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Consumption and Account Balances in Crises: Have We Neglected Cognitive Load?*

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Abstract

The complexities of geopolitical events, financial and fiscal crises, and the ebb and flow of personal life circumstances can weigh heavily on individuals' minds as they make critical economic decisions. To investigate the impact of cognitive load on such decisions, we conducted an incentivized online experiment involving a representative sample of 2,000 French households.. The results revealed that exposure to a taxing and persistent cognitive load significantly reduced consumption, particularly for individuals under the threat of furlough, while simultaneously increasing their account balances, particularly for those not facing such employment uncertainty. These effects were not driven by supply constraints or a worsening of credit constraints. Instead, cognitive load primarily affected the optimality of the chosen policy rules and impaired the ability of the standard economic model to accurately predict consumption patterns, although this effect was less pronounced among college-educated subjects.

Keywords: consumption, saving, borrowing, cognitive load, online experiments, RCT, crises, furlough.

JEL Codes: G5, C9, D15, D91.

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1 Introduction

The current century has been shaken by a series of financial, fiscal, environmental, health, and socio- and geo-political crises. These crises have not only disrupted the economic landscape but also imposed significant cognitive burdens on individuals, forcing them to navigate complex decisions amidst a backdrop of heightened uncertainty and mental fatigue.[1] Such cognitive load is pervasive, exacerbating the strain on our ability to process information, whether it results from general crises or from taxing aspects of our everyday lives, such as stressful work environments, young children, health concerns, and marriage problems. Individuals navigating these turbulent times must make crucial decisions about consumption, saving, and borrowing, while simultaneously juggling the multitude of challenges that daily life presents. Despite its presence in various forms of crisis, the impact of cognitive load on such basic economic and financial decision-making has received limited attention in the literature.

This paper seeks to fill this gap by asking the following question: does cognitive load, either standalone or in conjunction with adverse labor market shocks, affect individuals' consumption and saving decisions and how? We investigate, in the context of an online experiment with a representative population sample, whether cognitive load encourages over-consumption or promotes prudent financial planning. We also examine how cognitive load interacts with a potential for income reduction of unknown duration, such as a furlough or a transition to unemployment. Furthermore, we explore whether these effects disproportionately affect specific demographic groups, pointing to the need for targeted policy intervention. Finally, we assess how neglecting cognitive load influences the effectiveness of the traditional economic consumption-saving model to describe individual behavior, both on average and across heterogeneous individuals.

To investigate these effects, we conducted an online incentivized experiment with a sample of 1,881 adult respondents, representative of the French population along various

[1]For example, the outbreak of Covid-19 and the lockdown measures imposed in several countries generated considerable psychological costs, with symptoms like stress, anxiety, insomnia having been documented (Brooks et al., 2020; Pfefferbaum and North, 2020). Healthcare studies find that excessive stress, attentional narrowing, and distractibility are often associated with impaired performance (Bong et al., 2016).

dimensions. Participants were randomly assigned to four treatment groups, each with a different combination of cognitive load and labor market risk. We designed treatment and control groups to identify separately the effects of labor market shocks and of cognitive load, as well as of their interaction, on individuals' decision making.

Participants were tasked with consumption-saving choices. In the control group, they faced the neo-classical consumption-saving choice model with backgrhound labor income risk but no risk of furlough or cognitive load. In Group 2, participants faced a furlough risk – a 30% income drop for an unknown number of periods[2] – but no cognitive load. In Group 3, participants experienced cognitive load – a recurring numerical task[3] – but no furlough risk. Finally, Group 4 faced both cognitive load and furlough risk. They were tasked with making consumption-saving choices while simultaneously engaging, for some treatments, in a numerical task, creating persistent cognitive load. Subjects were informed that failure to execute this additional task within a given short time frame comes at a cost, so as to prevent that the implementation of the cognitive load is bypassed or ignored, reflecting the compelling nature of the crisis. To induce a preference for maximizing expected utility over a longer horizon and attention to the cognitive load, we designed the experiment to reward participants for making consistent and optimal decisions with reference to the corresponding standard model.

We employed a multifaceted approach that combined survey questions with preliminary tasks derived from established elicitation methods to gain a comprehensive understanding of participants. This comprehensive assessment enabled us to capture a wide range of characteristics, attitudes, and traits that could influence their decision-making processes. Initially, all subjects in the four groups underwent a series of standard tests designed to measure their risk attitudes, financial literacy, attention capacity, cognitive abilities, and memory capacity. These tests provided valuable insights into their mental faculties and their ability to process financial information. Furthermore, we delved into the participants' personality traits by asking questions that assessed their stress toler-

[2]This can also be thought of as unemployment risk involving a 30% drop in labor income, but we will be referring to it as furlough, given the size of the income drop.

[3]while the subjects decide on consumption/saving a sequence of numbers appears on the screen at a random frequency and subjects must press the space bar only if the number is in a certain range

ance and state-trait anxiety levels. This information allowed us to gauge their emotional resilience and potential susceptibility to psychological distress, which could impact their decision-making under stressful conditions. Given that the experiment took place during the ongoing COVID-19 crisis, we included a set of questions specifically focused on evaluating the psychological impact of the pandemic on the participants' daily lives. This allowed us to assess whether the crisis had exacerbated their stress levels or introduced additional sources of psychological distress. In essence, this multifaceted assessment methodology provided us with a holistic view of the participants, enabling us to identify potential factors that could influence their financial decision-making and its interaction with cognitive load and furlough risk.

We perform comparisons between various treatment and control group pairs using descriptive, as well as econometric, methods that control for a range of characteristics, attitudes, attributes, and subject performance during the experiment (e.g. demographics, financial literacy, risk aversion, stress tolerance, among others). [4]. Our analysis revealed a significant tendency for individuals facing cognitive load to under-consume and to over-accumulate account balances. The former effect was more pronounced for those not facing a prospect of furlough, while the latter was more pronounced for subjects facing such a prospect. These were separate from any effects that a furlough prospect alone had, and they did not arise from supply constraints or worsening of borrowing constraints, as these were not imposed.[5]. Cognitive load also worsened the ability of the standard intertemporal model to describe consumption behavior, primarily by interfering with the optimality of the policy rules chosen by subjects, and only to a lesser extent with the evolution of the endogenous state (net financial assets). We found that college-educated subjects facing cognitive load as well as furlough risk were less likely to deviate from optimal model behavior and reduced their consumption less in response to cognitive

[4]We measure financial literacy using the "big 3" questions, on interest compounding, real versus nominal interest rates, and diversification. We examine, for example, whether cognitive load and psychological distress loom larger in the mind of more anxious people (Ashcraft and Krause, 2007), or of those less financially literate or more risk averse.

[5]Reduced consumption and increased bank account balances were observed in various countries after the onset of the Covid crisis, but these were typically attributed exclusively to some combination of supply constraints and precautionary motives.

load. Additionally, subjects with greater short-term patience were more likely to lower their consumption and deviate more from the standard model. Other than these factors, and contrary to our expectations, we did not find that the importance of cognitive load for consumption and saving behavior was systematically lower for any specific group, e.g., for those with greater financial literacy, a particular gender, or a higher level of resources.

Our findings highlight the importance of incorporating cognitive load in studies of household economic decision-making. Our experiments suggest that cognitive load can have a significant impact on individuals' consumption-saving decisions. While we confirm that average behavior tends to get closer to the respective standard model as more experience with decision making under load is gained, we find that cognitive load creates a discrete extra distance from model-implied optimal behavior that needs to be bridged. Moreover, this applies both to average (macro) behavior and to the ability of the standard model to explain heterogeneous (micro) behavior under cognitive load. Improving our understanding of the effects of cognitive load and of its widespread influence is a first step towards future modeling and policy design aimed at improving behavior and financial well-being in conditions of crisis.

Section 2 provides a review of related literature and our contributions. Section 3 introduces the design of the experiment and associated survey, the data collection method, and the features of the sample. Section 4 compares average group behavior and its deviations from the standard model, both across treatment groups and over the life cycle of the model. Section 5 presents regression analysis of treatment effects focusing on the average behavior of each subject over the model life cycle, model departures, and any systematic relationship of both to subject characteristics. Section 6 concludes.

2 Related Literature

Literature in household finance, recently reviewed in Gomes et al. (2021), has traditionally focused on the role of cognitive abilities in shaping financial decisions. Particularly relevant is a strand focusing on the role of cognitive abilities for investment and borrowing decisions, and on the determinants of personal delinquencies, defaults, and financial distress (Agarwal and Mazumder, 2013; Christelis et al., 2010; Gerardi et al., 2013; Gomes et al., 2021). Recently, D'Acunto et al. (2021) studied the effect of IQ on consumption via inflation expectations, while D'Acunto et al. (2019) provided evidence that most households with below-median cognitive abilities fail to adjust their consumption and borrowing to fiscal and monetary policies. However, little attention has been paid to the impact of cognitive load – the mental effort required to process information and make decisions. This neglect is particularly concerning given the increasing prevalence of cognitive load in modern society, driven by factors such as stressful work environments, demanding personal lives, and the constant barrage of information from digital devices. Our paper contributes to this strand of literature by filling this gap and investigating the causal impact of cognitive load on financial decision making.

In the realm of experimental economics, several studies have explored the intricacies of financial choices and their optimality, albeit without delving into the influence of cognitive load. Two notable contributions to this field are the works of Meissner (2016) and Duffy and Li (2019). Meissner (2016) conducted a laboratory experiment involving 78 undergraduate participants who were tasked with making consumption decisions considering incentivized CARA utility over life cycles of 20 years under two stochastic income processes. The primary objective was to compare consumption patterns when borrowing was optimal versus when saving was the optimal strategy. The paper uncovered compelling evidence of under-consumption (debt aversion) among subjects when borrowing was the rational choice, with only weak evidence of over-consumption when saving was the optimal choice. Duffy and Li (2019) adopted a different approach by inducing logarithmic preferences with non-stochastic income and no borrowing possibilities to a sample of university students in a laboratory setting. They examined the impact of varying pension replacement rates on consumption patterns, assuming non-stochastic income and eliminating the possibility of borrowing. Their findings underscore the significant influence of pension replacement rates on individuals' consumption behavior, with higher replacement rates generally leading to lower consumption levels.

A growing body of research in experimental economics and psychology has begun to shed light on the effects of cognitive load on financial decision-making. These studies suggest that cognitive load can lead to a variety of biases and sub-optimal choices, including under-investment, excessive savings, risk aversion, and inconsistent decision-making. Studies by Ballinger et al. (2011) and Enke and Graeber (2023) delved into the intricate relationship between cognitive abilities and saving decisions. Ballinger et al. (2011) employed a laboratory experiment to assess how various cognitive abilities, measured through psychological assessments, influenced saving choices. Enke and Graeber (2023) studied cognitive processes associated with the valuation of payments across different time periods, considering factors such as uncertain discount rates and computational challenges faced by individuals. Their findings indicated a strong correlation between cognitive uncertainty – uncertainty regarding the utility-maximizing decision – and inelastic behavior regarding delayed payoffs. This uncertainty also impacted the likelihood of subjects adhering to financial advice. Moreover, the study revealed that incorporating a mathematical task into the experimental setup amplified cognitive uncertainty and lead to more hyperbolic discounting – a phenomenon characterized by an increasing preference for immediate rewards over future gains. Deck and Jahedi (2015) comprehensively reviewed experimental research examining the impact of cognitive load on various economic decisions, ranging from risk taking and inter-temporal choice to mathematical ability and generosity. Their analysis uncovered evidence that individuals under cognitive load tended to take fewer risks aligning with findings by Benjamin et al. (2013); Whitney et al. (2008). The effect of cognitive load on impatience remained less clear-cut. While Hinson et al. (2003) found a tendency towards greater impatience under cognitive load, Franco-Watkins et al. (2006) reinterpreted the same data to suggest increased randomness in behavior, and (Franco-Watkins et al., 2010) provided experimental evidence of more inconsistent choices under cognitive load. These mixed findings highlight the need for further research to fully comprehend the nuances of cognitive load's influence on financial decision-making.

The voluminous literature on the COVID-19 pandemic has studied its profound and multifaceted impact on labor markets and consumer behavior. Recent research has highlighted that the lockdowns imposed to curb the spread of the virus have had a significant impact on consumer spending, account balances, and subjective expectations (Coibion et al., 2020). It also found exacerbation of existing inequalities in labor market outcomes, particularly within countries (Adams-Prassl et al., 2020). The pandemic has imposed a heavy burden on individuals' cognitive resources, potentially impacting the soundness of their financial decisions. The COVID-19 crisis has underscored the importance of understanding the complex interplay between economic shocks, cognitive load, and individual resilience.

To our knowledge, our paper is the first to conduct an extensive experiment with a representative population sample to investigate the effects of cognitive load on economic decisions. Our study makes several contributions. First, it decouples the impact of cognitive load from the influence of purely economic (labor market) shocks that may not be relevant for all. Second, our findings reveal that cognitive load plays a significant role in shaping economic decision-making, in addition to that of labor market conditions. Third, the paper shows that cognitive load induces departures from optimal behavior both on the aggregate (average) level and on the micro (heterogeneity) level. Fourth, it points to departures from the optimal consumption rule (rather than the evolution of savings) as the key source of deviation. Fifth, it demonstrates the widespread importance of the effects of cognitive load by showing that these are systematically smaller for college graduates but not for various other demographic groups usually considered as less prone to investment mistakes.

