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COVID-19 Crisis: Are Preferences and Trading Behavior Affected During Extreme Events?

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COVID-19 Crisis: Are Preferences and Trading Behavior Affected During Extreme Events?*

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Abstract

This study shows that risk and time preferences are related to the severity of COVID-19 during the crisis, and they are related to economic outcomes. Using Convex Time Budgets (Andreoni and Sprenger, 2012) to simultaneously estimate risk and time preferences for 2240 individuals, we find that risk aversion and patience correlate positively with daily changes in national COVID-19 hospitalizations. Daily hospital changes are temporarily uncorrelated and a two standard deviation increase in the *daily* change in COVID-19 hospitalizations decreases the *annual* discount rate from 4.3% to 2.6%, increases the *annual* present-bias factor by 0.05, and increases risk aversion by 0.11. At the same time, the disposition effect declines when COVID-19 hospitalizations increase, as investors are more likely to hold on to winning stocks. This observation is in line with the increased patience and increased risk aversion. The Convex Time Budgets method is able to capture the time variation in preferences, but other experimental elicitation methods not.

Keywords: decision making under uncertainty, risk and time preferences, Convex Time Budgets, disposition effect

JEL Codes: D91, G11, G41

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I. Introduction

Are individuals' risk and time preferences affected during extreme events? And if so, do economic outcomes, such as trading behavior, relate to changes in preferences? Preferences form the foundation in almost any intertemporal-choice model. Standard models in economics and finance typically assume that individuals have stable and persistent preferences over time (Stigler and Becker, 1977). Research on the stability of preferences is conceptually at the heart of microeconomics. Changes in the stability of preferences have vital real-world consequences for economic outcomes, financial decision making, policy options and welfare analyses.

The literature on the relation between preferences, economic behavior, and exogenous shocks such as natural disasters, violent conflicts, economic crises and pandemics is relatively new, but growing rapidly (Chuang and Schechter, 2015; Schildberg-Hörisch, 2018; Drichoutis and Nayga, 2021). We contribute to this literature by examining empirically how individuals' preferences in financial-economic decision making develop *during* an exogenous shock and, at the same time, whether economic behavior is related to changes in preferences. The exogenous shock we study is the COVID-19 crisis, i.e., a pandemic, and the economic behavior we study is the disposition effect. The disposition effect is the stylized fact that paper losses are realized less than paper gains (Odean, 1998). Besides, we contribute to the literature by studying whether the disposition effect is stable *during* an exogenous shock (Bernard et al., 2022). Overall, we specifically contribute to the literature (i) by studying how preferences and economic behavior develop over time during a crisis rather than by means of a before-after analysis based on waves, (ii) by using multiple elicitation methods to measure preferences, and (iii) by analyzing economic behavior.

We use experimental approaches in two surveys to elicit preferences and trading behaviour on a daily basis during the COVID-19 crisis. We fielded our surveys during March 2020 (i.e., emergence COVID-19 and first lockdown) and December 2020 (i.e., second lockdown) using the Longitudinal Internet Studies for the Social Sciences (LISS). LISS yields a representative sample of the Dutch population. The first part of each survey elicits risk and time preferences, and the second part of each survey elicits the disposition effect. Our main measure of risk and time preferences is based on the Convex Time Budgets (CTB) approach of Andreoni and Sprenger (2012a) to simultaneously elicit and estimate preferences. We estimate risk

aversion, present bias, and patience, and we control for probability weighting. Using simpler and coarser methods (Dave et al., 2010) we also independently measure (i) risk aversion by the lottery task of Eckel and Grossman (2008), (ii) present bias and patience by the matching task of Rieger et al. (2015) and Wang (2017), and (iii) we use qualitative statements to measure these preferences. The second part of the survey is a trading experiment building upon the design of Ploner (2017) to measure the disposition effect. By combining preferences with trading behavior, we are able to study how elicited preferences are related to observed economic outcomes during an exogenous shock.[1]

In the event of COVID-19, people may experience fear. Guiso et al. (2018) find that individuals react to fear for an extreme negative exogenous shock (i.e., a horror movie and the financial crisis of 2007-2008), and Cohn et al. (2015) find that subjects primed with a financial bust are more fearful and risk averse. Faced with a negative shock, individuals are affected by fear that alters their willingness to take risks and to save for the future. Even if individuals do not experience the shock directly themselves (i.e., get infected or hospitalized by COVID-19), fear can be activated by watching and reading news about the exogenous shock (Guiso et al., 2018). Our experiments took place during the emergence of COVID-19 and the following lockdowns, times in which fear could be born naturally as there were growing concerns about the uncertain future. National COVID-19 hospitalization numbers were communicated daily on the news and via push notifications on mobile phones. Hospitalizations were especially salient, because there was a general concern that hospitals might reach full capacity with amongst others a potential health crisis consequently.[2] So, we measure the severity of COVID-19 by the relative change in hospitalizations and we argue that a potential channel for our findings is the emotion of fear, in line with Cohn et al. (2015) and Guiso et al. (2018).

Our results show that risk and time preferences strongly correlate with the severity of the COVID-19 crisis, indicating instability of preferences during an exogenous shock. Specifically, if daily national COVID-19 hospitalizations in The Netherlands increase, then risk aversion, time consistency, and long-term patience increase as well. Thus, individuals

[1]We study trading behavior in our paper, but it could actually have been any other economic decision. We merely use the observed trading behavior to demonstrate how preferences relate to financial-economic decision making.

[2]We do not use COVID-19 infected cases or deaths, because test capacity was absent or too low and deaths lagged behind the actual COVID-19 situation.

are less willing to take financial risks and prefer to save more for the future after an increase in the daily COVID-19 hospitalizations. The effect on time preferences is economically large: a two standard deviation increase (approximately 75%) in *daily* COVID-19 hospitalizations, decreases the *annual* discount rate from 4.3% to 2.6%, increases the *annual* present-bias factor by 0.05, and increases risk aversion by 0.11.

The increase in risk aversion is consistent with the fear-based mechanism and the findings of Cohn et al. (2015) and Guiso et al. (2018). Additionally, Meier (2022) identifies fear as a significant correlate with within-person increases in risk aversion, using a large panel dataset, and Haushofer and Fehr (2014) finds that fear decreases the amount invested in a risky asset. The literature on the connection between time preferences and emotions is limited (Meier, 2019). Experimental settings, especially in an investment context, regarding fear and time preferences are to the best of our knowledge absent. Given that our increase in risk aversion is consistent with the fear-based mechanism, we argue that we also shed light on the effect of fear on time preferences. In line with fear regarding the uncertain future, a potential motive for an increase in patience and time consistency might be precautionary savings for the future.

Contemporaneously with changes in preferences, the disposition effect decreases if there is an increase in daily COVID-19 hospitalizations. During the disposition effect experiment, investors are asked to sell an asset immediately or to hold it for one more year after they have observed the gains and losses on their chosen assets. We find a decrease of -10.58% in immediately selling assets that experienced a gain if COVID-19 hospitalizations increase. Consistent with investor's higher risk aversion and higher patience during rising COVID-19 hospitalizations, investors prefer to hold on to winning assets relatively more, possibly as a buffer for the uncertain future through the motive of precautionary savings. Present bias plays no significant role in the selling behavior. So, this suggests that the changes in the disposition effect during the crisis are at least partially driven by time-varying risk aversion and patience, through the domain of selling gains.

Our results are robust to alternative specifications. Decomposing within and between effects allows us to take into account unobserved individual specific heterogeneity and confirms our results. Moreover, our results are not driven by weekly seasonality effects in hospitalizations nor by changing beliefs in life expectancy. We also study the behavior of preferences with changes in COVID-19 hospitalizations on a province level rather than the national level.

These province-level estimations yield insignificant results, suggesting that fear from the national news concerning COVID-19 might indeed be the mechanism. We also provide some insight into how preferences develop during the crisis, that is, into differences between the start of the COVID-19 crisis in March 2020 and 10 months later when the COVID-19 crisis manifested itself tightly in December 2020.[3] We find that the level of risk and time preferences is statistically similar in both months, and the sensitivity of preferences to COVID-19 hospitalizations is similar in both months.

We find that cognitive simpler experimental measures, both quantitative and qualitative, are less able to capture the instability of preferences compared to the CTB method. The more cognitive demanding but finer CTB method might perform better in capturing preferences, especially in a developed country such as The Netherlands because the population on average exhibits high numerical skills (Dave et al., 2010; Chuang and Schechter, 2015). Other experimental measures might give too broad ranges for capturing the daily effect of the crisis on preferences, or these methods make too restrictive simplifying assumptions such that these measures have overall lower accuracy (Dave et al., 2010).

