4), 337–345.

Scherhaufer, S., Schuller, H., & Leverenz, D. (2012). Determination of discarded food and proposals for a minimization of food wastage in Germany. https://www.researchgate.net/profile/Gerold-Hafner/publication/262728113_Determination_of_discarded_food_and_proposals_for_a_minimization_of_food_wastage_in_Germany/links/5418425d0cf203f155ada2cc/Determination-of-discarded-food-and-proposals-for-a-minimization-of-food-wastage-in-Germany.pdf

Schneider, F., & Obersteiner, G. (2007). Food waste in residual waste of households–Regional and socioeconomic differences. In R. Cossu & R. S. L.F. Diaz (Eds.), *Proceedings of the Eleventh International Waste Management and Landfill Symposium* (pp. 469–470). St. Margherita di Pula, Sardinia, Italy.

Secondi, L., Principato, L., & Laureti, T. (2015). Household food waste behaviour in EU-27 countries: A multilevel analysis. *Food Policy*, *56*, 25–40.

Shachat, J., Walker, M. J., & Wei, L. (2021). How the onset of the Covid-19 pandemic impacted pro-social behaviour and individual preferences: Experimental evidence from China. *Journal of Economic Behavior & Organization*, *190*, 480–494.

Shelley, M. (1993). Outcome signs, question frames and discount rates. *Management Science*, *39*(7), 806–815.

Sjåstad, H., & Ekström, M. (2021). Ulyssean self-control: Pre-commitment is effective, but choosing it freely requires good self-control. *PsyArXiv*.

Stenmarck, Â., Jensen, C., Quested, T., Moates, G., Buksti, M., Cseh, B., Juul, S., Parry, A., Politano, A., Redlingshofer, B., et al. (2016). Estimates of European food waste levels. https://www.eu-fusions.org/

Strotz, R. H. (1955). Myopia and inconsistency in dynamic utility maximization. *Review of Economic Studies*, *23*(3), 165–180.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral Decision Making*, *12*(3), 183–206.

Thaler, R. H. (2018). From cashews to nudges: The evolution of behavioral economics. *American Economic Review*, *108*(6), 1265–1287.

Thaler, R. H., & Shefrin, H. M. (1981). An economic theory of self-control. *Journal of Political Economy*, *89*(2), 392–406.

Toensmeier, E., Mehra, M., Frischmann, C., & Foley, J. (2020). Farming our way out of the climate crisis. https://drawdown.org/sites/default/files/pdfs/DrawdownPrimer_FoodAgLandUse_Dec2020_01c.pdf

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science*, *211*(4481), 453–458.

Von Gaudecker, H.-M., Van Soest, A., & Wengstrom, E. (2011). Heterogeneity in risky choice behavior in a broad population. *American Economic Review*, *101*(2), 664–94.

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, *43*(3), 303–343.

Wansink, B., & Hanks, A. S. (2013). Slim by design: Serving healthy foods first in buffet lines improves overall meal selection. *PloS One*, *8*(10).

Westhoek, H., J., I., Van Berkum, S., Özay, L., & M., H. (2016). Food systems and natural resources. A report of the working group on food systems of the international resource panel. https://www.resourcepanel.org/reports/food-systems-and-natural-resources

WHO. (2022). WHO European regional obesity report 2022. https://apps.who.int/iris/bitstream/handle/10665/353747/9789289057738-eng.pdf

WHO/FAO. (2003). Diet, nutrition and the prevention of chronic diseases. *World Health Organization Technical Report Series*, *916*(i-viii), 1–149. http://apps.who.int/iris/bitstream/handle/10665/42665/WHO_TRS_916.pdf;jsessionid=15F515CF2FE5EEF2693487ADB05B7E07?sequence=1

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., et al. (2019). Food in the anthropocene: The EAT–Lancet Commission on healthy diets from sustainable food systems. *Lancet*, *393*(10170), 447–492.

Wood, W., & Neal, D. T. (2009). The habitual consumer. *Journal of Consumer Psychology*, *19*(4), 579–592.

Yu, Y., & Jaenicke, E. C. (2020). Estimating food waste as household production inefficiency. *American Journal of Agricultural Economics*, *102*(2), 525–547.