Recently, Sergeyev et al. (2023) developed a theoretical framework to study the impact of financial stress and the cognitive load it generates on consumption and labor supply. Their model posits that financial stress, conceptualized as the time spent worrying about financial matters, diminishes with increasing financial assets – a proxy for the distance from the borrowing limit. While they consider the case of manipulable financial stress, in the sense that stress can be reduced by individuals accumulating more assets, our study explores the effects of exogenous, background cognitive load, which crises impose but individuals cannot directly mitigate or eliminate through financial actions. Our findings, which highlight a different but potentially complementary channel to that of Sergeyev et al. (2023), demonstrate that individuals under exogenously imposed, non-manipulable cognitive load exhibit a tendency to reduce consumption and accumulate more financial assets, even if they face unchanged labor market conditions, supply conditions, and borrowing constraints. Our results underscore the importance of considering exogenous, non-manipulable cognitive load when analyzing economic decision-making and designing policies to promote financial well-being and resilience.

3 Data Collection, sample and experiment design

3.1 Data collection and sample characteristics

We employed a sample of the French population encompassing 1,881 respondents over age 18. The survey/experiment was conducted overa period spanning from December 17, 2021 to January 29, 2022. The survey company Qualtrics was responsible for distributing the survey and remunerating participants upon its completing. Upon clicking on the survey link, respondents were presented with a consent form outlining the objectives and nature of the survey. They were clearly informed that they were participating in an academic research survey and that their participation was entirely voluntary and anonymous. Our online survey-experiment offers a compelling advantage over traditional laboratory experiments in terms of external validity, boasting a vast sample size and representativeness of the French population. However, this approach carries a potential concern regarding internal validity. Participants may exhibit less attentiveness in an online environment compared to an in-person laboratory setting. To mitigate this issue we implemented a straightforward yet commonly used attention check to screen out participants who might provide low-quality data (Faia et al., 2021; Roth and Wohlfart, 2020). Beyond demographic and socioeconomic factors, we sought to gauge a range of subject attitudes, including financial literacy, risk aversion (financial and non-financial), and time preferences. To assess subjects' ability to suppress an intuitive yet incorrect response in favor of a more deliberate and accurate answer, we administered the Cognitive Reflection Test (CRT) (Frederick, 2005). We further incorporated standard questionnaires to evaluate respondents' levels of anxiety, procrastination, impulsivity, and perseverance. Finally, given the experiment's timing amidst a surge of COVID-19 infections, we included questions related to COVID-19, such as vaccination status and the perceived and expected impact of the pandemic on occupational status, health, and finances.

To systematically assess individual time preferences and estimate their corresponding discount factors, we employed the methodology outlined by Meier and Sprenger (2010). Initially, we presented participants with seven hypothetical choice scenarios involving multiple reward options. In each scenario, individuals were tasked with selecting between a smaller immediate reward in period t and a larger delayed reward ($y > x$) in period τ. The larger reward was fixed at $y = 50\$$, while the smaller rewards were $x = [49\$, 47\$, 44\$, 40\$, 35\$, 27\$, 22\$]$. We presented these choice scenarios under two distinct time frames: a short-run time perspective, where t represented the present and τ was one month hence; and a medium-run perspective, where t was six months into the future and τ was seven months from the present. To quantify individual time preferences across the distinct time frames, we calculated the individual discount factors $\beta_j = x^*/y$ using the ratio of the monetary value (x^*) at which participants' preferences switched from selecting the earlier payment (x) to the later payment (y). The index j distinguishes between the short-run ($j = 1$) and the medium-run ($j = 2$) time frames. x^* is the monetary choice corresponding to the point at which the participant switched from choosing the earlier payment to the later payment, y. Individuals were deemed present-biased if $\beta_2 > \beta_1$, indicating a stronger preference for immediate gratification, and future-biased if $\beta_2 < \beta_1$, reflecting a greater inclination towards delayed rewards.

The median completion time for the survey was 24:33 minutes. The sample was designed to be representative of the French population along the imposed quota dimensions of age, gender, and education. Additionally, it was representative of the non-targeted quotas, such as income, employment rate, and region of residence (Table A.1). Finally, as shown in Table A.2, the sample was carefully balanced across the control and treatment groups.

3.2 Experiment design

In Figure 1 we illustrate the survey structure. The survey is built around the experimental section, in which respondents were asked to make consumption-saving decisions. The full survey, translated into English, is reported in Appendix **??**.

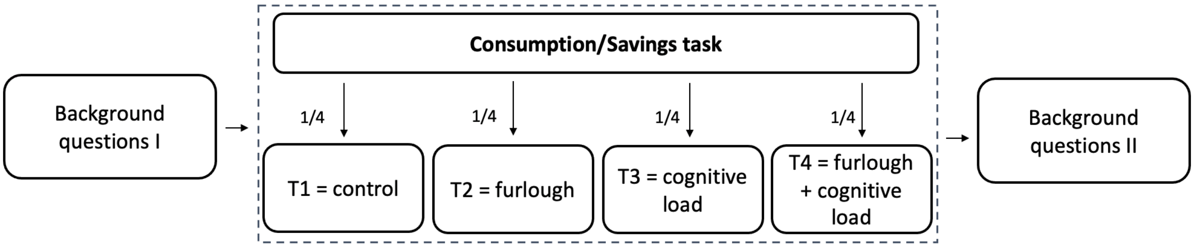

Figure 1: Survey structure

3.2.1 Consumption/savings task

The experimental section of the survey implements the standard consumption-saving choice model with stochastic labor income, a riskless asset, an interest-rate wedge between saving and borrowing, and a borrowing limit. We consider a finite horizon formulation of the model with the life cycle consisting of 20 periods. In particular, the first 15 periods represent working life while the last 5 periods represent the retirement age. A formal presentation of the model and its parametrization are presented in Appendix B.

Participants were provided with instructions describing the environment and a qualitative explanation of the model. For each model period, they were asked to decide on the level of consumption, which also implied the level of financial assets to be set aside for next period, given the exogenous labor income process and the borrowing limit. Given that there was no portfolio choice in the model, financial assets correspond either to the amount agents would put in a payment/savings account with their bank for future transactions purposes, or to loans. We refer to this amount as "account balances" for short. Moreover, we explained to participants their task and the incentive scheme. In order to make sure that they understood the instructions, they were asked a few questions at the end of the instructions block immediately before the task started. We also included a short training phase to allow subjects to familiarize themselves with the task and the screen appearance.[6]

We explained the task to subjects by making use of experimental tokens. The subjects' task consisted of choosing how many tokens they wanted to spend to purchase points in each period. They were also told that this choice could imply debt up to a borrowing limit. They received (paid) an interest rate on account balances (borrowing) in the form of tokens at the beginning of the next period.

Moreover, we explained to them that their choice of tokens in each period would be converted into "points", taking into account both the current period decision and the maximum number of points that their current choice would allow them to achieve in the remaining periods with the wealth they set aside (positive or negative), while staying within the budget and borrowing limits. In addition to the intuitive description, we also showed to subjects the function through which tokens chosen would be converted into points in each experimental period (P_t):

$$P_t = -\frac{1}{2(Tokens_t)^2} + 0.96EP^r \tag{1}$$

where the term EP^r indicates the number of points that could be achieved in the remaining periods with the financial assets set aside (positive or negative), while satisfying the budget and borrowing limits by an agent behaving rationally from period t on.

Finally, at the end of each experimental period, subjects observed a visual summary (Figure 2) of their total amount of tokens, their number of tokens chosen to be buy points, their account balances, and their payoffs (described in section 3.2.4 below). We tested their understanding of the reward mechanism with specific examples prior to launching the experiment, giving them feedback on whether their answer was correct, and the correct answer.

[6]This should avoid biased results due to a learning process in the first few periods.

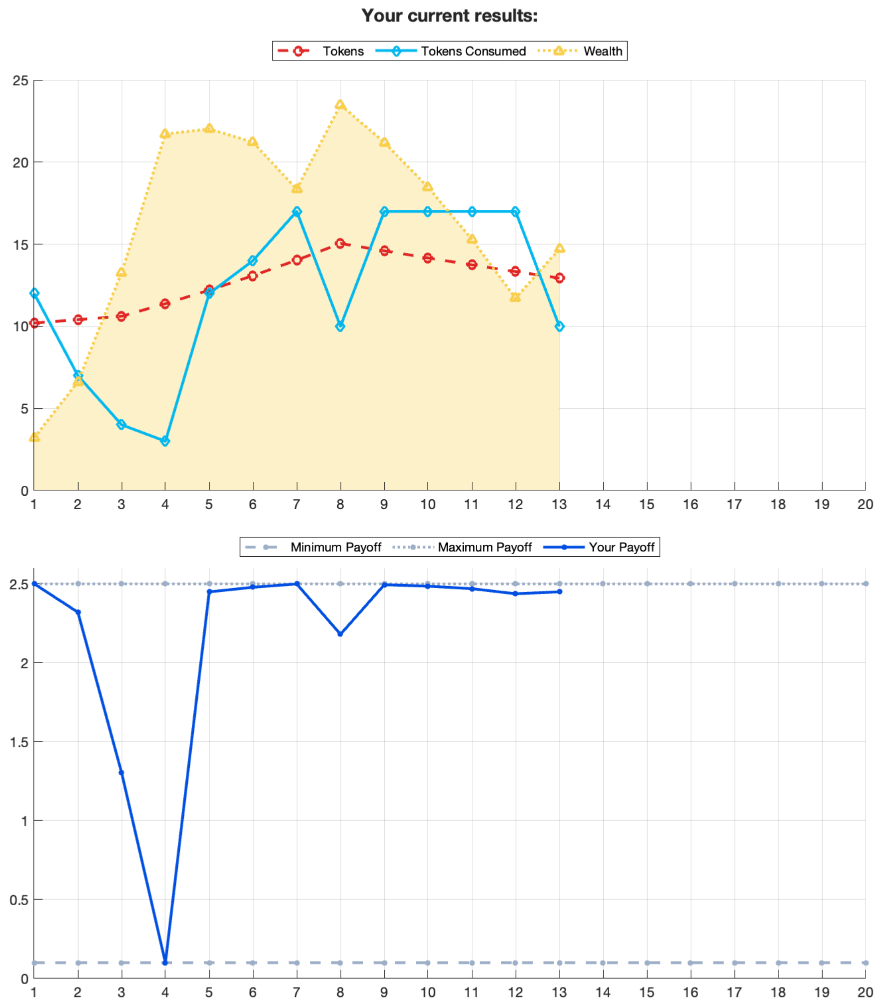

Figure 2: Screenshot information to participants

3.2.2 Treatments

We splitted the sample randomly into four groups to implemented a control group and three treatments. In all four groups respondents' main task consists in making consumption/saving decisions. Treatments differ for the presence of the furlough shock and/or the cognitive load shock. Table 1 reports a summary. The control group (T1) represents our benchmark, participants in the control do not face any exogenous shock. In treatment T2 we implement a scenario in which a furlough shock hits participants during their working life. This shock is modeled as a two state Markov chain with symmetric transition matrix where the probability of staying in the same state is equal to 0.9. In the bad state the agent experiences a 30% drop in income w.r.t income in the previous period. In treatment T3 we implement the cognitive load scenario such that participants

Table 1: Treatments

	Cognitive load	**Furlough shock**
T1	No	No
T2	No	Yes
T3	Yes	No
T4	Yes	Yes

Notes. Treatments summary.

face a permanent costly cognitive load (while making consumption/saving decisions) in each and every experimental period with random frequency. Finally, in treatment T4 subjects face simultaneously a furlough shock (as in T2) and the cognitive load (as in T3).

Notice that by comparing the outcomes of T1 vs. T2 we can assess whether the introduction of the furlough shock *per se* may significantly affect subjects' decisions. While by comparing the outcomes of T1 vs. T3 we can study whether the introduction of the cognitive load *per se* may significantly impact subjects' consumption/saving decisions. Moreover, by comparing the results of T2 vs T4 we can analyse the impact of the cognitive load on individuals' decisions in the presence of the furlough shock. Finally, by comparing T3 vs T4 we can assess the effects of the introduction of furlough on subjects' decisions in the presence of the cognitive load.

3.2.3 Cognitive load task

In treatments 3 and 4, the agents had to fulfil a cognitive load task, while making consumption/saving decisions. The task was a *digit-search* task, similar to Greene et al. (2008). In each period, while deciding consumption, a sequence of numbers randomly drawn between 1 and 10 appeared on the screen. Each number remained on the screen for a random number of seconds. The agent's task was the following: If a number between 3 and 7 (both included) appeared, she had to press the space bar of the keyboard within 2 seconds. Hence, the agent made a mistake when: *i)* she did not press the space bar within 2 seconds when the right number appeared; *ii)* she pressed the space bar when a number that was not between 3 and 7 appeared. Agents were told that mistakes in the task would negatively impact their final payoff and payment.

3.2.4 Payoff function

We designed the incentive schemes such that agents were required to maximize the utility function. Subjects were told that in each period the deviation of their choice from the choice of a "reference individual who would obtain the best results at the end of the experiment" determines their payoff. The deviation is:

$$x_t = \frac{P_t - P_t^r}{P_t^r} * 100$$

Moreover, we define the following payoff function:

$$PO_t = \begin{cases} 0.10 & \text{if } x_t \geq 100 \\ 2.5 - 0.025x_t & \text{if } 0 \leq x_t < 100 \end{cases}$$

Hence, in each period we have that $0.10 \leq PO_t \leq 2.5$ Euro. We tested the understanding of these payoff functions by the subjects before the experiment was launched, through questions on specific examples. We provided feedback as to whether their response was correct, and we also gave to those who made errors the correct responses.