Our contribution to the literature is threefold. First, we study how preferences develop *during* an exogenous shock. The review papers of Chuang and Schechter (2015) and Schildberg-Hörisch (2018) classify shocks in natural catastrophes (i.e., earthquakes, tsunami's, famines, floods, droughts, hurricanes and epidemics), violent conflict (i.e., wars and political violence) and economic shocks (i.e., macroeconomic conditions, financial crises, job search, income and education). The COVID-19 crisis is a combination of a pandemic and an economic shock. Research on the effects of the COVID-19 crisis on preferences finds divergent and inconclusive empirical results. Studies suggest that the COVID-19 crisis increases risk aversion (Bu et al., 2020) for men only (Lohnmann et al., 2020), decreases risk aversion (Ikeda et al., 2020), has no effect on risk preferences (Angrisani et al., 2020; Drichoutis and Nayga, 2021; Bokern et al., 2021), or has no consistent effect on risk preferences (Shachat et al., 2020); decreases impatience for men (Lohnmann et al., 2020), or has no effect on time preferences (Drichoutis and Nayga, 2021; Bokern et al., 2021). [4] Additional research is needed to understand theoretical predictions about the circumstances when we

[3]The crisis in The Netherlands started roughly 6 March 2020 with the first COVID-19 death, 1 April 2020 1173 deaths, and 31 December 2020 the total number of COVID-19 deaths was 11843.

[4]Drichoutis and Nayga (2021) give an overview of papers studying the stability of preferences during the COVID-19 pandemic.

should expect an increase or decrease in preferences.

However, all these studies analyze the effect of the COVID-19 crisis by means of surveys before and after the outbreak, or by means of short waves during the crisis (i.e., a few days to respond to the questionnaire within a specific time interval).[5] Typically, researchers study whether preferences are different from one wave to another. We differ here from the previous studies, because we study how preferences develop over time within and during the COVID-19 crisis itself by measuring preferences over a relatively long period. We find that preferences change with respect to the severity of the COVID-19 crisis, but by comparing aggregate preference levels between both our two waves (i.e., March 2020 and December 2020) we observe no differences in risk and time preferences. The potential mechanism behind our findings relates to systematic but temporary variations in preferences due to temporary variations in the emotion of fear (Schildberg-Hörisch, 2018).

Second, our article uses multiple experimental methods to measure preferences during the COVID-19 crisis. While we see that there are many other papers studying the stability of preferences, most of these focus only on one type of preference (with a majority studying risk preferences) or one type of elicitation method. We contribute to the literature here by eliciting and estimating risk and time preferences simultaneously including beliefs, and by studying the methodological stability of preferences over multiple elicitation methods such as Eckel and Grossman (2002), Andreoni and Sprenger (2012a), and Rieger et al. (2015). Despite its economic importance, especially relatively little is known about the stability of time preferences (Meier and Sprenger, 2015), and the relation between fear and time preferences (Meier, 2019).

The paper closest to our main measure is Lohnmann et al. (2020), as they also use the CTB method. However, the authors only use it to measure time preferences (i.e., present bias and long-term patience), since they measure risk preferences independently by the methods of Eckel and Grossman (2002) and Gneezy and Potters (1997). We simultaneously elicit and estimate risk and time preferences with CTB including a correction for probability weighting (Potters et al., 2016) and risk capacity through the channel of background income in our preference estimations.[6] Compared to the previous experimental literature (e.g., see the

[5] Another possibility is a long-term view such as life-cycle or cohort effects on preferences as studied by Malmendier and Nagel (2011), but we abstain from this in our current research.

[6] Rather than assuming two separate mental accounts for experimental and real-life earnings, we assume that participants integrate experimental earnings with real-life earnings in their survey decisions.

review of Andersen, Harrison, Lau, et al., 2014), our CTB setup uses long horizons up to 6 years with large stakes of €10.000 and a large non-student sample representative for the Dutch population. Lohnmann et al. (2020) study a smaller sample ($N = 793$) of Chinese students in Beijing using waves before and after the outbreak of COVID-19. Our approach arguably yields more individual heterogeneity in the exposure to the crisis than studying students only.

Third, our research contributes to the literature regarding (in)stability of the disposition effect (Bernard et al., 2022), and the relation between preferences and the disposition effect. Existing studies implicitly assume the disposition effect to be unaffected by market cycles, while Bernard et al. (2022) find that the disposition effect is higher during bursts than booms. We add to this literature by showing that the disposition effect varies over time as it is sensitive to fluctuations in preferences, possibly caused by fear. Additionally, we show that time-varying risk aversion and time-varying patience form at least a part of the explanation for the variation in the disposition effect during the COVID-19 crisis such that we provide additional evidence for asset pricing models with time-varying risk aversion (Campbell and Cochrane, 1999).

The rest of the paper is organized as follows. Section 2 describes the experimental designs. Section 3 presents the estimated preferences and how they develop during the COVID-19 crisis. Section 4 confirms the existence of a disposition effect and shows the time variation during the crisis. It also presents the relation between preferences and trading behavior. Section 5 concludes the paper.

II. Methodology

We adopt an experimental approach in a survey to elicit preferences and the disposition effect. The first part of the survey elicits risk and time preferences. Our main measure of risk and time preferences is based on the CTB approach (Andreoni and Sprenger, 2012a). We additionally use simpler quantitative and qualitative methods to elicit risk and time preferences. The second part of the survey uses the experimental setup of Ploner (2017) to investigate the disposition effect.

This section describes the elicitation of preferences and trading behavior, including the experimental procedure. We then describe our sample, and the COVID-19 data. We conclude

with the preference parameter estimation based on the CTB.

A. Elicitation of preferences

In the first part of the survey, we use the CTB (Andreoni and Sprenger, 2012a) to measure risk aversion, present bias and patience simultaneously. We also measure these preferences independently. To measure risk aversion separately, we use the Eckel and Grossman (2008) lottery task and a qualitative question from the Dutch Central Bank Household Survey (DHS). To measure present bias and patience separately, we use the matching task from the INTRA study of Rieger et al. (2015) and qualitative questions from Gathergood (2012).

Simultaneous elicitation

An important advantage of the CTB is that it allows to measure risk and time preferences simultaneously. For this reason, we avoid the assumption of linear utility and we avoid upward biased discount rate estimates if true utility is concave (Andersen, Harrison, Lau, et al., 2008) We simultaneously measure risk aversion, present bias and patience, and we also correct for probability weighting. Therefore, our approach is a combination of the original approach of Andreoni and Sprenger (2012a) and Potters et al. (2016). Andreoni and Sprenger (2012a) measure risk aversion, present bias and patience, while Potters et al. (2016) measure risk aversion, patience and probability weighting.

The simultaneous elicitation method asks individuals to allocate an initial budget $m =$ €10.000 between payments, available at two points in time: an early payment at time t and a delayed payment at time $t + k$. The early payment is either today $t = 0$ or next year $t = 1$, and the late payment is delayed by either one year $k = 1$ or five years $k = 5$. Subjects receive an interest rate r on delayed payments, which varies between 0% to 800% interest on an annual basis. The allocations must be made such that their budget constraint is satisfied, i.e., the early payment and the present value of the delayed payment must equal the initial budget m. Early payments are certainly paid (i.e., payment probability 1), but delayed payments have a payment probability p_{t+k} of 0.5, 0.75 or 1.

Individuals make 20 consecutive CTB decisions between early and delayed payments. Our method consists of five different decision sets, and within each set we have four different interest rate scenarios. The first three choice sets use $t = 0$ and $k = 1$, and the three choice

sets differ in the delayed payment probability $p_{t+k} = \{0.5, 0.75, 1\}$. The fourth choice set uses $t = 0$ and $k = 5$, and the fifth choice set uses $t = 1$ and $k = 5$, both sets having certain early and late payment probabilities. Table 10 in Appendix A presents an overview of our experimental design.

Differences between the early payment dates t (i.e., front-end delay) elicit present bias, while differences between the delayed payment dates $t + k$ (i.e., back-end delay) elicit long-term patience. Sensitivity to variation in the interest rates identifies curvature of the utility function, while variation in the payment probabilities enables the measurement of probability weighting. Figure 4 summarizes aggregate choice behavior in the CTB. We plot the mean and median allocated Euros at the early payment, c_t, against the gross interest rate, $(1+r)$, for each of the five decision sets.

The amount of Euros allocated to the early payment declines monotonically with the interest, showing that our participants are willing to wait for a late payment when interest rates are higher. Additionally, the amount of Euros allocated to the early payment increases when the late payment probability is lower. Both observations reveal that choices respond to changing interest rates and payment probabilities in an intuitive predicted way. Evidence for strong present bias would be observed if the earlier allocated Euros are higher when $(t = 0, k = 5, p_{t+k} = 1)$ compared to $(t = 1, k = 5, p_{t+k} = 1)$. We observe that the early allocated budgets for these decision sets are roughly constant at each interest rate, indicating not too much evidence for strong present bias.

To estimate risk and time preferences, we identify the experimental allocated payments as solutions to standard intertemporal optimization problems. These solutions are supposed to be functions of our parameters of interest (present bias, discounting, risk aversion and probability weighting), and experimentally varied parameters (interest rates, delay lengths and payment probabilities). Given assumptions on the functional form of utility, the nature of discounting, and the nature of probability weighting, our experimental tasks provide a natural context to jointly estimate individual.

We assume that the agent has a standard CRRA utility function with curvature parameter γ, that the agent is a quasi-hyperbolic discounter with $\beta - \delta$ preferences, and that the agent distorts probabilities according to a simple Prelec weighting function with parameter η. We estimate time preferences, i.e., present-bias factor β and long-term discount factor δ, and we estimate risk preferences, i.e., risk aversion γ and probability weighting η.

As such, we combine the CTB approaches of Andreoni and Sprenger (2012a) and Potters et al. (2016). Andreoni and Sprenger (2012a) estimate present bias, patience, and CRRA curvature, while Potters et al. (2016) estimate patience, CRRA curvature, and probability weighting. Additionally, we also control for background consumption through annual income in our estimations of preferences. Appendix B provides more details on the estimation.

Independent elicitation

In addition to the CTB method described above, we measure risk aversion, present bias and patience independently by using arguably simpler methods (Dave et al., 2010). We measure risk aversion with a lottery task as developed by Eckel and Grossman (2002) and Eckel and Grossman (2008). Table 11 in Appendix A shows the tasks.

The task involves a single choice among six gambles, all with probability 0.5 of winning a higher prize. The range of gambles includes a safe choice involving a sure payoff of €5600 with zero risk. Then, moving from Gamble 1 to 5, the gambles increase in both expected return and risk (standard deviation). Gamble 6 involves only an increase in risk, with an expected return equal to Gamble 5. More risk-averse subjects choose low risk, low return gambles; risk-neutral subjects choose Gamble 5 or 6; risk-seeking subjects choose Gamble 6. This simple but coarser method only allows categorization of individuals into six risk categories, whereas the more complex but finer CTB allow categorization of individuals' risk aversion on a continuous scale.

We measure present bias and patience together, using a matching task from Rieger et al. (2015) and Wang (2017), which was originally inspired by Frederick (2005). Table 12 in Appendix A shows the task. The task asks participants to give an amount for a delayed payment which makes them indifferent with an immediate payment of €10.000. Participants give an amount €X_1 for a delayed payment of 1 year and an amount €X_5 for a delayed payment of 5 years. Assuming risk neutrality, the present-bias factor and discount factor can together be inferred from these two responses.[7]

Finally, we use three qualitative statements to measure financial risk-taking behavior, financial impulsiveness and financial patience. These statements proxy respectively for risk aversion, present bias and patience. Subjects answer the questions on a 7-point Likert scale

[7]Assuming risk neutrality, the two matching questions can be represented as two equations with two unknowns: $10000 = \beta\delta X_1$ and $10000 = \beta\delta^5 X_5$, which can simply be solved for β and δ.

from strongly disagree to strongly agree. The risk taking questions comes from the Dutch Central Bank Household Survey, and the impulsiveness and patience questions are taken from Gathergood (2012). We also ask the subjects a question about their trust in insurers. Table 12 in Appendix A shows the qualitative questions.

B. Measuring the disposition effect

In the second part of the survey, we select a random fraction of our total sample to participate in the trading experiment. Only those individuals that are head of the household and make the main financial household's decisions are eligible. The trading experiment is specifically designed to measure the disposition effect. The disposition effect is the well-known stylized fact that paper losses are realized less than paper gains (Odean, 1998). We implement the experimental method developed by Ploner (2017) to assess the existence of a disposition effect.

Subjects in the experiment make four investment choices regarding risky products.[8] All products are simple 50/50 win/loss gambles. The win and loss outcomes differ across the four products, and outcomes follow from a coin toss (heads or tails). Table 13 in Appendix A presents an overview of the products.

The investors in our experiment are given an endowment of €10.000 for each of the four choices. In each choice, the investor must choose to invest the complete endowment in one product. For example, in choice 1 the investor chooses to invest in product A or in product B, in choice 2 the investor chooses to invest in product C or product D, and so forth. The investors are aware that products A, C, and E warrant a win if the outcome of a coin toss is heads, and a loss otherwise. The opposite holds for products B, D, and F. As such, the assets are ex-ante identical and perfectly anti-correlated. The investors are unaware of the sizes of the gains or losses for the products in choices 1 to 3. Choice 1 always yields a product with a negative expected return, while choice 3 always yields a product with a positive expected return.

In choice 4, the investor chooses to invest in product X or product Y. Product X has a lower expected return and higher standard deviation than asset Y. X warrants a win if the outcome of a coin toss is heads, and Y warrants a win if the outcome of a coin toss is tails.

[8] We deliberately use the neutral wording of 'product' in the experiment to avoid framing.

The investors are aware of the sizes of the gains and losses when choosing between product X and Y in choice 4.

After the investors have invested in their four chosen products, we toss a coin. Investors become aware of the outcome of the first coin toss, and each investor must choose whether she wants to hold the product for one year or whether she wants to sell the product immediately. If the investor holds her chosen product, we (hypothetically) perform a second coin toss next year and earnings are computed as in the first coin toss. If the investor sells her chosen product, the earnings after the first coin toss are immediately paid to the subject.

This setting yields a straightforward measure of the disposition. Simply compare the fraction of sell choices among those winning and those losing after the first coin toss. Evidence for a disposition effect would be that investors sell their products more after gains than after losses (i.e., the sell rate after gains is higher).

C. Experimental procedure

Upon starting the online experiment, subjects read through the instructions for the CTB experiment. The instructions indicate that the budget should be allocated to an early payment or a later payment. The instructions state that there is no inflation. We also avoid arbitrage opportunities by stating that the allocated budget could be consumed or saved in a deposit account without interest, but could not be used to invest or to payoff a mortgage.[9]

Figure 2 in Appendix A shows a screenshot of a decision set in the experiment. Subjects are told to divide an amount of €10.000 between the early payment today (i.e., no front-end delay) and a late payment next year. The likelihood that the late payment is paid equals 100% in this particular decision screen. The subjects have to make four budget decisions presented in order of increasing interest rates from 1.00 to 4.50. In subsequent decision screens, the varying early and later payment dates are emphasized by <u>underlining</u> the dates, and probabilities of uncertain late payment were <u>underlined</u> as well. Subjects face a total of five such decision screen sets, such that they complete 20 decisions.

After the 20 CTB decisions, subjects answer the questions regarding the independent elicitation methods. They additionally answer questions about their estimated life expectancy and financial literacy.

[9]See Andreoni and Sprenger (2012b) and Augenblick et al. (2015) for a detailed discussion on arbitrage opportunities in discounting studies.

Finally, the randomly selected household heads start with the disposition effect experiment by reading through the instructions. The subjects read that they themselves are going to invest €10.000 each time in several products. These products yield a gain or loss, which depends on the outcome of toin cosses. The instructions state that they will invest three times: once in product A or B, once in product C or D, and once in product E or F. The instructions end by stating that for each investment a coin will be tossed. After these three choices and realizations of outcomes, the subjects are told to invest once more €10.000 in product X or Y and that their chosen product can make a gain or loss, depending on a coin toss.

D. Data

Here we firstly describe our sample. Then, we sketch the COVID-19 timeline and we introduce our main measure for studying time variation in preferences and trading behavior.

Sample

For the online experiment, we use the LISS (Longitudinal Internet Study in the Social Sciences) panel gathered by CentERdata in The Netherlands. The panel is recruited through address based sampling (no self-selection), and households without a computer and/or internet connection receive an internet connection and computer free of charge. This household panel, representative for the Dutch population, receives online questionnaires each month on different topics. When respondents complete a questionnaire, they receive a monthly incentive. Our experiment is not incentivized based according to the experimental answers of the subjects, which avoids the need for complex equalization of payments, transaction costs and payment confidence. Some researchers argue that answer-based incentives in economic experiments lead to more truthful reveal of preferences, however Cohen et al. (2020) in their overview study find little evidence for systematic differences between incentivized and unincentivized time preference experiments. More specifically, Potters et al. (2016) find little differences between financially incentivized and hypothetical decisions in their CTB experiments.

We invite a total of 2998 LISS panel members between the ages of 40 and 70 during March 2020 and December 2020. A total of 2631 panel members responded during both months, so

Table 1: **Summary statistics.** *Partner* equals 1 if the participant lives together with a partner (married or unmarried). *Education low*, *Education medium* and *Education high* are education dummies, and the ordering is based on the categories of Statistics Netherlands. *Income* is individual monthly after-tax income. $1-year\ life\ expectancy$ and $5-year\ life\ expectancy$ are self-reported probabilities for reaching at least your current *age* plus 1 year and your current *age* plus 5 years, respectively. $\Delta Hosp$ is the daily percentage change in national hospitalizations.