In treatments 3 and 4 we also compute the score in each t for the cognitive load task according to:

$$z_t = \frac{Tot_t - Errors_t}{Tot_t} * 100$$

where Tot_t represents how many numbers were shown to the subject in period t; $Errors_t$ is the number of mistakes in period t. Hence, $0 \leq z_t \leq 100$, with $z_t = 0$ indicating the agent made a mistake for every number shown in the cognitive load task, while $z_t = 100$ indicating she made no mistakes. Hence, the payoff function in treatment 3 and 4 were defined over life-time utility maximization and performance in the cognitive load task:

$$PO_t = \begin{cases} 0.001 z_t & \text{if } x_t \geq 100 \\ (2.5 - 0.025 x_t) 0.01 z_t & \text{if } 0 \leq x_t < 100 \end{cases}$$

Hence, in each period the payoff is between $0 \leq PO_t \leq 0.10$ Euro if $x_t \geq 100$. While it is $0 \leq PO_t \leq 2.5$ Euro if $0 \leq x_t < 100$.

Again, we presented subjects with specific examples, test their understanding of the reward function, and provide the correct answers prior to launching the experiment.

Moreover, in all treatments, we informed subjects that, at the end of the task, the computer would randomly draw 2 of the 20 periods, and we would pay them the sum of the corresponding monetary payoffs earned for those two periods.

4 Differences in average group behavior

In this section, we provide a description of differences in the behavior of groups facing alternative combinations of cognitive load and risk of furlough or unemployment, and how these evolve over model time. We start with an analysis of how the levels of consumption and account balances differ across the control and treatment groups. We then investigate how close to *average* group behavior a model without cognitive load would be as a function of model time, and whether the answer varies based on group characteristics, such as gender, education, financial literacy, and risk aversion. In a further step, we ask how the ability of the model to capture *heterogeneous* within-group behavior evolves over model time.

4.1 Average group consumption and account balances

We start with average group behavior over model periods. Figure 3 reports average consumption choices of subjects, distinguished by treatment. We see that average consumption choices of the subjects were highest in the control group that did not operate under cognitive load or a threat of furlough, and this was consistent throughout the model periods ($T1$). The introduction of the possibility of furlough ($T2$) depressed consumption from early on, consistent with a precautionary motive, and consumption remained at a lower level on average throughout the model periods, even after subjects entered retirement when the threat of furlough was no longer present.

$T3$ introduced cognitive load without a threat of furlough. Average consumption experienced a downward shift relative to $T1$, again throughout the model periods, despite the absence of labor market changes. This suggests that a drop in consumption can be induced simply by subjects having more on their minds, even without having to deal with labor market developments or supply constraints.

$T4$ is the most demanding treatment, as it asked subjects to deal both with a cognitive load and a prospect of furlough. We see that, compared to $T2$ where only the furlough was present, subjects clearly reduced their consumption on average, regardless of the model period. Thus, the imposition of cognitive load depressed average consumption both for people who were dealing with the possibility of furlough (those who could not work online), and for those who could work online and did not face such labor market developments. Not surprisingly, those who could not work online ($T4$) exhibited lower average consumption than those who could, for most of their model life.

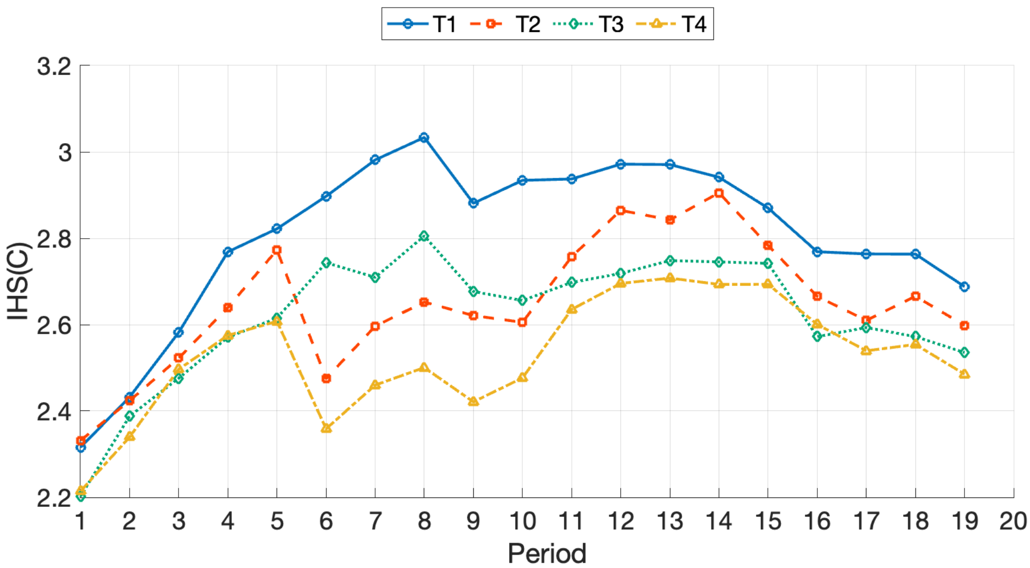

Figure 3: Average consumption (in IHS) per treatment.

Figure 4 shows the treatment effects on average financial assets or account balances.

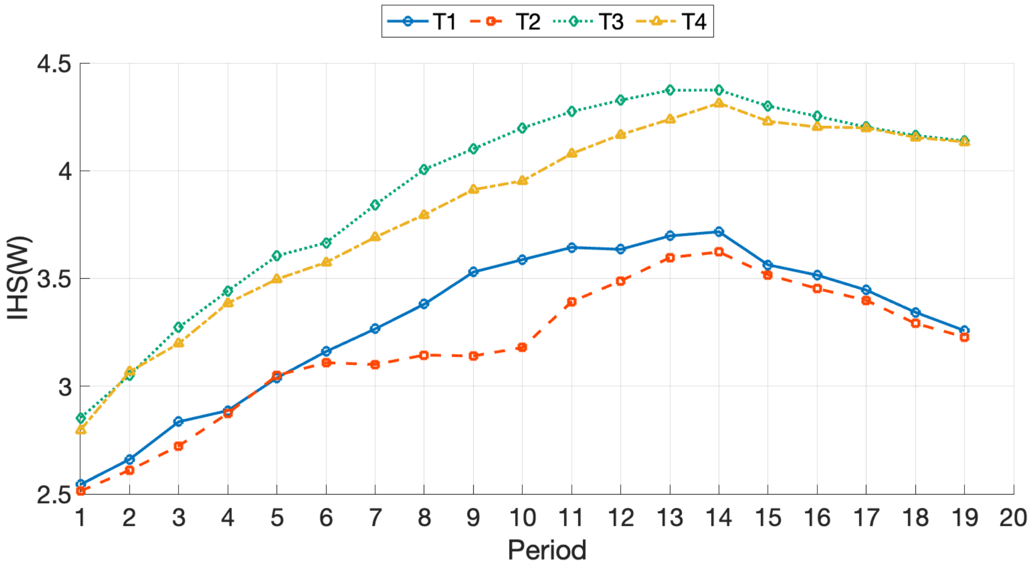

Figure 4: Average account balances (in IHS) per treatment.

Comparing $T2$ to $T1$, the precautionary reduction in consumption resulting from the introduction of furlough without any cognitive load was not sufficient to maintain average account balances at the same level for all of the working life following the occurrence of furlough. In the early part of working life and in the retirement period, subjects chose on average to keep balances at roughly the same levels as those not experiencing furlough.

Remarkably, the mere imposition of cognitive load without labor market consequences or supply constraints ($T3$ versus $T1$) generated a parallel upward shift in average account balances during model working life, and this increase widened during model retirement years. The same was true under conditions of a furlough risk ($T4$ versus $T2$). In fact, the size of the upward shift was comparable for those who faced furlough risk and those who did not.

4.2 Deviations from model-based optimality

4.2.1 Average group behavior

We first ask how well the model without cognitive load captures *average* group behavior as a function of model time, which can be thought of as a traditional 'macro' perspective, abstracting from individual heterogeneity. Figure 5 illustrates our findings for (the IHS of) consumption. Formally, the figure plots

$$macrodev_t^m = \left\{ \text{arsinh } C_t^m(a_t^r) - \frac{1}{N} \sum_{i=1}^{N} \text{arsinh } C_{i,t}^{xp}(a_{i,t}) \right\}, \tag{2}$$

where arsinh $C_t^m(a_t^r)$ represents the inverse hyperbolic sine (IHS) of consumption behavior predicted by the model for period t, namely C_t^m, as a function of the optimally evolving endogenous state, a_t^r, and this is being compared to the average IHS of actual consumption choices of the N group members in the same model period, t. The figure shows that, for all treatment groups, average group behavior has a tendency to approximate more closely the rational choices implied by the model as model time evolves, albeit the extent of convergence differs across treatments. A plausible source of this finding on average group behavior is learning from the performance feedback given to subjects by the experimental platform, based on the rational model. We alerted subjects to the importance of minimizing the policy rule deviation, we incentivized them, and we gave them feedback on how they were performing in this respect. In essence, subjects got a fresh start in each period, conditional on the account balances they had accumulated up to then, and they were asked to make a consumption choice fully consistent with the rational standard model, taking into account optimal decisions from that time onwards. This interpretation is reinforced by observing the jumps for all groups right after period 14, when the model switches to the retirement period and the nature of the income process significantly changes, as described in the description of our model.

Despite this first pattern of convergence, Figure 5 also shows that the average consumption of groups that faced cognitive load was higher and farther from the implications of the respective model than that of groups not facing load, and that this held for all time periods and both with and without the prospect of furlough. Appendix E explores whether such deviations were systematically larger for subsamples with characteristics often associated in the literature with more limited ability to handle financial matters (lower education, limited financial literacy) or greater aversion to risk (high stated risk

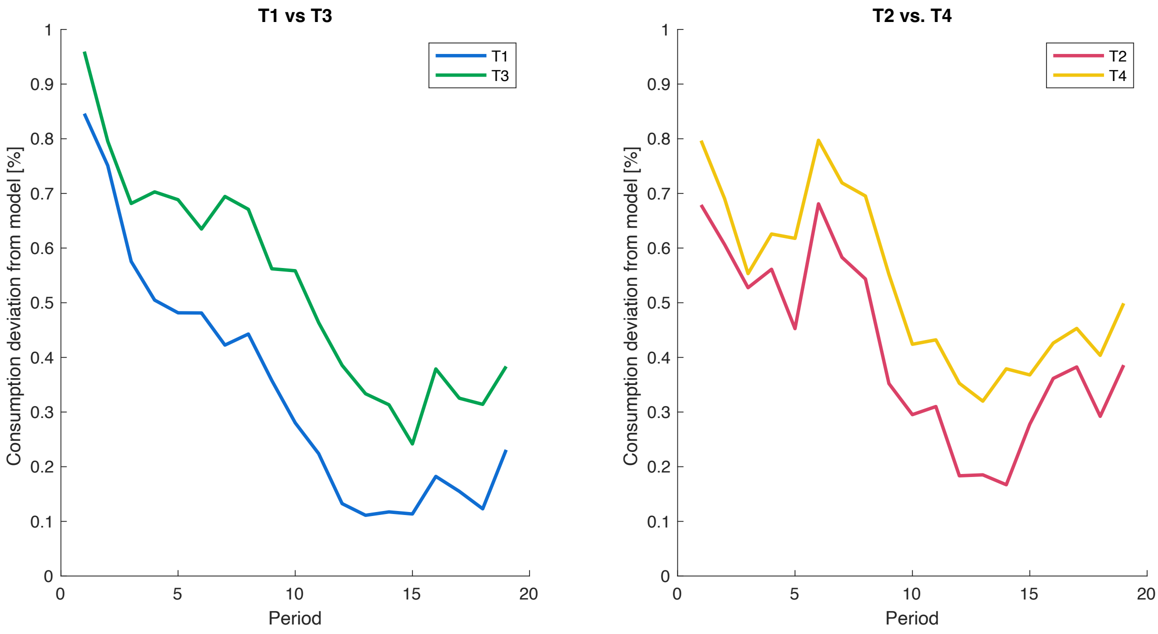

Figure 5: Average consumption deviation from the model for the whole sample.

aversion, female). Interestingly, we do not find a consistent pattern, whereby the average behavior of a certain subsample is systematically farther from, or closer to the model without cognitive load regardless of the income process considered: cognitive load seems to be relevant for all these sample cuts.

4.2.2 Individual heterogeneity

We turn next to the question of how close heterogeneous behavior across subjects is to the model predictions. To this end, we first compute the root mean squared deviation of individual group member consumption choices in each model period and the corresponding (IHS of) consumption for that period, dev_t^m, where

$$dev_t^m = \left\{ \frac{1}{N} \sum_{i=1}^{N} [\text{arsinh } C_{i,t}^m(a_{i,t}^r) - \text{arsinh } C_{i,t}^{xp}(a_{i,t})]^2 \right\}^{\frac{1}{2}} \tag{3}$$

$C_{i,t}^m$ is the optimal consumption implied by the model for period t; $C_{i,t}^{xp}$ is consumption chosen by agents in the experiment for that period; $a_{i,t}^r$ is the model-implied optimal level of cash on hand in period t, while the level actually attained in the experiment is $a_{i,t}$.

!