	Mean	St. dev.	Min	Max	N
Male	0.48	0.50	0.00	1.00	2240
Age (years)	56.61	8.56	40.00	70.00	2240
Partner	0.71	0.45	0.00	1.00	2240
Education low	0.25	0.43	0.00	1.00	2240
Education medium	0.37	0.48	0.00	1.00	2240
Education high	0.38	0.48	0.00	1.00	2240
Income (€)	1884	1143	0.00	10000	2240
$\Delta Hosp$	16.02	36.49	-52.63	144.44	2240
1-year life expectancy	93.02	15.61	0.00	100.00	2239
5-year life expectancy	85.36	18.36	0.00	100.00	2239

we have a response rate of about 88% across both months. We drop 385 individuals because they have no reported income, they did not fully complete the CTB, or they made exactly the same allocations — being strictly corner solutions also — in each CTB decision. We require to have individual's income, because we use it as a proxy for background consumption in the estimation of the CTB preference parameters. Incomplete CTB experiments and individuals that did not alter their decision from specific corner solutions provide insufficient variation for the calculation of preference parameters. Thus, similar to Andreoni, Kuhn, et al. (2015) we drop these observations. We additionally drop 6 individuals because we require to have data on gender, age, partner status, and education as these function as main controls in our analysis. Overall, we drop a total of 391 individuals such that our final sample contains 2240 subjects.

Table 1 presents descriptive statistics for the main characteristics of our sample. The male to female ratio is nearly 50%, and the average age is 56.61 years. The sample is roughly uniformly distributed across education levels, 38% has a degree from a higher vocational education or a university. The average individual monthly after-tax income is €1884. Participants on average estimate that they have 93% chance of surviving one more year and

85% chance of surviving the next five years. Respondents took on average 15 minutes to complete the survey.

COVID-19

The experiment took place in the period between 2 March 2020 and 31 March 2020, and between 7 December 2020 and 29 December 2020. We have 1997 observations during March, and 243 observations during December. The observations in December are lower, because we only invited the household heads that participated in the trading experiment in March as well. The average amount of respondents per day during March is 67 and during December 11. Figure 3 in Appendix A shows the number of daily observations throughout March and December.

Our first survey (i.e., in March 2020) took place during the emergence of the COVID-19 crisis in The Netherlands, the peak of global stock market crashes, and severe lockdown measures in The Netherlands. On March 1 The Netherlands had 0 deaths, 10 confirmed cases and no lockdown measures, while April 1 The Netherlands had 1.173 deaths, 13.614 contaminations, and a so-called intelligent lockdown. Our second survey (i.e., in December 2020) took place during the second lockdown in The Netherlands, and the total number of COVID-19 deaths was 11.843 at 31 December 2020.

To study how extreme events, in our case COVID-19, affect preferences and trading behavior, we use the daily percentage change in national COVID-19 hospitalizations in The Netherlands ($\Delta Hosp$) to proxy for the severity of the exogenous shock. We download the national hospitalizations from the website of the National Institute for Public Health and the Environment, based on the data reported by the Public Health Service (GGD). To download the hospitalizations on a province level, we use the National Intensive Care Evaluation (NICE) reported numbers. If $\Delta Hosp > 0$, then the number of COVID-19 hospitalizations from day $t-1$ to day t is increasing. Table 1 shows that, on average, daily COVID-19 hospitalizations are increasing during March 2020 and December 2020. The minimum and maximum show that the daily percentage change in hospitalizations ranges between roughly -53% and +144%. Table 15 in Appendix A shows that on average the increase in COVID-19 hospitalizations is about 3 percentage points higher in March 2020 (i.e., Panel B) than December 2020 (i.e., Panel C).

We hypothesize that the COVID-19 crisis affects preferences and trading behaviour

through changes in emotions because of an extreme event. Based on the findings of Guiso et al. (2018), we consider the possibility that individuals react to fear for an extreme negative exogenous shock. Even if individuals do not experience the shock directly themselves (i.e., get infected or hospitalized by COVID-19), fear can be activated by watching and reading news about the COVID-19 crisis. During March and December 2020, national infection and hospitalization numbers were communicated daily on the news and via push notifications on phones.

We use hospitalizations rather than the number of infected individuals, because test capacity during especially the emergence of COVID-19 in March 2020 was absent or too constrained and, therefore, forms an imperfect measure of the severity of the crisis. Another possibility would be to use COVID-19 death rates, however deaths severe lag behind the actual situation and, therefore, is imperfect as well. We use hospitalizations because that was the most salient number in the COVID-19 crisis because citizens, the government, and institutions had the fear that hospitals would become overcrowded. We use the percentage change in hospitalizations rather than levels, since COVID expanded exponentially. In the beginning of March 2020 the absolute level of hospital admissions was low, but the impact of the large relative hospital changes was big. Figure 1) graphs the daily percentage changes in hospitalizations and shows that these changes are temporarily uncorrelated.

III. Results preferences

This section presents evidence that the estimated risk and time preferences are related to the severity of COVID-19 during the crisis by means of daily changes in national hospitalizations. Our results remain when we take individual specific unobserved heterogeneity into account. Furthermore, we study whether preferences behave differently in the months during the crisis, and whether preferences react to COVID-19 hospitalizations on a province level. Finally, we present evidence that the simpler, independent elicited preferences do not show time variation.

A. Aggregated preferences

Table 2, Panel A, shows the estimated risk and time preferences for the population. The preferences are aggregated, meaning that for each subject we estimate the preferences by (10) and, then, we compute the 25th, 50th and 75th percentiles of the population's distribution. Echoing the results in Figure 4, we do not find evidence for strong present bias at the median. We estimate a median present-bias factor β of 0.968. The median annual discount factor δ equals 0.958, which yields an annual discount rate of 4.3%.[10] The median CRRA risk aversion γ equals 1.520, implying that respondents behave risk averse. Finally, we estimate a probability weighting parameter η strictly larger than 1, which implies that respondents underweight probabilities larger than 50%. Overall, the 25th and 75th percentiles reveal heterogeneity in risk and time preferences.

Our estimated present-bias factor is similar to the value of Augenblick et al. (2015), who estimate $\beta = 0.97$ in the financial domain using a CTB design. Our estimated annual discount rate is similar to prevailing market interest rates and lower than most previous studies. Frederick (2005) show in their overview article that estimates of annual discount rates in the literature over hundred percent are not uncommon. Cheung (2020) estimates an annual discount rate of 62.2% in the discounted utility model, when controlling for CRRA curvature. Andreoni and Sprenger (2012a) estimate an annual discount rate of 27.5% in their CTB design, when controlling for CRRA curvature and present bias. Our estimated CRRA risk aversion parameter γ is similar to the value of Balakrishnan et al. (2020), they estimate a CRRA risk aversion parameter $\gamma = 1.4$ using also a CTB design with individually varying background income and two-limit Tobit regressions. Finally, our finding that subjects underweight higher probabilities is consistent with prospect theory (Tversky and Kahneman, 1992) and our estimate is in line with the estimated value of Potters et al. (2016) who also use a CTB design, late payment probabilities larger than 50% and a simple Prelec weighting function.

A potential reason for our lower, but plausible, annual discount rate is the magnitude of the experimental budget and the long-term decision horizon. Thaler (1981) already shows that discount rates drop sharply as the size of wealth increases, which is known as the magnitude effect, and he reports that discount rates drop sharply as the length of time

[10] In line with Potters et al. (2016), the discount factors are already yearly, so the annual discount rate follows from $1/\hat{\delta} - 1$.

Table 2: **Aggregate risk and time preferences from Convex Time Budgets.** Two-limit Tobit maximum likelihood estimates for quasi-hyperbolic β, δ discounting, CRRA utility $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$ and Prelec-weighting function $\pi(p) = p^{\eta}$. Background consumption equals annual after-tax income, which varies across subjects.

	Median	25th Percentile	75th Percentile	N
Panel A: Aggregate				
Risk aversion $\hat{\gamma}$	1.520	1.117	2.061	2240
Present-bias factor $\hat{\beta}$	0.968	0.854	1.222	2240
Discount factor $\hat{\delta}$	0.958	0.876	1.038	2240
Annual discount rate	0.043	-0.037	0.141	2240
Probability weighting $\hat{\eta}$	1.063	-0.134	2.139	2240
Panel B: March				
Risk aversion $\hat{\gamma}$	1.515	1.112	2.065	1997
Present-bias factor $\hat{\beta}$	0.970	0.853	1.227	1997
Discount factor $\hat{\delta}$	0.959	0.875	1.039	1997
Annual discount rate	0.043	-0.038	0.143	1997
Probability weighting $\hat{\eta}$	1.030	-0.155	2.124	1997
Panel C: December				
Risk aversion $\hat{\gamma}$	1.538	1.159	2.026	243
Present-bias factor $\hat{\beta}$	0.961	0.869	1.204	243
Discount factor $\hat{\delta}$	0.956	0.888	1.022	243
Annual discount rate	0.046	-0.021	0.126	243
Probability weighting $\hat{\eta}$	1.321	0.036	2.275	243

increase. The experimental budget of €10,000 for our subjects, combined with the time delays of 5 years, are both larger than in most previous studies. Horizons are frequently used up to several weeks (Augenblick et al., 2015), 3 months (Tanaka et al., 2010), 6 months (Andersen, Harrison, Lauc, et al., 2010), 1 year (Dohmen et al., 2010; Andersen, Harrison, Lau, et al., 2014), 2 years (Goda et al., 2015) and 3 years (Harrison et al., 2002). A paper that comes close to ours in terms of large stakes and long decision horizons is Potters et al. (2016), who use a lower, but still relatively high, experimental budget of €1,000 with a decision horizon up to retirement age. They report an annual discount rate of 1%.