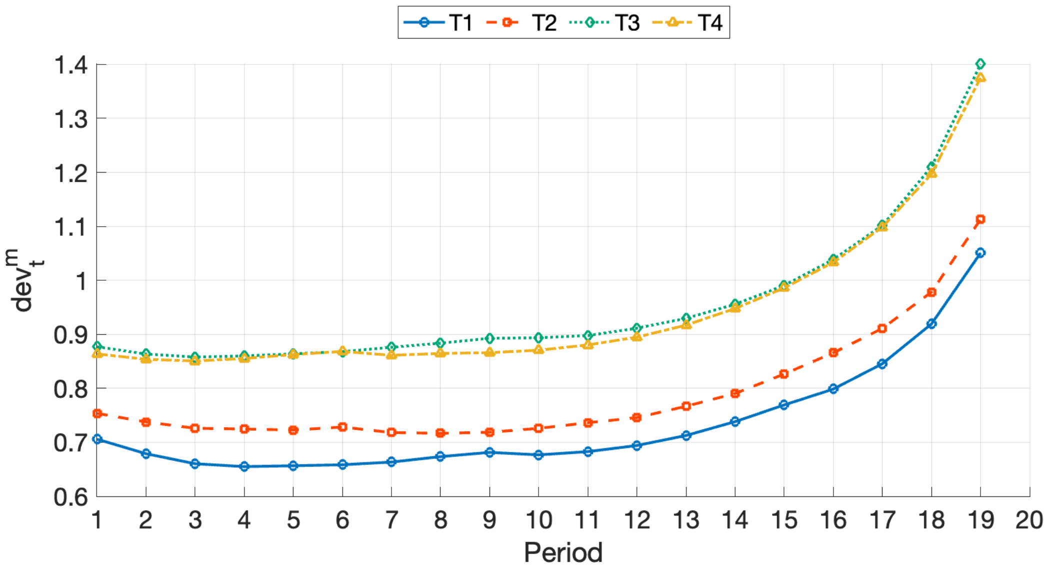

Figure 6: Average value of dev_t^m per treatment.

Figure 6 shows that the imposition of cognitive load induced greater deviations of actual consumption behavior from the model, and that the observed deviations from the respective model were of the same order, regardless of the presence or absence of the threat of furlough. Not surprisingly, introduction of the prospect of a furlough induced a parallel upward shift in average deviations of chosen consumption from the respective model, given the more challenging task facing subjects. In all cases, average deviations of actual subject consumption behavior from that implied by the model were fairly flat during working life, but grew during the retirement years. This was a result of cumulative underconsumption in the early part of the model life cycle: the ensuing overaccumulation of balances in the early model years allowed some subjects to consume much more during retirement than the model would imply.

Next, we decompose each group's average deviation from optimal consumption in period t, dev_t^m, into the part arising from a suboptimal consumption policy rule, dev_t^r, and that arising from having started period t with a suboptimal level of the endogenous state, dev_t^s. Specifically, we compute:

$$dev_t^r = \left\{ \frac{1}{N} \sum_{i=1}^{N} [\text{arsinh } C_{i,t}^r(a_{i,t}) - \text{arsinh } C_{i,t}^{xp}(a_{i,t})]^2 \right\}^{\frac{1}{2}} \tag{4}$$

$C^r_{i,t}$ is the consumption agents should have optimally chosen in each t, given the actual endogenous state $a_{i,t}$ attained in the experiment, had they been rational from t onwards; and dev^r_t is the average squared deviation between (the inverse hyperbolic sines of) this measure and the actual level of consumption chosen across all subjects at time t. This measures the extent to which subjects depart from optimal consumption implied by the model because they failed to optimize their chosen consumption level given the amount of cash on hand available to them at the start of the period. In other words, this is the deviation in consumption behavior resulting from a suboptimal policy rule in period t. The measure of the other component is:

$$dev^s_t = \left\{ \frac{1}{N} \sum_{i=1}^{N} [\text{arsinh } C^m_{i,t}(a^r_{i,t}) - \text{arsinh } C^r_{i,t}(a_{i,t})]^2 \right\}^{\frac{1}{2}} \tag{5}$$

This measures the extent to which a rational optimizing agent would depart from the optimal level of consumption for that period implied by the model, as a result of not having attained the model-implied optimal level of cash on hand in period t, $a^r_{i,t}$, but rather the one actually attained in the experiment, $a_{i,t}$. In view of Bellman's principle of optimality, the policy rule of the fully rational model agent and the one where the agent optimizes from period t onwards, are the same ($C^m_{i,t}(.) = C^r_{i,t}(.)$).

A comparison of Figures 7 and 8, where these two measures are respectively reported, shows that the largest part of the deviations from optimal individual behavior that were induced by cognitive load had to do with the use of a suboptimal policy rule for consumption given the level of account balances, rather than with suboptimal accumulated account balances per se. Subjects were not doing the best they could with the balances they had accumulated up to then rather than being constrained by them.

Taking all findings reported in this section together, they suggest that deviations from the standard model without cognitive load were higher in the presence of that load, and that this was true whether one is interested in the evolution of within-group average behavior or in heterogeneous behavior of households over model time. We next turn to regression analysis of treatment effects on average subject behavior across model periods.

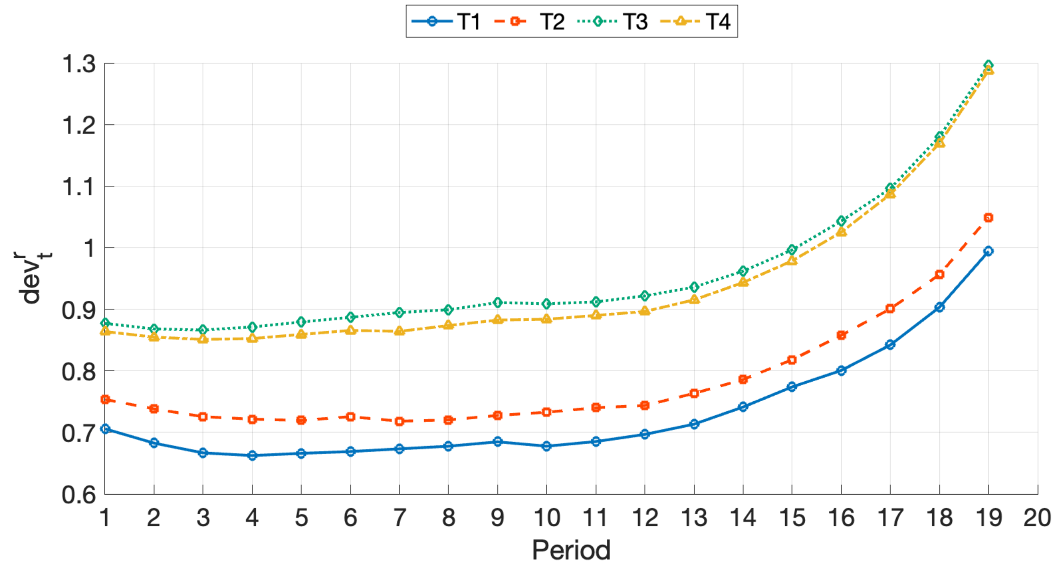

Figure 7: Average value of dev_t^r per treatment.

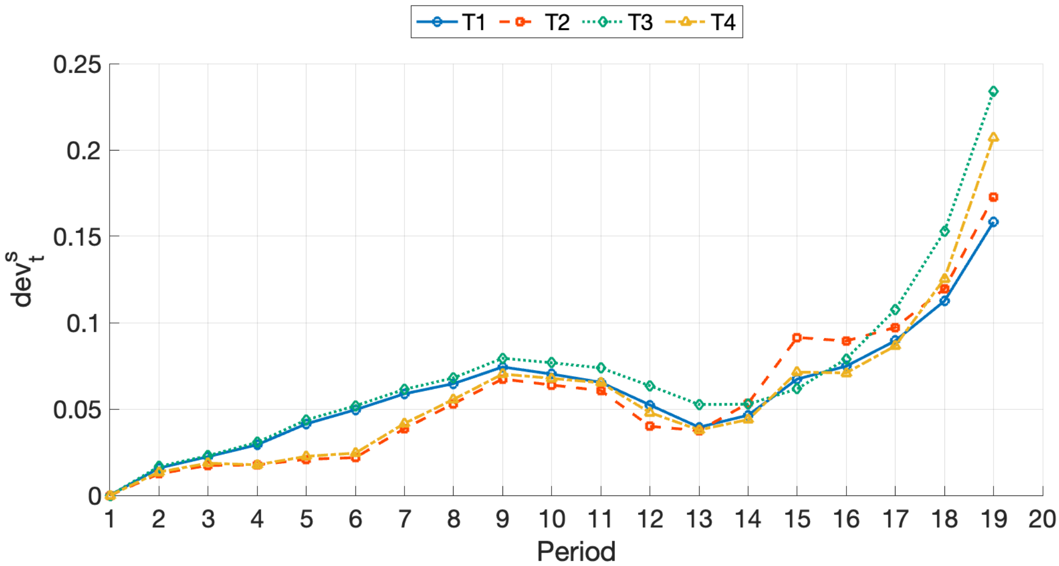

Figure 8: Average value of dev_t^s per treatment.

5 Regression analysis of treatment effects

5.1 Measures and specification

In this section, we report cross-sectional regression results regarding the magnitude and statistical significance of treatment effects on average consumption, account balances, and deviations from optimality of a subject across the model life cyle. The deviations from optimal behavior introduced in section 4 are now expressed as average deviations over the duration of the experiment for a given participant i, denoted by dev_i^m, dev_i^r, dev_i^s:

$$dev_i^m = \left\{ \frac{1}{T} \sum_{t=0}^{T-1} [\text{arsinh } C_{i,t}^m(a_{i,t}^r) - \text{arsinh } C_{i,t}^{xp}(a_{i,t})]^2 \right\}^{\frac{1}{2}}. \tag{6}$$

$C_{i,t}^m$ is the optimal consumption implied by the model for period t; $C_{i,t}^{xp}$ is consumption chosen by subject i for that period; and dev_i^m is the average squared deviation between the (inverse hyperbolic sines of) the two measures of consumption chosen by subject i across all model time periods. This provides a measure of the extent to which the theoretical model captures the consumption behavior of subject i in the experiment (or, equivalently, the extent to which the consumption choices of subject i were consistent with optimal behavior based on the model). Also,

$$dev_i^r = \left\{ \frac{1}{T} \sum_{t=o}^{T-1} [\text{arsinh } C_{i,t}^r(a_{i,t}) - \text{arsinh } C_{i,t}^{xp}(a_{i,t})]^2 \right\}^{\frac{1}{2}}. \tag{7}$$

$C_{i,t}^r$ is the consumption level subject i should have optimally chosen in t, given the endogenous state $a_{i,t}$ attained in the experiment, had the subject been rational from t onwards; dev_t^r is the average squared deviation between the (inverse hyperbolic sines of) this measure and the consumption level actually chosen by subject i across all experiment time periods. This measures the extent to which subject i departed from optimal consumption implied by the model because of a suboptimal policy rule. Also,

$$dev_i^s = \left\{ \frac{1}{T} \sum_{t=0}^{T-1} [\text{arsinh } C_{i,t}^m(a_{i,t}^r) - \text{arsinh } C_{i,t}^r(a_{i,t})]^2 \right\}^{\frac{1}{2}}. \tag{8}$$

This measures the average extent, across the model life cycle, to which a rational optimizing agent would depart from the optimal level of consumption implied by the model as a result of not having attained the model-implied optimal level of cash on hand in each period t but rather the one chosen by subject i in the experiment. In view of Bellman's principle of optimality, the policy rule of the fully rational model agent and the one where the agent optimizes from period t onwards are the same ($C_{i,t}^m(.) = C_{i,t}^r(.)$).

We run OLS regressions on T_i, i.e. a dummy variable equal to 1 if subjects belonged to the selected treatment group, and 0 if they belonged to the chosen reference group. We also control for various subject characteristics. As we discuss the separate effects of different treatments, we vary the group chosen as the control group for the relevant comparison. Thus, T_2 versus T_1 refers to introduction of the furlough possibility in the absence of cognitive load, while T_4 versus T_2 refers to introducing furlough when cognitive load is present. Our baseline model is as follows:

$$Y_i = \alpha_0 + \alpha_1 Treat_i + \beta \mathbf{Z}_i + \epsilon_i \tag{9}$$

where Y_i is an outcome: consumption, account balances, the measure of deviation from conditionally rational behavior (x), and the three deviations we introduced above; $Treat_i$ is the variable of interest, the treatment dummy that equals one if individual i is in the group facing the furlough or the cognitive load and zero otherwise; $\mathbf{Z}_i$ represents a vector of subject socio-demographic characteristics: age group, gender, income group, educational attainment, work status, residential area, marital status, and religion as a proxy for culture. We expand this list with indicators of subject performance during the experiment in the robustness section below.

5.2 The effect of furlough

Our baseline findings are reported in Table 2. Comparison of treatment $T2$ to the control $T1$ in Panel A shows a statistically significant negative effect on average consumption choices upon introduction of the furlough possibility in the absence of cognitive load, relative to those of a participant in the control group with similar socio-demographic characteristics. Subjects' reaction to the introduction of a possible furlough is appropriate, given the expected drop in lifetime income and the increase in background labor income risk, based on precautionary saving models that include the standard model employed here. Respondents' behavior given the furlough risk was not only in the right direction, but also by a magnitude that does not generate a statistically significant effect

Table 2: Treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)
	$Consumption_i$	$AccountBalances_i$	x	dev_i^m	dev_i^r	dev_i^s
Panel A: T2 vs T1						
$Treat_i$	-0.142***	-0.140	-0.628	0.051	0.044	-0.002
	(0.021)	(0.103)	(0.710)	(0.030)	(0.029)	(0.002)
Observations	984	984	923	984	984	984
Adj. R^2	0.047	0.027	-0.003	0.002	0.001	-0.001
Panel B: T3 vs T1						
$Treat_i$	-0.144***	0.563***	2.130**	0.231***	0.224***	0.018***
	(0.020)	(0.090)	(0.762)	(0.030)	(0.029)	(0.002)
Observations	913	913	854	913	913	913
Adj. R^2	0.063	0.056	0.011	0.070	0.068	0.071
Panel C: T4 vs T2						
$Treat_i$	-0.092***	0.639***	2.606***	0.171***	0.166***	0.006***
	(0.021)	(0.096)	(0.723)	(0.029)	(0.028)	(0.002)
Observations	968	968	904	968	968	968
Adj. R^2	0.013	0.047	0.013	0.031	0.030	0.017
Panel D: T4 vs T3						
$Treat_i$	-0.090***	-0.091	-0.225	-0.011	-0.016	-0.014***
	(0.021)	(0.083)	(0.789)	(0.028)	(0.027)	(0.002)
Observations	897	897	835	897	897	897
Adj. R^2	0.029	0.010	-0.003	0.006	0.006	0.053

Notes. OLS estimates of the Treatment effect. All specifications control for age group, gender, income group, education attained, work status, residential area, marital status, and religion. Robust standard errors in parentheses. $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$

on average account balance choices over the model periods, nor on the average percentage deviations of the subject's chosen behavior from the theoretical model, x.[7]

5.3 The effect of cognitive load

Panel B in Table 2 shows that introducing a cognitive load to subjects not facing furlough risk produced a significant effect across all observed outcomes. In fact, subjects facing the cognitive load displayed both significantly lower consumption and greater account balances relative to subjects with comparable socio-economic characteristics who did not face such cognitive load. Interestingly, this combined effect on consumption and account balances is not only in accordance with the respective changes observed during the onset

[7]While this table uses the full sample for the other variables, the regression for x only is based on a winsorized sample that excludes the top 0.5% observations of x as extreme outliers in x. Table D.1 shows that the findings for the remaining variables described here are robust to this winsorization. Moreover, we did not find any systematic relation of the excluded extreme values of x to subject characteristics.

of the Covid crisis, but it was also observed among our subjects in the absence of any perceived supply constraints (e.g., of the type associated with lockdowns) and of changes in future borrowing constraints. The effects are also quantitatively significant, representing average reductions of 14.5% in consumption, and increases of 56.3% in account balances across the run of the experiment.

We also find that participants subjected to that load deviated more from the model on average. This is to be expected, as the model did not incorporate any effect of cognitive load. Nevertheless, there is a statistically significant effect on the average deviation from optimal behavior, x, and on all three root-mean-squared deviations (RMSE) considered. While most of the induced deviation is reflected in the use of a model-suboptimal policy rule for consumption, there are also statistically significant effects arising from a suboptimal evolution of the account balances that would have affected consumption even if the model-implied consumption rules were followed by subjects. These findings suggest that cognitive load represents a factor accounting for significant deviations of observed consumption and account balance behavior from what could have been expected on the basis of models estimated over periods in which cognitive load was not present or not as widespread. This deterioration in performance comes from the demand side and not from any additional restrictions to behavior arising from supply bottlenecks or lending restrictions imposed by the financial sector.

5.4 The effect of cognitive load under furlough

Do our findings imply bigger or smaller estimated effects of cognitive load among subjects facing the prospect of furlough? This question is relevant for the part of the population that could not work online during the Covid crisis, for example, or more generally for those suffering labor market consequences as a result of the crisis. To answer this question, we compare treatments $T4$ and $T2$ in Panel C. In this case, too, the effect of introducing cognitive load is statistically significant throughout the six outcomes we consider. Introducing cognitive load on top of the prospect of a furlough depressed consumption by 9% on average in our experiment, and increased average money holdings by about 63%.

This worsened the performance of the standard model in capturing subjects' consumption behavior, with both policy-rule deviations and suboptimal evolution of the endogenous state contributing significantly to this.

So cognitive load was important regardless of whether subjects could avoid labor market consequences or faced the possibility of furlough. Comparing its importance in the absence and in the presence of furlough (Panel B to Panel C), we see that the percentage average drop in consumption among people who already moderated their consumption in response to the furlough was estimated to be lower, and the increase in average account balances higher. The effect of the cognitive load on the ability of the model to describe heterogeneity in average consumption behavior over the life cycle, as described by the three RMSE measures, was smaller when the model incorporated the prospect of a furlough, than when it did not. [8]

5.5 The effect of furlough under cognitive load

Our experiment further allows us to examine the effects of introducing the prospect of furlough in the presence of cognitive load (Panel D) and to compare these to what happened when furlough was introduced in the absence of cognitive load (Panel A). Panel D shows that subjects facing furlough in addition to cognitive load reduced their average consumption significantly (by about 9%), but less so than comparable subjects did in the absence of cognitive load (14%). Moreover, the response of subjects to furlough under cognitive load triggered significant average deviations from the model related to a suboptimal evolution of the endogenous state, namely account balances, while no such significant contribution to deviations from optimality was observed in the absence of cognitive load (Panel A). Thus, our findings suggest that cognitive load contributed to a muted reaction of consumption to the prospect of furlough, and a significant deviation from standard model consumption arising from a suboptimal evolution of account balances. Nevertheless, taking panels A and D together, we find little evidence that the furlough (which entered both people's minds and the model) lead to important devia-

[8] On the other hand, the model with furlough registered greater percentage deviations from optimal average life cycle consumption, x, when cognitive load was introduced.

tions of participant behavior from the overall implications of the respective model for consumption.

5.6 Robustness to additional controls

We have examined robustness of the above findings on the size, direction, and statistical significance of treatments for the five outcomes under consideration to controlling for the behavior of subjects during the experiment. Using all socio-economic controls as in the base regression analysis, namely age group, gender, income group, education attained, work status, residential area, marital status and religion, we added (in turn, and then all together) controls for whether the subject reported not having answered randomly at any point during the survey (Non-random responses), the average time spent in each model period in the task (Time), and the normalized score on the questions, aimed at testing the understanding of the instructions (CQ score). Results are reported in Tables C.1 to C.5, starting with treatment effects on the IHS of consumption and ending with treatment effects on the deviation from model consumption that arises from suboptimal account balances, dev_i^s.

With one exception, allowing for the behavior of subjects during the experiment did not alter our conclusions regarding the size, direction, and statistical significance of the treatments considered in Table 2. The only exception suggests additional significant treatment effects. Introducing the prospect of furlough ($T2$ versus $T1$) now has a positive and statistically significant effect on the deviation of consumption behavior from the theoretical model, dev_i^m, and on the part of this deviation associated with a suboptimal policy rule for consumption, dev_i^r. Both of these deviations from optimal behavior were significantly mitigated in the treatment and control groups, by spending more time performing the experimental tasks on average, and by having stated that there was no point in the experiment where choices were made at random. Controlling for such factors essentially compares subjects that were similar in these respects as well, and yields significant treatment effects of furlough not only on consumption but also on model and policy rule deviations, even in the absence of cognitive load.

As regards other treatments and the associated outcomes, where results are essentially unchanged, we find that the average time spent on the task, giving non-random responses, and having better understanding of the instructions, are occasionally significant, in the direction of reducing deviations from model implications in treatment and in the control group. This suggests that average time spent was an indicator of engagement with the problem rather than of difficulty with the execution of the task. When significant, better understanding of the experiment (higher CQ) contributed to lower consumption and higher account balances. A longer average time spent tended to raise consumption choices (rarely) and to lower account balances (in several cases) across treatment and control groups. Finally, non-random responses tended to lower account balances but they were only significant in one case for (raising) consumption. All in all, these robustness exercises confirm our baseline findings and suggest that subjects' greater engagement and understanding led them to exhibit smaller deviations from the behavior prescribed by the standard model.

5.7 The role of household heterogeneity

In this section, we explore whether the effects of treatments on consumption and account balances, as well as on deviations from the model, were more pronounced for participants with particular individual characteristics. This would suggest that the problems posed by cognitive load tend to be concentrated in specific groups, and that targeted policies would be in order. The opposite case would suggest that the problem is quite widespread.

We adopt an exploratory approach, augmenting the estimation model in Equation (9) through an interaction term of the treatment dummy, T_i, with individual level socio-demographic factors, preferences, and attitudes. Table 3 reports the results from cases where the interaction term was significant for at least one of the five outcome variables.

In panel A, we find only scattered significant effects, suggesting that heterogeneity did not play a major role in subjects' responses to the prospect of furlough in the absence of cognitive load, or even to the introduction of cognitive load for people who did not simultaneously face the furlough. By contrast, panel B provides evidence of a significant

Table 3: Treatment effects with interactions

	(1) $Consumption_i$	(2) $Account\ balances_i$	(3) dev_i^m	(4) dev_i^r	(5) dev_i^s
Panel A: T2 vs T1					
$Treat_i$ x CRT_i		0.250**			
		(2.57)			
Observations	984	984	984	984	984
Panel B: T4 vs T2					
$Treat_i$ x CRT_i		-0.195**			
		(-2.25)			
$Treat_i$ x FL_i		-0.244*			
		(-2.09)			
$Treat_i$ x β_1	-0.199***		0.239**	0.230**	0.0168**
	(-2.52)		(2.14)	(2.13)	(2.50)
$Treat_i$ x β_2					0.0158*
					(1.92)
$Treat_i$ x aged 41-65		0.344*	0.100*	0.0999*	
		(1.80)	(1.74)	(1.78)	
$Treat_i$ x $College_i$	0.073*		-0.118**	-0.114**	
	(1.73)		(-2.06)	(-2.06)	
$Treat_i$ x $F-bias_i$				0.118	
				(1.66)	
Observations	968	968	968	968	968
Panel C: T4 vs T3					
$Treat_i$ x β_1	-0.180**		0.198*		0.0191**
	(-2.27)		(1.70)		(2.24)
$Treat_i$ x $F-bias_i$	-0.138**		0.159**	0.155**	0.0149**
	(-2.42)		(2.07)	(2.06)	(2.55)
Observations	897	897	897	897	897
Controls	Yes	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect, interacted with the score in the Cognitive Reflection Test (CRT), a dummy equal to 1 if subjects are present-biased (P-bias), the financial literacy score (FL), the short-run discount factor (β_1), the medium-run discount factor (β_2), the age category (= 41–65), a dummy equal to 1 if subjects have college education (College), a dummy equal to 1 if subjects are future-biased (F-bias). Significant coefficients only. All specifications control for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

role of college education and of short-run patience in shaping responses to cognitive load among those who faced the prospect of furlough. College-educated subjects facing treatment $T4$, and thus cognitive load as well as furlough, tended to lower their consumption less in response to cognitive load than their less educated counterparts in the same treatment. They also exhibited a smaller deviation from optimal model behavior and from the optimal consumption rule under conditions of furlough. On the other hand, those who exhibited greater short-term patience (a larger one-period-ahead discount factor) responded to cognitive load by lowering their consumption even more than their less patient counterparts in $T4$, in a manner that made their behavior depart even more from the prescriptions of the model, mostly but not solely because of departures from the optimal policy rule for consumption.

Financial literacy, as measured by the "Big 3" questions on interest compounding, real interest rates, and diversification, failed to register pervasive effects in this experiment. It did register a significant moderating effect on the upward response of account balances to the introduction of cognitive load among subjects facing furlough (Panel B), but this did not generate significant departures from model-implied optimal behavior in the presence of the furlough prospect.[9]

Finally, panel C indicates that both short-run patience and forward bias play a significant role in shaping the reaction of subjects to introduction of furlough in the presence of cognitive load. The more patient and the forward-biased subjects facing cognitive load tended to lower consumption more when also faced with furlough, and deviated more from model-implied optimal behavior, mostly in terms of the consumption policy rule.

In the Appendix, we also consider whether subjects' measured risk aversion influenced the effect of each treatment on the ability of the model to explain subjects' choices, both as a whole and in the decomposition of policy rule versus endogenous state. We find no statistically significant interaction of measured risk aversion with any of the treatment effects on overall deviation from model behavior, or on the deviation from the model policy rule (Table C.6). This was also true for deviations resulting from the evolution of the endogenous state, but with three small exceptions of low statistical significance.[10]

[9] A similar reaction was found for CRT, proxying for intuitive thinking, while an opposite and more sizeable effect was observed among subjects aged 41-65 relative to the youngest group.

[10] High risk aversion boosted the treatment effect of introducing furlough prospects in the absence of cognitive load; and high and low risk aversion reduced the deviation resulting from the endogenous state when furlough was imposed on top of cognitive load. The statistical significance level is 10% in all cases

6 Conclusions

In this paper, we designed and conducted an incentivized online experiment involving a representative sample of close to 2000 households in France. Our primary objective was to investigate whether and how the presence of a taxing and persistent cognitive load and its interaction with adverse labor market shocks influences household consumption, saving, and borrowing choices, potentially hindering individuals' ability to achieve their life-cycle objectives. In addition to overall results, we delved into the heterogeneity of these effects across a diverse range of socio-economic characteristics, and how they related to the way in which subjects engaged with the experiment.