Panel B and Panel C in Table 2 show the estimated population's preferences in March 2020 (i.e., emergence of COVID-19 and first lockdown) and December 2020 (i.e., second lockdown), respectively. The population's preferences do not differ much between these two periods of the crisis. Table 14 in Appendix A displays the risk and time preferences

for only the sample that participated in the trading experiment. Again the distribution of preferences is similar. Overall, by studying the preferences at an aggregated level during these two periods of the crisis, we find that the distribution of preferences remains similar based on a partial before-after analysis, which is in line with Bokern et al. (2021).[11]

Table 15, Panel A, in Appendix A shows the outcomes for the independent preference elicitation methods. The qualitative measures show moderate risk taking behavior and low impulsiveness, in line with our estimated risk aversion parameter and present-bias factor. The quantitative risk aversion measure (Eckel and Grossman, 2008) confirms that our respondents are risk averse. Finally, the quantitative measures for time preferences (Rieger et al., 2015; Wang, 2017), assuming linear utility, yield a somewhat higher present bias and a somewhat higher discount rate than in the CTB experiment. These findings indeed corroborate the claim that time preferences are upward biased if true utility is concave (Andersen, Harrison, Lau, et al., 2008), which is true since our subjects are risk averse and, therefore, simultaneous estimation of risk and time preferences is preferred over independent measurements. Panels B and C show that on a population level the preferences are stable throughout March 2020 and December 2020. Only trust in insurers is higher in December 2020 than March 2020.

B. Preferences during the crisis

Figure 1 shows the estimated risk and time preferences from the CTB experiment on a daily frequency throughout March 2020, i.e., the emergence of COVID-19 in The Netherlands and the first lockdown. From top to bottom, the panels displays the present-bias factor β, the discount factor δ, and the the risk aversion γ. Clearly, the preferences vary over time. Specifically, the preference parameters show a strong positive correlation with the daily percentage change in COVID-19 hospitalizations.[12] Individuals become more risk averse, less present biased, and more patient when COVID-19 hospitalizations rise. The correlation of the daily percentage in COVID-19 hospitalizations (i) with risk aversion equals 0.36 (p-value < 0.05), (ii) with the present-bias factor equals 0.53 (p-value < 0.01), and (iii) with the

[11] We use the term partial before-after analysis, because the COVID measures and, thereby, the pandemic lasted actually to at least March 2022 in The Netherlands.

[12] To fit both the change in hospitalizations and the preference parameters in the graphs, we normalize both variables. Let $X = (X_1, X_2, ..., X_n)$ be a vector of n observations, then the normalized value equals $\frac{X_i - \min(X)}{\max(X) - \min(X)}$ such that both series in each graph lie in the interval of 0 and 1.

discount factor equals 0.51 (p-value < 0.01). Intuitively, fear increases risk aversion (Guiso et al., 2018) and participants fear the unknown and uncertain future, so they save more to accrue a buffer as precautionary savings.

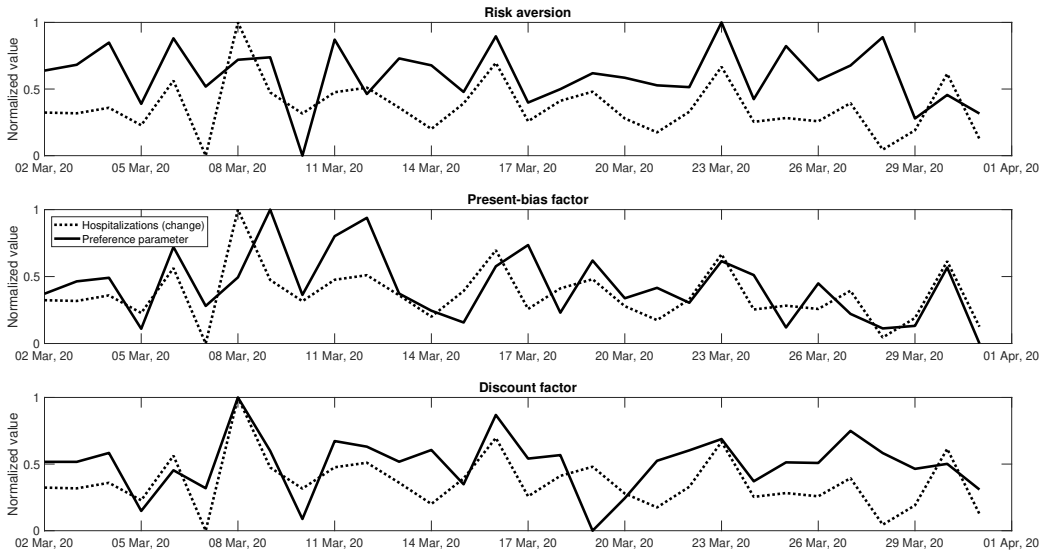

Figure 1: **Risk and time preferences with COVID-19 hospitalizations during the crisis.** Preferences (solid lines) are simultaneously estimated from Convex Time Budgets. Hospitalizations (dotted lines) are daily percentage changes in COVID-19 hospitalizations on a national level.

Figure 5 in Appendix A shows the estimated risk and time preferences from the CTB experiment on a daily frequency throughout December 2020, i.e., the second lockdown. There appears to be some time variation in preferences, but the correlation with the daily percentage change in hospitalizations is insignificant at all reasonable significance levels.[13] These results are in line with the argument that fear for the COVID-19 crisis during March 2020 might have been stronger than December 2020. The pandemic was completely new during March 2020 and most implications were unknown, but during December 2020 people get more used to the situation. Thus, implying strong correlations between preferences and the COVID-19 crisis during March 2020 and less so during December 2020.

[13]The correlation of the daily percentage in COVID-19 hospitalizations (i) with the risk aversion equals 0.09 (p-value = 0.68), (ii) with the present-bias factor equals -0.16 (p-value = 0.46), and (iii) with the discount factor equals 0.00 (p-value = 0.99).

To formalize this suggestive evidence for time-varying preferences, we regress the estimated preferences on hospitalizations while controlling for multiple variables. Specifically, we analyze the effect of the percentage change in COVID-19 hospitalizations on individuals' preferences by estimating the following regressions equation:

$$y_{i,t} = a_0 + a_1 \Delta Hosp_{i,t} + bX_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where observations occur at the individual (i) and day (t) level. $y_{i,t}$ is the estimated preference parameter (i.e., present-bias factor, discount factor, or risk aversion) for individual i measured at day t. $\Delta Hosp_{i,t}$ is the daily percentage change in national COVID-19 hospitalizations from day $t-1$ to day t. $X_{i,t}$ is a vector of control variables. The control variables compromise gender, age, having a partner, education, income, a dummy for answering the survey in December, and day fixed effects. We include day fixed effects to address potential concerns regarding daily seasonality in hospitalizations. We use quantile regressions to estimate the conditional median of the preference parameters, because it is more robust to extreme observations.

Our coefficient of main interest is a_1. Based on the suggestive evidence from Figure 1, we expect a_1 to be positive. If the number of COVID-19 hospitalizations is increasing, then fear increases such that the risk aversion parameter, the present-bias factor, and the discount factor increase. Individuals become less willing to take risks and want to save more, since they fear the unknown and uncertain future. Because individuals' decisions are likely to be cross-sectionally correlated, we cluster standard errors at the individual level in all regressions.

Table 3 shows that our coefficient of interest, a_1, is positive and statistically significant for risk and time preferences. Hence, when national COVID-19 hospitalizations rise, individuals are more risk averse, less present biased and more patient. Specifically the change in time preferences is economically sizeable. A two-standard deviation increase in the change in COVID-19 hospitalizations (about 73%) leads to an increase of 0.11 in the risk-aversion parameter γ, 0.047 in the present-bias factor β, and 0.017 in the annual discount factor δ. Regarding the latter, this yields a decrease in the annual discount rate of 1.7%. Thus, individuals discount the future less and behave more patient, namely by 1.7 percentage points compared to a median annual discount rate of 4.3%. Table 16 in Appendix A corroborates