Our unique approach allowed us to isolate the effects of cognitive load in the absence and presence of furlough risk; and of furlough in the absence and presence of cognitive load. We further decomposed departures from model-implied optimality into two components: sub-optimal consumption policy rule and sub-optimal evolution of the endogenous state (account balances).

Our findings revealed that cognitive load exerted a significant downward pressure on chosen consumption and an upward influence on chosen account balances. The former effect was proportionately bigger for workers not facing furlough and the latter being more pronounced for workers facing it. The treatment and control groups were chosen so that these effects of cognitive load were in addition to any effects that furlough itself had, and they did not arise from supply constraints or worsening of borrowing constraints. Moreover, cognitive load worsened the ability of the standard model to describe consumption behavior, both in terms of policy rule and in terms of the underlying endogenous state, with such effects being proportionately bigger for those who did not face furlough (as was, for example, the case with online workers during the Covid-19 pandemic).

There was overall limited evidence suggesting that cognitive load tends to affect only specific demographic groups. We found that college-educated subjects facing both cognitive load and furlough risk exhibit less pronounced responses to cognitive load, demonstrating a smaller deviation from optimal model behavior. In contrast, individuals with greater short-term patience (reflected in a higher one-period-ahead discount factor) respond to cognitive load by lowering their consumption and deviating further from the model and the optimal policy rule. Interestingly, financial literacy itself, as measured by our indicator, did not exert a pervasive significant impact on behavior, presumably because the choice task did not involve portfolio choice.

In the absence of cognitive load, the introduction of furlough risk generally lead to reduced consumption, as predicted by precautionary models. However, it did not significantly impair the model's ability to explain behavior. The presence of cognitive load, however, mitigated the downward effect of furlough on consumption. Interestingly, more patient and forward-biased subjects facing cognitive load exibited a further decrease in consumption when also confronted with furlough risk, and deviated more from model-implied optimal behavior, mostly in terms of the consumption policy rule.

Our findings regarding reduced consumption, higher account balances, and deviations from model-implied behavior, driven by cognitive load and differentiated across individuals based on their labor market exposure, hold significant implications, both for the Covid-19 crisis, and scenarios where cognitive load is heightened. While our priors might have been that cognitive load tends to encourage irresponsible behavior and excessive spending, our findings suggest that it tends to make people more cautious, limiting consumption and leading to accumulation of high account balances. By understanding such complex interactions, policymakers and individuals alike can better navigate challenges and promote financial well-being in the face of cognitive strain and economic uncertainties. To do so, policymakers and practitioners need to develop strategies that can mitigate the negative effects of cognitive load on financial decision-making. These strategies could include design of information and education policies and development of financial products that can help consumers navigate the troubled waters of crisis management and the cognitive demands crises impose.

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APPENDIX

A Descriptive Statistics

Table A.1: Sample characteristics

	(1) France	(2) Survey
Female	51.64%	51.83%
Median age	41.28	46.63
Married or domestic partnership(*)	58.8%	64.75%
Average household size(*)	2.19	2.62
Employment rate	67.30%	63.00%
Income(*)		
€0–€14,999	12.95	11.96
€15,000–€24,999	25.19	21.48
€25,000–€49,999	40.85	44.07
€50,000–€74,999	11.53	12.81
€75,000–€99,999	1.35	3.46
€100,000–€149,999	2.71	2.97(+)
€150,000–€199,999	2.71	1.75(+)
€200,000+	2.71	1.49(+)
Region of residence (%)		
Auvergne-Rhône-Alpes	0.12	0.12
Bourgogne-Franche-Comté	0.04	0.05
Bretagne	0.05	0.05
Centre-Val de Loire	0.04	0.05
Corse	0.005	0.003
Grand Est	0.08	0.09
Hauts-de-France	0.09	0.12
Île-de-France	0.19	0.16
Normandie	0.05	0.05
Nouvelle-Aquitaine	0.09	0.08
Occitanie	0.09	0.09
Pays de la Loire	0.06	0.05
Provence-Alpes-Côte d'Azur	0.08	0.08
COVID: two doses of vaccine received(−)	78.30%	83.63%

Notes. The table reports French representative statistics from the INSEE in the year 2021 (column 1) alongside summary statistics from our survey (column 2). (*) latest data available 2018. The data for income distribution for France are obtained through interpolation of the survey data with the true data (expressed in deciles). (+) We assume that the 4.15% of respondents choosing "Prefer not to answer" are equally distributed in the three last categories of higher income. The median age in France population is determined over the total population, while in our survey is calculated only over the population age 18 and over. The employment rate in France is calculated over the population between age 15 and 64, in our survey is calculated over the population age 18 and over. (−) Data on January 30, 2022 (source: ameli.fr)

Table A.2: Balance of sample

	(1) T1	(2) T2	(3) T3	(4) T4
Age	47.38	46.86	45.73	46.42
Women	48.23	52.67	52.76	53.78
Married or domestic partnership	66.39	60.99	66.59	65.44
Income (€25,000 - €49,999)	47.81	41.98	42.63	43.84
College education	42.59	44.16	41.94	38.23
Currently employed	62.84	61.58	62.21	65.44
Observations	479	505	434	463

Notes. Share of subjects in each condition across socio-demographic variables [for Age: average value].

B Optimal behavior in the model

In the experimental section of the survey we use a standard consumption/savings life cycle model with stochastic income, a furlough shock and a borrowing constraint described by

$$\begin{aligned}\max_{\{C_t\}} \quad \mathbb{E}_0 \quad & \sum_{t=0}^{T-1} \beta^t U(C_t) \\ \text{s.t.} \quad A_{t+1} & = (1+r)A_t + \theta_t Y_t - C_t \\ A_{t+1} & \geq \phi Y_t, \quad C_t \geq 0, \quad A_T = 0\end{aligned} \tag{10}$$

where $Y_t = (1+g)Y_{t-1}e^{x_t}$ with $x_t \sim AR(1)$; θ is the furlough parameter that lowers income to 70% when it materializes, while being equal to one, otherwise; ϕ is the borrowing constraint parameter; r is a risk-free rate that can take a low ($r = r_f$) or high value ($r = r_c$) when the agent is saving or borrowing respectively. Note that the subjects' choice of consumption determines the net borrowing or net saving amount, given cash on hand.

In the following, we assume a CRRA utility function $U(C_t) = \dfrac{C_t^{1-\sigma}}{1-\sigma}$ with σ representing the degree of (constant) relative risk aversion. Moreover, we can re-write the individual's problem in terms of the value function:

$$v(a_t, s_t) = \max_{c_t} \gamma_t^{1-\sigma} \left[\frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t v(a_{t+1}, s_{t+1}) \right] \tag{11}$$

$$\gamma_t = \frac{Y_t}{Y_{t-1}} = (1+g)e^{x_t} \tag{12}$$

where $c_t = \frac{C_t}{Y_t}$, $a_{t+1} = \frac{A_{t+1}}{Y_t}$ and $s_t = (x_t, \theta_t)$.

For each model period, subjects choose the level of consumption (C_t) that maximizes expected lifetime utility under the budget constraint and the borrowing constraint. When solving numerically the model and in the experiment we assume the life-cycle consists of 20 periods and is split into two time windows, i.e., the working life until period 14, and from period 15 until the end when the agent retires and receives a retirement pension equal to 74% of her income in period 14.

The chosen values for the key model parameters are reported in Table A.3.

Table A.3: Model parametrization

Parameter	Interpretation	Value
T	number of periods	20
β	discount factor	0.96
σ	degree of relative risk aversion	3
r_c	interest rate on loans	0.015
r_f	risk-free return	0.005
g	deterministic growth rate	0.02
θ	furlough shock	0.7
ϕ	borrowing constraint parameter	-0.45

Notes. $\theta = 0.7$ in the periods in which the furlough shock materializes. Otherwise, it equals one.

Figure A.1 shows the optimal path for consumption and financial assets, given the chosen income realization, in the absence of the furlough shock, namely when $\theta = 1$ in all periods. On the contrary, Figure A.2 displays the optimal path for consumption and financial assets, when the furlough shock hits from periods 6 until 10.

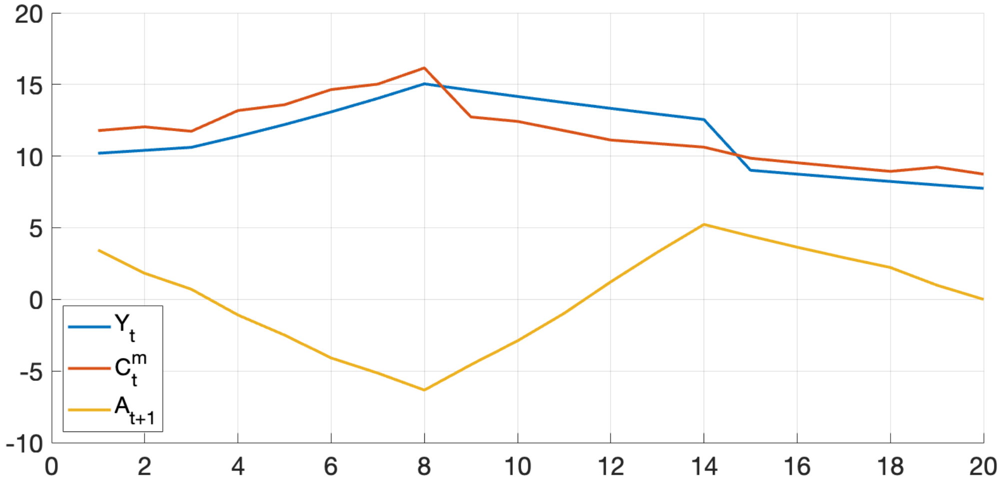

Figure A.1: Income and optimal path for consumption and financial assets in the absence of furlough shocks.

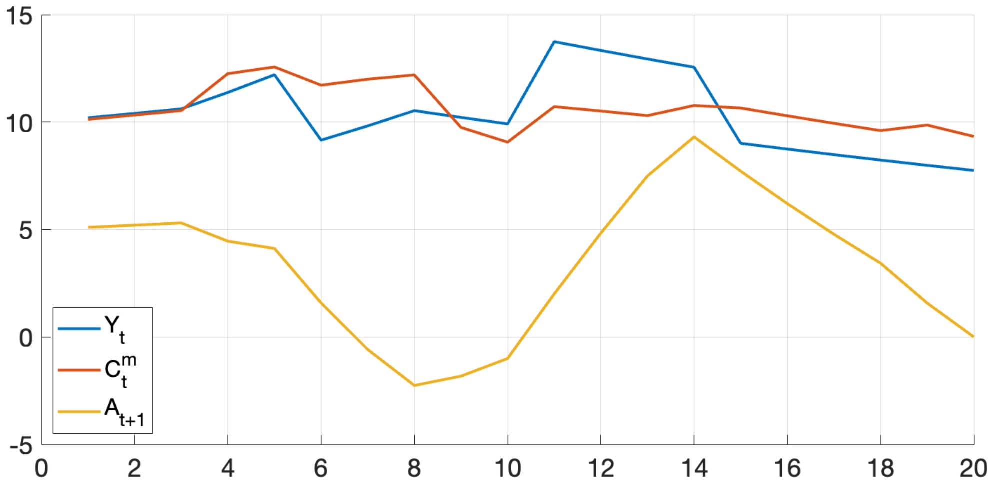

Figure A.2: Income and optimal path for consumption and financial assets in the presence of furlough shocks.

C Engagement, Performance, and Risk Aversion

This section first presents regression estimates that control, in addition to the socio-economic characteristics of the subjects, for various indicators of their engagement and performance in the experiment (Tables C.1-C.5). It then reports, in Table C.6, estimates of the importance of risk aversion for deviations of actual behavior from the model and their decomposition across different treatments.

Table C.1: Treatment effects on the IHS of consumption

Dependent variable: IHS of consumption	(1)	(2)	(3)	(4)
Panel A: T2 vs T1				
$Treat_i$	-0.142***	-0.142***	-0.142***	-0.144***
	(-6.86)	(-6.88)	(-6.86)	(-7.01)
$Non-random\ responses_i$	0.0288			0.0312
	(1.36)			(1.44)
$Time_i$		0.004**		0.0043**
		(2.33)		(2.35)
$CQ\ score_i$			-0.0334	-0.0578
			(-0.59)	(-0.98)
Observations	984	984	984	984
Adjusted R^2	0.05	0.051	0.048	0.052
Panel B: T3 vs T1				
$Treat_i$	-0.145***	-0.148***	-0.144***	-0.147***
	(-7.21)	(-7.34)	(-7.10)	(-7.33)
$Non-random\ responses_i$	0.0426**			0.0456**
	(2.02)			(2.12)
$Time_i$		0.0027		0.00312
		(1.36)		(1.56)
$CQ\ score_i$			-0.0674	-0.098*
			(-1.18)	(-1.67)
Observations	913	913	913	913
Adjusted R^2	0.065	0.062	0.062	0.067
Panel C: T4 vs T2				
$Treat_i$	-0.0912***	-0.0924***	-0.0907***	-0.0916***
	(-4.29)	(-4.34)	(-4.27)	(-4.19)
$Non-random\ responses_i$	0.0031			0.0054
	(0.15)			(0.26)
$Time_i$		0.0011		0.0014
		(0.72)		(0.89)
$CQ\ score_i$			-0.0715	-0.0798
			(-1.24)	(-1.36)
Observations	968	968	968	968
Adjusted R^2	0.015	0.015	0.015	0.015
Panel D: T4 vs T3				
$Treat_i$	-0.0897***	-0.0903***	-0.0937***	-0.0932***
	(-4.36)	(-4.40)	(-4.57)	(-4.55)
$Non-random\ responses_i$	0.0167			0.0199
	(0.80)			(0.94)
$Time_i$		0.005		0.001
		(0.39)		(0.69)
$CQ\ score_i$			-0.0937***	-0.108*
			(-4.57)	(-1.82)
Observations	897	897	897	897
Adjusted R^2	0.027	0.026	0.029	0.028
Controls	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect. The specifications control for a dummy equal to 1 if subjects report they do not answer randomly at any point during the survey (Non-random responses); the average time spent in each period in the task (Time); the normalized score in the control questions (CQ score). All specifications control also for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

Table C.2: Treatment effects on the IHS of account balances

Dependent variable: IHS of account balances	(1)	(2)	(3)	(4)
Panel A: T2 vs T1				
$Treat_i$	-0.143	-0.135	-0.111	-0.0958
	(-6.86)	(-1.33)	(-1.09)	(-0.95)
$Non-random\ responses_i$	-0.00175			-0.0616
	(-0.02)			(-0.59)
$Time_i$		-0.0267**		-0.0342***
		(-2.43)		(-3.01)
$CQ\ score_i$			1.284***	1.421***
			(-4.58)	(-4.99)
Observations	984	984	984	984
Adjusted R^2	0.025	0.031	0.046	0.054
Panel B: T3 vs T1				
$Treat_i$	0.563***	0.579***	0.546***	0.570***
	(6.22)	(6.33)	(6.09)	(6.29)
$Non-random\ responses_i$	0.0055			-0.0352
	(0.06)			(-0.37)
$Time_i$		-0.013		-0.0207**
		(-1.42)		(-2.21)
$CQ\ score_i$			0.984***	1.103***
			(3.77)	(4.15)
Observations	913	913	913	913
Adjusted R^2	0.055	0.057	0.071	0.074
Panel C: T4 vs T2				
$Treat_i$	0.627***	0.646***	0.619***	0.627***
	(6.43)	(6.71)	(6.50)	(6.60)
$Non-random\ responses_i$	-0.118			-0.166*
	(-1.23)			(-1.71)
$Time_i$		-0.0137		-0.0195*
		(-1.52)		(-1.91)
$CQ\ score_i$			1.407***	1.550***
			(5.15)	(5.50)
Observations	968	968	968	968
Adjusted R^2	0.046	0.048	0.072	0.08
Panel D: T4 vs T3				
$Treat_i$	-0.0939	-0.0892	-0.0562	-0.0595
	(-1.13)	(-1.08)	(-0.68)	(-0.72)
$Non-random\ responses_i$	-0.133			-0.162*
	(-1.63)			(-1.94)
$Time_i$		-0.0072		-0.0115 *
		(-1.05)		(-1.54)
$CQ\ score_i$			0.935***	1.061***
			(3.87)	(4.23)
Observations	897	897	897	897
Adjusted R^2	0.005	0.003	0.02	0.026
Controls	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect. The specifications control for a dummy equal to 1 if subjects report they do not answer randomly at any point during the survey (Non-random responses); the average time spent in each period in the task (Time); the normalized score in the control questions (CQ score). All specifications control also for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

Table C.3: Treatment effects on dev_i^m

Dependent variable: dev_i^m	(1)	(2)	(3)	(4)
Panel A: T2 vs T1				
$Treat_i$	0.05603*	0.0522*	0.051*	0.0560*
	(1.68)	(1.74)	(1.70)	(1.88)
$Non-random\ responses_i$	-0.0480			-0.0525*
	(-1.54)			(-1.66)
$Time_i$		-0.0091***		-0.00967***
		(-3.35)		(-3.50)
$CQ\ score_i$			0.0604	0.11
			(0.72)	(1.28)
Observations	984	984	984	984
Adjusted R^2	0.005	0.01	0.003	0.013
Panel B: T3 vs T1				
$Treat_i$	0.232***	0.238***	0.230***	0.236***
	(7.86)	(8.02)	(7.73)	(8.01)
$Non-random\ responses_i$	-0.0665**			-0.0716**
	(-2.13)			(-2.27)
$Time_i$		-0.00494*		-0.00578*
		(-1.69)		(-1.96)
$CQ\ score_i$			0.121*	0.175**
			(1.43)	(2.02)
Observations	913	913	913	913
Adjusted R^2	0.073	0.071	0.070	0.078
Panel C: T4 vs T2				
$Treat_i$	0.170***	0.174***	0.170***	0.172***
	(5.91)	(6.04)	(5.92)	(5.96)
$Non-random\ responses_i$	-0.0181			-0.0207
	(-0.63)			(-0.71)
$Time_i$		-0.00288		-0.00326
		(-1.18)		(-1.29)
$CQ\ score_i$			0.108	0.108
			(0.78)	(1.32)
Observations	968	968	968	968
Adjusted R^2	0.033	0.034	0.033	0.034
Panel D: T4 vs T3				
$Treat_i$	-0.0113	-0.00994	-0.00534	-0.00634
	(-0.40)	(-0.35)	(-0.19)	(-0.23)
$Non-random\ responses_i$	-0.0358			-0.0401
	(-1.26)			(-1.41)
$Time_i$		-0.00099		-0.00151
		(-0.53)		(-0.79)
$CQ\ score_i$			0.130	0.152*
			(1.60)	(1.85)
Observations	897	897	897	897
Adjusted R^2	0.006	0.004	0.007	0.008
Controls	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect. The specifications control for a dummy equal to 1 if subjects report they do not answer randomly at any point during the survey (Non-random responses); the average time spent in each period in the task (Time); the normalized score in the control questions (CQ score). All specifications control also for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

Table C.4: Treatment effects on dev_i^r

Dependent variable: dev_i^r	(1)	(2)	(3)	(4)
Panel A: T2 vs T1				
$Treat_i$	0.0437	0.0455	0.0446	0.0495*
	(1.49)	(1.56)	(1.53)	(1.71)
$Non-random\ responses_i$	-0.0567			-0.0510*
	(-1.63)			(-1.65)
$Time_i$		-0.0087***		-0.0093***
		(-3.28)		(-3.45)
$CQ\ score_i$			0.0688	0.117
			(0.84)	(1.39)
Observations	984	984	984	984
Adjusted R^2	0.004	0.009	0.002	0.012
Panel B: T3 vs T1				
$Treat_i$	0.225***	0.230***	0.222***	0.229***
	(7.77)	(7.94)	(7.64)	(7.92)
$Non-random\ responses_i$	-0.0643**			-0.0699**
	(-2.10)			(-2.26)
$Time_i$		-0.0048*		-0.0057**
		(-1.69)		(-1.99)
$CQ\ score_i$			0.131	0.184**
			(1.57)	(2.26)
Observations	913	913	913	913
Adjusted R^2	0.071	0.069	0.069	0.077
Panel C: T4 vs T2				
$Treat_i$	0.164***	0.168***	0.164***	0.166***
	(5.87)	(6.00)	(5.88)	(5.92)
$Non-random\ responses_i$	-0.0180			-0.0205
	(-0.64)			(-0.72)
$Time_i$		-0.0028		-0.00319
		(-1.19)		(-1.30)
$CQ\ score_i$			0.0870	0.108
			(1.10)	(1.35)
Observations	968	968	968	968
Adjusted R^2	0.032	0.033	0.033	0.034
Panel D: T4 vs T3				
$Treat_i$	-0.0165	-0.0152	-0.0105	-0.0115
	(-0.60)	(-0.55)	(-0.38)	(-0.42)
$Non-random\ responses_i$	-0.0355			-0.0398
	(-1.28)			(-1.43)
$Time_i$		-0.00104		-0.00157
		(-0.57)		(-0.84)
$CQ\ score_i$			0.132*	0.154*
			(1.66)	(1.91)
Observations	897	897	897	897
Adjusted R^2	0.006	0.004	0.007	0.008
Controls	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect. The specifications control for a dummy equal to 1 if subjects report they do not answer randomly at any point during the survey (Non-random responses); the average time spent in each period in the task (Time); the normalized score in the control questions (CQ score). All specifications control also for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

Table C.5: Treatment effects on dev_i^s

Dependent variable: dev_i^s	(1)	(2)	(3)	(4)
Panel A: T2 vs T1				
$Treat_i$	-0.00178	-0.0017	-0.00196	-0.00172
	(-0.94)	(-0.89)	(-1.03)	(-0.91)
$Non-random\ responses_i$	-0.00236			-0.0022
	(-1.24)			(-1.15)
$Time_i$		-0.00049***		-0.0005***
		(-3.07)		(-2.88)
$CQ\ score_i$			-0.0058	-0.0035
			(-1.18)	(-0.69)
Observations	984	984	984	984
Adjusted R^2	0.004	0.009	0.004	0.009
Panel B: T3 vs T1				
$Treat_i$	0.0184***	0.0187***	0.0183***	0.0187***
	(7.85)	(7.98)	(7.82)	(7.98)
$Non-random\ responses_i$	-0.0039			-0.0039
	(-1.63)			(-1.61)
$Time_i$		-0.0032		-0.00029
		(-1.26)		(-1.23)
$CQ\ score_i$			-0.0005	0.00291
			(0.01)	(0.45)
Observations	913	913	913	913
Adjusted R^2	0.072	0.071	0.07	0.072
Panel C: T4 vs T2				
$Treat_i$	0.00602***	0.00607***	0.006***	0.0061***
	(3.54)	(3.57)	(3.54)	(3.57)
$Non-random\ responses_i$	0.0001			0.0001
	(0.08)			(0.09)
$Time_i$		-0.0001		-0.0006
		(-0.51)		(-0.5)
$CQ\ score_i$			-0.0002	0.0001
			(-0.04)	(0.02)
Observations	968	968	968	968
Adjusted R^2	0.019	0.019	0.019	0.017
Panel D: T4 vs T3				
$Treat_i$	-0.0064***	-0.0064***	-0.0063***	-0.0063***
	(-3.34)	(-3.32)	(-3.22)	(-3.24)
$Non-random\ responses_i$	-0.0001			-0.0012
	(-0.49)			(-0.6)
$Time_i$		-0.0001		-0.0001
		(0.22)		(0.06)
$CQ\ score_i$			0.00528	0.0056
			(-0.98)	(1.02)
Observations	897	897	897	897
Adjusted R^2	0.024	0.022	0.024	0.022
Controls	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect. The specifications control for a dummy equal to 1 if subjects report they do not answer randomly at any point during the survey (Non-random responses); the average time spent in each period in the task (Time); the normalized score in the control questions (CQ score). All specifications control also for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

Table C.6: Model Deviations and risk aversion

	(1) $Consumption_i$	(2) $Account\ Balances_i$	(3) dev_i^m	(4) dev_i^r	(5) dev_i^s
Panel A: T2 vs T1					
$Treat_i$ x No-Risk	-0.0701*	-0.105	0.0810	0.0799	0.00889**
	(-1.68)	(-0.51)	(1.34)	(1.35)	(2.36)
Observations	984	984	984	984	984
Adjusted R^2	0.047	0.027	0.002	0.001	-0.001
Panel B: T3 vs T1					
$Treat_i$ x No-Risk	-0.0381	0.0859	0.0440	0.0427	0.00590
	(-0.92)	(0.47)	(0.73)	(0.72)	(1.23)
Observations	913	913	913	913	913
Adjusted R^2	0.063	0.056	0.070	0.068	0.071
Panel C: T4 vs T2					
$Treat_i$ x No-Risk	0.0285	-0.0919	-0.0359	-0.0336	-0.00447
	(0.68)	(-0.48)	(-0.63)	(-0.61)	(-1.34)
Observations	968	968	968	968	968
Adjusted R^2	0.013	0.047	0.031	0.030	0.017
Panel D: T4 vs T3					
$Treat_i$ x No-Risk	0.00353	-0.103	-0.00652	-0.00402	-0.00183
	(0.08)	(-0.63)	(-0.11)	(-0.07)	(-0.41)
Observations	897	897	897	897	897
Adjusted R^2	0.029	0.010	0.006	0.006	0.053
Controls	Yes	Yes	Yes	Yes	Yes

Notes. OLS estimates of the treatment effect, interacted with a dummy that is one if the individual is willing to take no financial risks at all. All specifications control for age group, gender, income group, education attained, work status, residential area, marital status and religion. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

D Winsorized Regression

Table D.1: Treatment effects using winsorized sample

	(1)	(2)	(3)	(4)	(5)	(6)
	$Consumption_i$	$Account\ Balances_i$	x_i	dev_i^m	dev_i^r	dev_i^s
Panel A: T2 vs T1						
$Treat_i$	-0.120***	-0.183	-0.628	0.029	0.023	-0.003
	(0.018)	(0.107)	(0.710)	(0.027)	(0.026)	(0.002)
Observations	923	923	923.000	923	923	923
Adj. R^2	0.052	0.032	-0.003	-0.001	-0.001	0.004
Panel B: T3 vs T1						
$Treat_i$	-0.139***	0.573***	2.130**	0.226***	0.218***	0.018***
	(0.018)	(0.095)	(0.762)	(0.027)	(0.026)	(0.002)
Observations	854	854	854.000	854	854	854
Adj. R^2	0.072	0.058	0.011	0.081	0.080	0.071
Panel C: T4 vs T2						
$Treat_i$	-0.117***	0.728***	2.606***	0.202***	0.195***	0.008***
	(0.019)	(0.101)	(0.723)	(0.026)	(0.025)	(0.002)
Observations	904	904	904	904	904	904
Adj. R^2	0.044	0.061	0.013	0.060	0.060	0.032
Panel D: T4 vs T3						
$Treat_i$	-0.098***	-0.072	-0.225	0.003	-0.002	-0.012***
	(0.019)	(0.087)	(0.789)	(0.027)	(0.026)	(0.002)
Observations	835	835	835	835	835	835
Adj. R^2	0.030	0.013	-0.003	-0.001	-0.002	0.041