Table 3: **Risk and time preferences during the crisis.** This table reports all coefficients of the pooled median regressions $y_{i,t} = a_0 + a_1 \Delta Hosp_{i,t} + bX_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ represents the preference parameter for individual i at day t (per column): risk aversion γ, present-bias factor β, annual discount factor δ, 1-year and 5-year self-reported life expectancy. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Risk aversion	Present-bias factor	Discount factor	1-year life exp.	5-year life exp.
$\Delta Hosp$ ($\times$100)	0.152***	0.064***	0.023**	-0.932	-0.477
	(0.049)	(0.023)	(0.010)	(1.197)	(1.432)
December	-0.060	-0.018	-0.003	-2.346**	-2.743**
	(0.052)	(0.016)	(0.007)	(1.160)	(1.252)
Male	-0.072**	-0.007	-0.001	-0.609	-1.350
	(0.034)	(0.012)	(0.006)	(0.755)	(0.891)
Age (years)	0.010***	0.002***	0.000	0.050	-0.237***
	(0.002)	(0.001)	(0.000)	(0.040)	(0.046)
Partner	-0.116***	-0.009	-0.009	-0.511	0.548
	(0.033)	(0.012)	(0.006)	(0.760)	(0.890)
Edu. medium	-0.103**	-0.010	-0.017**	2.425**	2.677**
	(0.044)	(0.019)	(0.008)	(1.062)	(1.181)
Edu. high	-0.242***	-0.039**	-0.030***	4.116***	4.840***
	(0.043)	(0.018)	(0.008)	(1.053)	(1.201)
Income ($\times$1000)	0.396***	-0.014***	0.008***	0.618*	0.894**
	(0.019)	(0.004)	(0.002)	(0.327)	(0.386)
Constant	0.365***	0.897***	0.963***	88.031***	95.784***
	(0.116)	(0.041)	(0.018)	(2.680)	(3.067)
Observations	2240	2240	2240	2239	2239
Day FE	Yes	Yes	Yes	Yes	Yes

this finding: we regress the experimentally allocated amounts to the late payments on changes in COVID-19 hospitalizations, and we find that the experimentally allocated amounts to the late payments increase the median (mean) by €1759 (€971) when COVID-19 hospitalizations rise.

Our results are not driven by simultaneous changes in beliefs regarding individual's life expectancy, as shown in the last two columns of Table 3. There is no statistically significant correlation between self-reported life expectancy probabilities and changes in COVID-19 hospitalizations. Table 17 in Appendix A shows that our results are robust to using OLS rather

than median regressions, using monthly background income w in the estimated preference parameters rather than annual background income, different sets of controls (i.e., only demographic variables, life expectancy, and financial literacy), and the unbalanced panel test of Verbeek and Nijman (1992).

Though not the main focus of the paper, Table 3 shows that education and income consistently affect preferences and beliefs. Higher educated individuals are less risk averse, more present biased and less patient. Income is correlated with preferences, which might not be too surprising since we use income to proxy for background consumption in the estimation of the preference parameters. Additionally, higher education and higher income yield higher beliefs regarding the individuals' 1-year and 5-year life expectancy probabilities. Finally, we find that risk aversion increases with age — consistent with Schildberg-Hörisch (2018) — the present-bias factor increases with age, and females are more risk averse than males — consistent with Eckel and Grossman (2002) and Eckel and Grossman (2008).

Alternative specifications

Model (1) assumes the error term to be independent of the explanatory variables. For example, it is assumed that individuals who fill in the questionnaire on a day in which hospital admissions increase are comparable to individuals who fill in the questionnaire on a day in which hospital admissions decline. To test for this, we separate within and between effects below. The specification in equation (2) relaxes the assumption. Analyzing the within effect allows individual specific unobserved heterogeneity to be correlated with the explanatory variables. We are particularly interested in our main explanatory variable of interest $\Delta Hosp_{i,t}$. We estimate the between and within effects for each preference parameter using the approach of Allison (2009). Specifically, we estimate the following regression equation

$$y_{i,t} = \tilde{a}_0 + \tilde{a}_1(\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}) + \tilde{a}_2\overline{\Delta Hosp_i} + \tilde{b}X_{i,t} + \tilde{\varepsilon}_{i,t}. \tag{2}$$

The between effect is given by $\overline{\Delta Hosp_i} = n_i^{-1}\sum_{t=1}^{n_i} Hosp_{i,t}$ and the within effect is given by $\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}$. In this model, $\tilde{a}_1$ is the within effect (comparable to a fixed-effects estimator) and $\tilde{a}_2$ is the between effect (Mundlak, 1978). An advantage of this approach is that it allows us to test for the equivalence of within and between estimates using a Wald

test. If between and within effects are the same, then it should hold under the null hypothesis that $\tilde{a}_1 = \tilde{a}_2$. Again, we use quantile regressions to estimate the conditional medians of the preference parameters as dependent variables.

Table 4, Panel A, shows the results of the estimated hybrid model. If we compare the between and within estimates for each preference, then we firstly observe that the between and within effects are very similar, although standard errors are larger for within effects. Secondly the estimated coefficients are almost identical to the estimates from model (1), as shown in Table 3. The Wald test suggests strongly that we can not reject the null hypothesis of equality for between and within estimates. This suggests that individual specific unobserved variables are not correlated with hospitalizations. This is in favor of model (1). Furthermore, self-reported life expectancies are not particularly affected by between or within effects.

Additionally, one might wonder whether the time variation in preferences is different between March 2020 (i.e., emergence COVID-19 and first lockdown) and December 2020 (i.e., second lockdown). Panel B, Table 4, shows that the time variation in preferences during December 2020 is not different from March 2020, since the coefficient for the interaction between hospitalizations and December is statistically insignificant.

Finally, we test whether preferences react to news regarding COVID-19 hospitalizations on a province level, rather than using news regarding COVID-19 hospitalizations on a national level.[14] Since we argue that a potential channel for time-varying preferences is fear from the news, it should be that province level COVID-19 hospitalizations do not matter for time-varying preferences as the news on TV, internet, and smartphones based almost utterly based on national COVID-19 hospitalizations. To explore this, we regress preferences on province level COVID-19 hospitalizations $\Delta Hosp_p$ and we control for province fixed effects. Indeed, COVID-19 hospitalizations on a province level do not matter for the time variation in preferences (and neither for life expectancy). So, this provides additional suggestive evidence for the channel of fear coming from the national news which induces time variation in risk and time preferences.

[14] A province in The Netherlands is very similar to a county in the U.S.

Table 4: **Alternative specifications.** This table reports the coefficients of median regressions from within and between analyses among individuals, between months, and at a province level. Panel A reports the estimated coefficients $\tilde{a}_1$ and $\tilde{a}_2$ from $y_{i,t} = \tilde{a}_0 + \tilde{a}_1(\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}) + \tilde{a}_2\overline{\Delta Hosp_i} + \tilde{b}X_{i,t} + \tilde{\varepsilon}_{i,t}$. Panel B reports the estimated coefficients $\tilde{a}_1$, $\tilde{a}_2$ and $\tilde{a}_3$ from $y_{i,t} = \tilde{a}_0 + \tilde{a}_1(\Delta Hosp_{i,t} \times Dec) + \tilde{a}_2\Delta Hosp_{i,t} + \tilde{a}_3 Dec + \tilde{b}X_{i,t} + \tilde{\varepsilon}_{i,t}$. Panel C reports the estimated coefficients $\tilde{a}_1$ from $y_{i,t,p} = \tilde{a}_0 + \tilde{a}_1\Delta Hosp_{t,p} + \tilde{b}X_{i,t} + \tilde{\varepsilon}_{i,t,p}$, in which $\Delta Hosp_{t,p}$ is measured on a province level. Controls $X_{i,t}$ include *December*, *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, and *Income*. The Wald tests show the null hypotheses between parentheses. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Risk aversion	Present-bias factor	Discount factor	1-year life exp.	5-year life exp.
Panel A: Within and between					
$\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}$ ($\times$100)	0.162*	0.058	0.022	-0.498	0.055
	(0.098)	(0.041)	(0.016)	(2.420)	(2.685)
$\overline{\Delta Hosp_i}$ ($\times$100)	0.152***	0.063***	0.023**	-0.990	-0.548
	(0.055)	(0.023)	(0.010)	(1.268)	(1.514)
Observations	2240	2240	2240	2239	2239
Controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Wald test ($\tilde{a}_1 = \tilde{a}_2$)	0.9286	0.8887	0.9506	0.8468	0.8299
Panel B: March and December					
$\Delta Hosp \times Dec$ ($\times$100)	0.029	-0.071	-0.021	-3.893	1.120
	(0.163)	(0.050)	(0.018)	(3.526)	(4.087)
$\Delta Hosp$ ($\times$100)	0.152***	0.079***	0.024**	-0.640	-0.561
	(0.049)	(0.026)	(0.010)	(1.188)	(1.441)
December	-0.077	-0.001	0.002	-1.829	-2.892**
	(0.056)	(0.021)	(0.007)	(1.187)	(1.384)
Observations	2240	2240	2240	2239	2239
Controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Wald test ($\tilde{a}_1 = \tilde{a}_3 = 0$)	0.3789	0.1934	0.4970	0.0914	0.0895
Panel C: Province					
$\Delta Hosp_p$ ($\times$100)	0.049*	0.003	0.004	-0.694	-0.353
	(0.025)	(0.008)	(0.003)	(0.520)	(0.641)
Observations	2230	2230	2230	2229	2229
Controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes

C. Independent measures

In addition to the simultaneously estimated preference parameters from the CTB, we measured risk and time preferences independently using simpler but coarser elicitation methods. Panels A and B in Table 5 show that these simpler, coarser, and independent qualitative and quantitative preference measures are unable to capture the time variation in preferences. National COVID-19 hospitalizations do not correlate with the preference measures. Table 18 in Appendix A reveals that within and between effects are similar, but remain insignificant. We also observe no differences between March and December 2020, and province level hospitalizations have no consistent effect on preferences as well. Only trust in insurers seems to vary over time. Specifically, individuals indicate to have more trust in insurers during December 2020 compared to March 2020. Correlations between the CTB measure, qualitative measures, and quantitative measures are small and weak, as shown by Table 19 in Appendix A.

Table 5: **Preferences according to simpler measures during the crisis.** This table reports the estimated coefficients $\bar{a}_1$ and $\bar{a}_2$ of the pooled OLS regressions $\bar{y}_{i,t} = \bar{a}_0 + \bar{a}_1 \Delta Hosp_{i,t} + \bar{a}_2 Dec + \bar{b} X_{i,t} + \bar{\varepsilon}_{i,t}$. Panel A shows the qualitatively-measured binary dependent variable $\bar{y}_{i,t}$ (per column): risk taking, impulsiveness, impatience and trust. Panel B shows the quantitatively-measured dependent variable $\bar{y}_{i,t}$ (per column): risk aversion (Eckel and Grossman, 2008), present-bias factor $\hat{\beta}$ and annual discount factor $\hat{\delta}$ assuming risk neutrality (Rieger et al., 2015; Wang, 2017). Controls $X_{i,t}$ include *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, and *Income*. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Qualitative measures				
	Risk taking	Impulsiveness	Impatience	Trust
$\Delta Hosp$ ($\times$100)	-0.035	-0.024	-0.061*	-0.027
	(0.033)	(0.018)	(0.032)	(0.030)
December	0.034	-0.000	-0.008	0.074**
	(0.031)	(0.016)	(0.028)	(0.030)
Constant	0.222***	0.275***	0.272***	0.119
	(0.083)	(0.047)	(0.074)	(0.075)
Observations	2154	2210	2203	2172
Controls	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Panel B: Quantitative measures			
	Risk aversion (EG)	Present-bias factor (RN)	Discount factor (RN)
$\Delta Hosp$ ($\times$100)	-0.084	-0.006	-0.002
	(0.107)	(0.018)	(0.007)
December	-0.069	0.015	0.002
	(0.094)	(0.013)	(0.006)
Constant	2.294***	0.790***	0.846***
	(0.252)	(0.041)	(0.017)
Observations	2240	1764	1764
Controls	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

IV. Results trading behavior

Firstly, we confirm the existence of an aggregate disposition effect in our trading experiment. Then, we present evidence that the disposition effect is time varying and correlates negatively with COVID-19 hospitalizations. Investors are less likely to realize gains during rising COVID-19 hospitalizations. Finally, we investigate the relation between preferences and the disposition effect.

A. Aggregate findings

Investors make a sell and hold decision for four products after they have observed their losses or gains on each product. If investors sell a product, then they realize the trading outcome immediately and if investors hold a product, then they hold the product for another year and realize the trading outcome next year. The outcome of a loss or gain is determined by a fair coin toss and, thus, should be around 50% in our sample. 537 individuals participated in the trading experiment aggregated over March 2020 (i.e., emergence COVID-19 and first lockdown) and December 2020 (i.e., second lockdown). We lose five individuals because they did not fully complete the disposition effect experiment, so we have a total of 2128 trading observations for 532 unique individuals.

Table 6 shows that 1040 gains (i.e., 49% of the total trading decisions) and 1088 losses (i.e., 51% of the total trading decisions) occurred in our sample. The table provides suggestive evidence for a disposition effect. We want to test whether individuals exhibit a higher tendency to sell assets that are at a gain rather than those that are at a loss, or vice versa holding losses more than holding gains. Indeed, the conditional fraction of products sold for a gain is 76%, while losses are only realized for 51%. Likewise, investors hold on to losses more often than holding on to gains. On average, investors are more reluctant to hold products (i.e., 37%) than to sell products (i.e., 63%).

Odean (1998) proposes a proportion-based measure to calculate the disposition, but thereby possibly neglects other variables affecting investor's trading behavior, as is also the case for our suggestive evidence. Thus, we follow the regression technique approach of Chang et al. (2016) and we estimate the regressions equation

$$Sell_{i,t} = d_0 + d_1 Gain_{i,t} + fX_{i,t} + e_{i,t}, \tag{3}$$

Table 6: **Sell and hold rates after gains and losses.**

	Sell	Hold	N
Unconditional			
Gain	37%	12%	2128
Loss	26%	25%	2128
Conditional			
Gain	76%	24%	1040
Loss	51%	49%	1088

where observations occur at individual level i and day t. The dependent variable *Sell* is a dummy variable that equals one if the investor sells the product, and zero if the investor holds the product for one more year. *Gain* is a dummy variable that is equal to one if the investor experienced a gain after the first coin toss, and zero if the investor suffered a loss. X is a vector of controls, similar to the set of controls in regression equation (1) for time-varying preferences. Additionally, we now consider asset fixed effects. These capture the expected value and volatility (i.e., standard deviation) of each asset.

Table 7 confirms that those experiencing a gain are more likely to sell the investment than those experiencing a loss. Specifically, column (1) shows that investors are 25% more likely to sell a gain compared to a loss. Conditional on suffering a loss, investors sell directly 51% of their investments, while conditional on experiencing a gain, investors sell directly 76% of their investments. Columns (1) to (4) confirm a clean randomisation as the coefficient for individuals experiencing a gain remains similar throughout the different specifications. As shown by column (4), the selling behavior of assets is heterogeneous across levels of the population, because the decision to sell is uncorrelated to socio-demographic variables.

However, socio-demographic variables may have an asymmetric effect on assets trading at a gain or loss, i.e., the disposition effect. In Table 20 in Appendix A, we redo the regressions for the sample of assets trading at a gain and those trading at a loss. Interestingly, we observe that age correlates positively with selling gains and income correlates negatively with selling gains, however socio-demographic variables are heterogeneous in the domain of losses. Stated differently, older investors are more likely to sell assets after a gain (i.e., higher disposition effect), and wealthy investors are less likely to sell assets after a gain (i.e., lower

disposition effect).

Table 7: **Aggregate disposition effect.** This table reports all coefficients of the panel OLS regressions $Sell_{i,t} = d_0 + d_1 Gain_{i,t} + fX_{i,t} + e_{i,t}$. The dependent variable $Sell_{i,t}$ is a dummy variable equal to one if the investor sells an asset. $Gain_{i,t}$ is a dummy variable equal to one when the investor experienced a gain after the toin coss, and equal to zero otherwise. Columns (1) - (4) use different sets of control variables. Demographics include *Dec*, *Male*, *Age*, and Controls additionally include *Partner*, *Edu. medium*, *Edu. high*, and *Income*. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Sell	(1)	(2)	(3)	(4)
Gain	0.251***	0.248***	0.247***	0.246***
	(0.028)	(0.028)	(0.028)	(0.027)
December		-0.019	-0.020	-0.019
		(0.025)	(0.025)	(0.026)
Male		-0.047	-0.036	-0.035
		(0.029)	(0.033)	(0.034)
Age (years)		0.000	0.000	0.000
		(0.002)	(0.002)	(0.002)
Partner			0.029	0.029
			(0.031)	(0.031)
Edu. medium			0.018	0.017
			(0.038)	(0.038)
Edu. high			0.002	0.002
			(0.041)	(0.041)
Income (×1000)			-0.011	-0.012
			(0.017)	(0.017)
Constant	0.513***	10.083	9.266	9.260
	(0.022)	(41.259)	(41.186)	(41.095)
Observations	2128	2128	2128	2128
Demographics	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Asset FE	No	No	No	Yes
Day FE	No	Yes	Yes	Yes

B. Disposition effect during the crisis

We want to study whether COVID-19 hospitalizations, i.e., fear for news regarding a negative shock, influences the trading behavior of investors. This provides insights in the time variation of the disposition effect. Similar to our analyses above, we regress the decision to sell an investment immediately on national COVID-19 hospitalizations while controlling for multiple variables:

$$Sell_{i,t} = \tilde{d}_0 + \tilde{d}_1 \Delta Hosp_{i,t} + \tilde{f} X_{i,t} + \tilde{e}_{i,t}. \tag{4}$$

Since the effect of fear on trading might be asymmetric, we perform the analysis for the assets trading at a gain and for those trading at a loss. Our coefficient of interest is $\tilde{d}_1$.

Table 8 shows that the change in COVID-19 hospitalizations affects the selling of gains (Panel A), but not the selling of losses (Panel B). From Panel A we conclude that an increase in COVID-19 hospitalizations decreases the assets sold after a gain. In other words, if COVID-19 hospitalizations increase, then the disposition effect decreases. A two-standard deviation increase in the change in COVID-19 hospitalizations (about 75%) yields a decrease of -10.58% in selling assets after a gain. The mechanism is through a higher reluctance for selling gains rather than through the domain of losses, as investors prefer to hold their winning assets for one more year.