Notes. OLS estimates of the Treatment effect. All specifications control for age group, gender, income group, education attained, work status, residential area, marital status, and religion. Column (3) reports the estimates for depended variable X which is the arithmetic average of the per individual period-specific percentage deviation x_t. Robust standard errors in parentheses. $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$

E Consumption paths by treatment and demographic

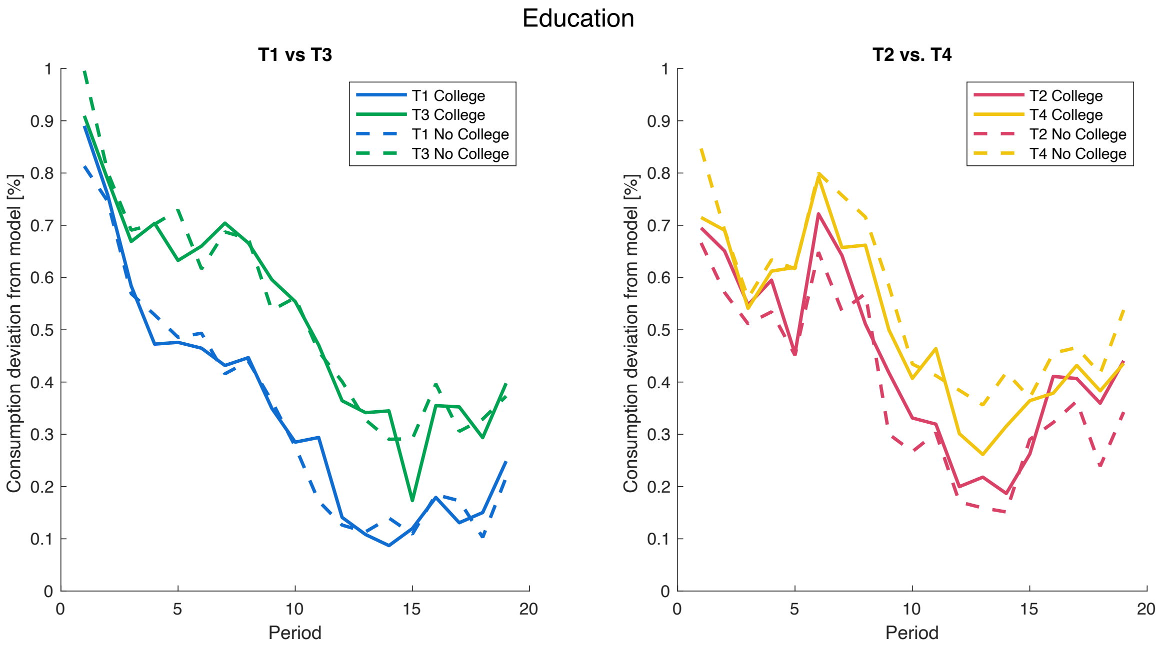

Figure E.1: Average consumption deviation from the model by education.

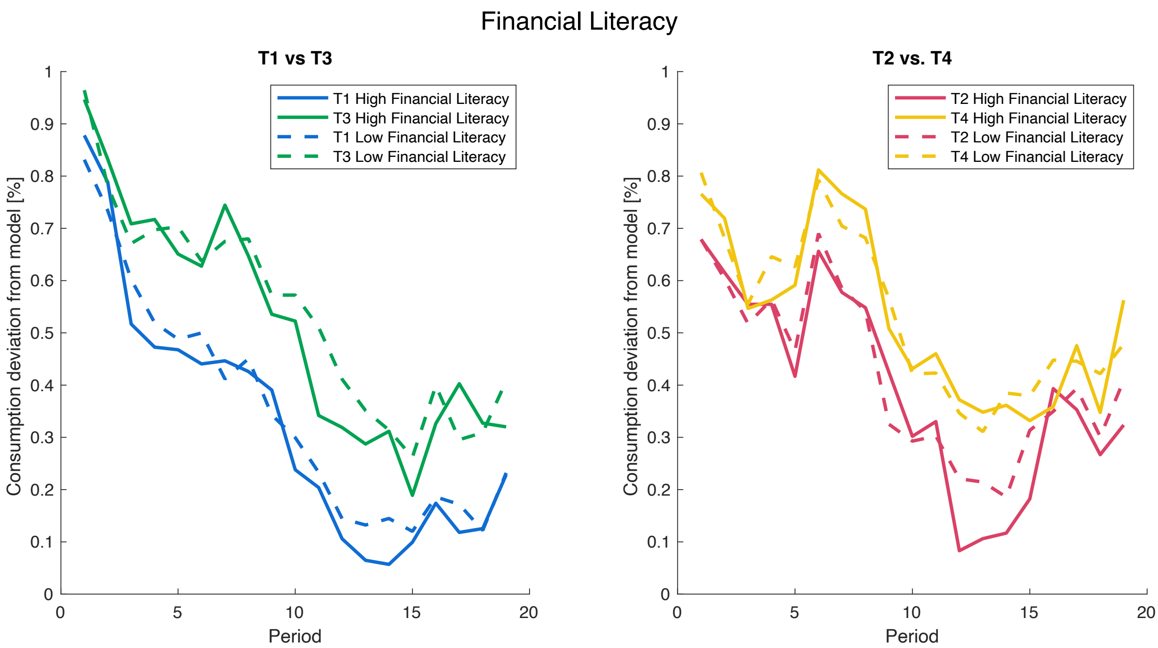

Figure E.2: Average consumption deviation from the model by financial literacy.

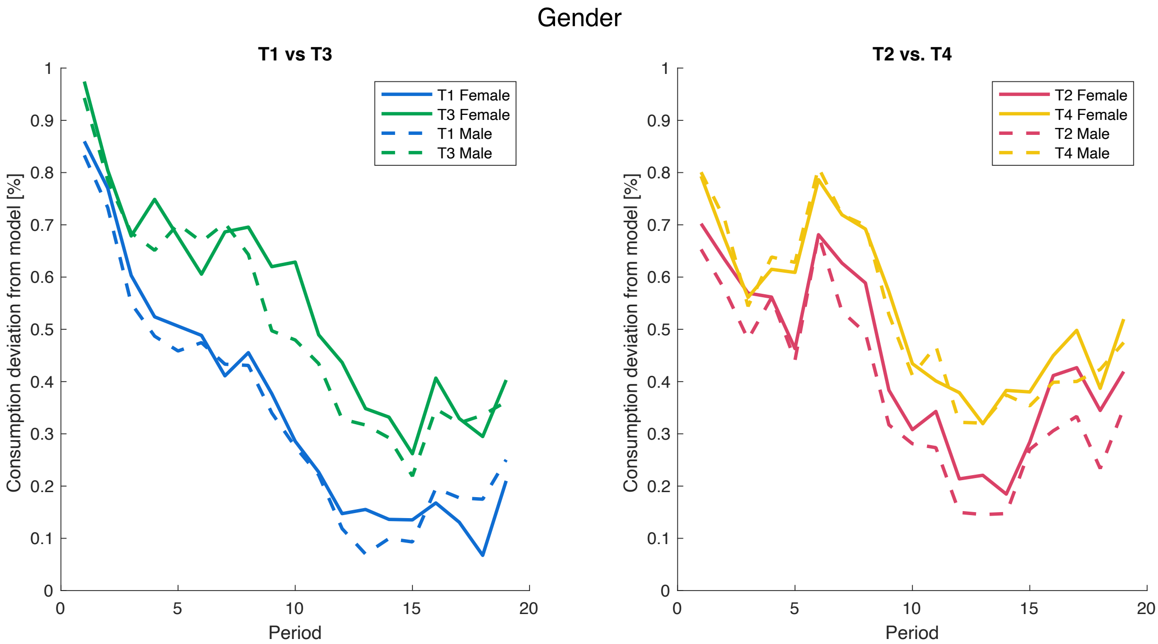

Figure E.3: Average consumption deviation from the model by financial gender.

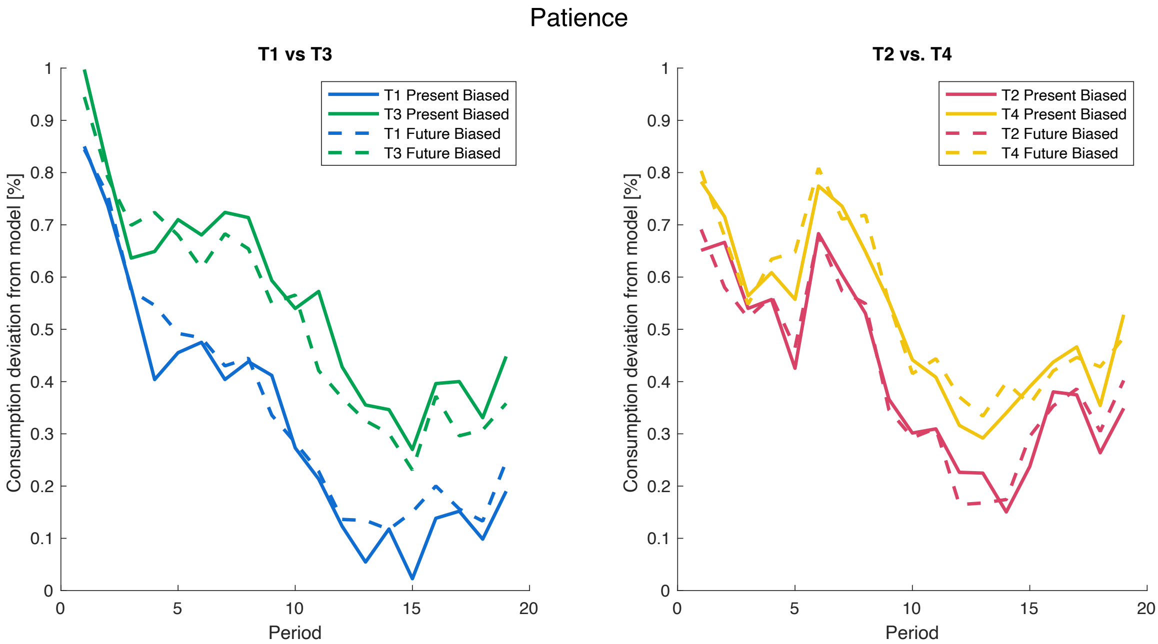

Figure E.4: Average consumption deviation from the model by financial patience.

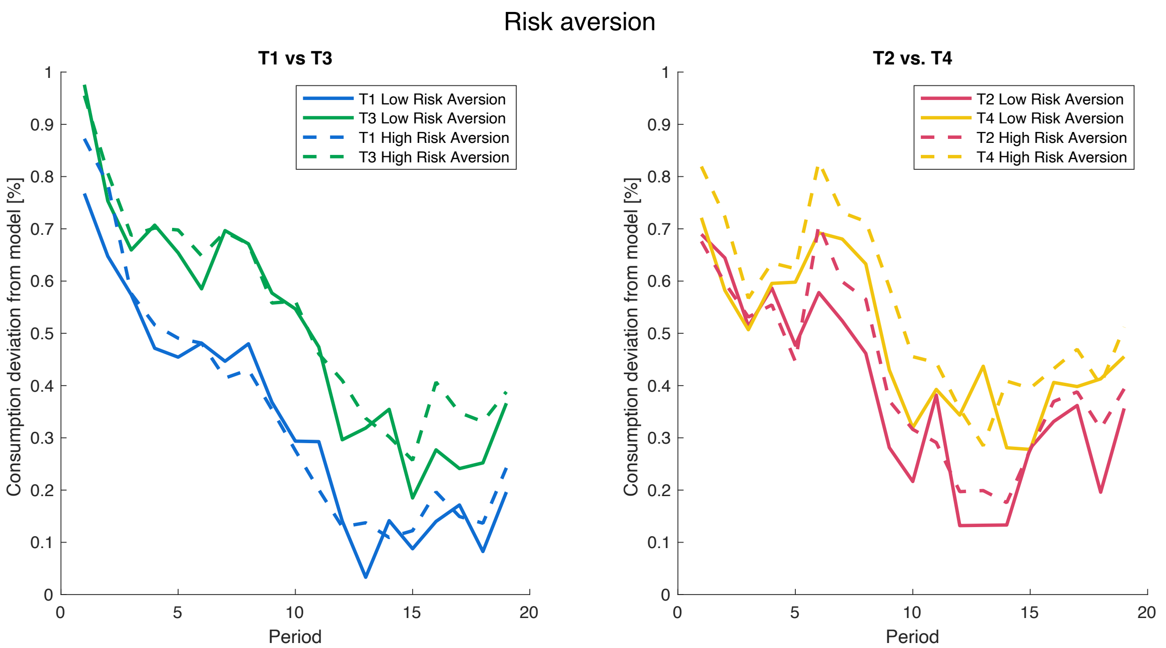

Figure E.5: Average consumption deviation from the model by financial risk aversion.