C. Preferences and disposition effect

In this section, we study the relation between the elicited CTB preferences and the disposition effect. We are interested in the correlations of risk and time preferences with the selling behavior of investors after experiencing a gain or loss.

In Table 9 we report the median risk aversion, present-bias factor, and discount factor for investors that sell their assets after a gain and a loss. The sample in Panel A includes all observations from March 2020 and December 2020, and Panel B includes the observations from March 2020 only. Investors that sell their asset after experiencing a gain (i.e., Sell Gain is Yes) are less risk averse and less patient. The difference is statistically significant at any reasonable significance level, as indicated by the Wilcoxon rank-sum test p-values, for the aggregated sample in Panel A and, to a somewhat less extent, for the March sample in Panel

Table 8: **Disposition effect during the crisis.** This table reports the results of the panel OLS regressions $Sell_{i,t} = \tilde{d}_0 + \tilde{d}_1 \Delta Hosp_{i,t} + \tilde{f} X_{i,t} + \tilde{e}_{i,t}$. Panel A contains all assets trading at a gain (i.e., $Gain_{i,t} = 1$), and Panel B contains all assets trading at a loss. The dependent variable $Sell_{i,t}$ is a dummy variable equal to one if the investor sells an asset. Columns (1) - (4) use different sets of control variables. Demographics include *Dec*, *Male*, *Age*, and Controls additionally include *Partner*, *Edu. medium*, *Edu. high*, and *Income*. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: Sell	(1)	(2)	(3)	(4)
	Panel A: Gains			
$\Delta Hosp$ ($\times$100)		-0.132**	-0.148**	-0.145**
		(0.061)	(0.062)	(0.062)
December		-0.057*	-0.059*	-0.058*
		(0.032)	(0.032)	(0.032)
Constant	.763***	110.154**	92.021*	89.601*
	(.018)	(49.739)	(50.620)	(50.578)
Observations	1040	1040	1040	1040
Demographics	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Asset FE	No	No	No	Yes
Day FE	No	Yes	Yes	Yes
	Panel B: Losses			
$\Delta Hosp$ ($\times$100)		0.083	0.082	0.082
		(0.078)	(0.078)	(0.078)
December		0.008	0.006	0.006
		(0.036)	(0.036)	(0.036)
Constant	.513***	-88.393	-79.390	-74.513
	(.022)	(59.206)	(59.133)	(58.873)
Observations	1088	1088	1088	1088
Demographics	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Asset FE	No	No	No	Yes
Day FE	No	Yes	Yes	Yes

B.

This is consistent with our earlier findings, and a potential mechanism is as follows. We have seen that an increase in the change of COVID-19 hospitalizations induces more risk aversion and more patience, and an increase in the change of COVID-19 hospitalizations yields a lower disposition effect as investors are less likely to sell their gains. Now, we consistently find that indeed more risk averse, $\gamma = 1.67$, and more patient, $\delta = 0.97$, investors are less likely to sell their gains (i.e., Sell Gain is No). Consistent with the idea of fear, investors prefer to take less risks and want to accrue savings for the future by not selling their gains directly. As we would expect based on the absence of time variation in selling losses, we do not observe any relationship between preferences and selling losses. So, this suggests that the time variation in the disposition effect is at least partially driven by time-varying preferences and through the domain of gains.

Table 9: **Preferences and disposition effect.** This table reports the medians of the preference parameters if an investor holds (i.e., Sell Gain is 'No') an asset after a gain and sells (i.e., Sell Gain is 'Yes') an asset after a gain. The column 'Difference' reports the difference in preference parameters for holding and selling a gain. Wilcoxon rank-sum test p-values are reported between parentheses, which tests the null hypothesis H_0 : preference(sell gain = No) = preference(sell gain = Yes). Likewise, the table reports the values of the preferences parameters for holding or selling after a loss. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Aggregated						
	Sell Gain			Sell Loss		
	No	Yes	Difference (p-value)	No	Yes	Difference (p-value)
Risk aversion	1.67	1.54	0.13 (0.00***)	1.61	1.56	0.05 (0.35)
Present-bias factor	0.96	0.96	0.00 (0.24)	0.95	0.96	-0.02 (0.50)
Discount factor	0.97	0.95	0.02 (0.01***)	0.96	0.95	0.01 (0.16)
Observations	246	794	1040	530	558	1088
Panel B: March						
	Sell Gain			Sell Loss		
	No	Yes	Difference (p-value)	No	Yes	Difference (p-value)
Risk aversion	1.68	1.55	0.12 (0.01**)	1.62	1.63	0.00 (0.82)
Present-bias factor	0.98	0.95	0.02 (0.69)	0.94	0.97	-0.03 (0.90)
Discount factor	0.97	0.96	0.01 (0.07*)	0.96	0.94	0.02 (0.22)
Observations	131	452	583	279	298	577

V. Conclusion

Typically, individuals' preferences are assumed to be stable and persistent over time (Stigler and Becker, 1977). However, we show that preferences and economic outcomes are related

to the severity of COVID-19 during the crisis. Furthermore, changes in economic outcomes are related to changes in preferences.

We elicit and estimate risk and time preferences during the COVID-19 crisis, and we find a strong correlation between preferences and news regarding daily changes in the national COVID-19 hospitalizations. In particular, we show that the risk aversion, the present-bias factor, and the discount factor correlate positively with daily changes in national COVID-19 hospitalizations. Individuals become more risk averse, more time consistent, and more patient when hospitalizations increase. Individuals decrease their long-term annual discount rate from 4.3% to 2.6% when COVID-19 hospitalizations increase by two standard deviations. Our findings are not driven by weekly seasonality in hospitalizations or beliefs regarding life expectancy, and are robust to alternative specifications. Preferences measured by the CTB are only weakly correlated with cognitive simpler measures, which show no association with COVID-19 hospitalizations.

At the same time, the disposition effect declines when COVID-19 hospitalizations increase. We observe that investors are less willing to sell assets that experienced gain, while we find no effects in the loss domain. We find that investors who are subject to a lower disposition effect are more risk averse and more patient. This finding is in line with the fear-based mechanism of precautionary savings for the uncertain future through the motive of holding on to winning assets for one more year. Thus, consistent with our findings regarding preferences, this provides evidence that at least part of the variation in the disposition effect is driven by risk aversion and patience. Present bias plays no significant role in the trading behavior of investors.

Overall, our findings cast doubt on the stability of preferences and the disposition effect during a crisis. Our results support studies arguing that individuals' preferences and selling behavior vary with negative exogenous shocks through a fear-based mechanism. By linking preferences to trading behavior, we highlight the importance of preferences for financial-economic decision making. Changes in the stability of preferences and, consequently, economic outcomes have vital real-world consequences for policy making and welfare analyses.

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Appendix A

Design

Each time below, allocate €10,000 between today and 1 year later.

	Euro's today (with certainty)	Euro's that you receive 1 year later with certainty
Suppose that per paid euro 1 year later you receive €0.00 additionally	€0	€10,000
Suppose that per paid euro 1 year later you receive €0.50 additionally	€0	€15,000
Suppose that per paid euro 1 year later you receive €1.50 additionally	€0	€25,000
Suppose that per paid euro 1 year later you receive €3.50 additionally	€0	€45,000

Figure 2: **Decision set Convex Time Budgets.** In this decision screen, the subject allocates $m = 10.000$ Euro between an early payment today and a late payment with delay $k = 1$ year. The late payment is with a probability p_{t+k} of 100%. The gross interest rate $1 + r$ over k years in the 4 scenarios varies from 1.00 to 4.50. The allocated amount of €0 today is for illustration purposes only, the default values were blanks (subjects must actively allocate). The text is translated from Dutch to English.

Table 10: **Overview experimental design: Convex Time Budgets.** Choice sets in the Convex Time Budgets. t and k are front and end delays in years, and c_t and c_{t+k} are allocated amounts in Euros. $1+r$ is the implied gross interest rate. Annual r is the yearly interest rate in percent and calculated as $((1+r)^{1/k}-1)\times 100$. r' is the interest rate adjusted for the late payment probability p_{t+k}.

						Interest			Risk adjusted interest	
Decision	Set	t	k	c_t	c_{t+k}	$1+r$	Annual r	p_{t+k}	$1+r'$	Annual r'
1	1	0	1	10,000	10,000	1	0	1	1	0
2	1	0	1	10,000	15,000	1.5	50	1	1.5	50
3	1	0	1	10,000	25,000	2.5	150	1	2.5	150
4	1	0	1	10,000	45,000	4.5	350	1	4.5	350
5	2	0	1	10,000	20,000	2	100	0.5	1	0
6	2	0	1	10,000	30,000	3	200	0.5	1.5	50
7	2	0	1	10,000	50,000	5	400	0.5	2.5	150
8	2	0	1	10,000	90,000	9	800	0.5	4.5	350
9	3	0	1	10,000	13,300	1.33	33.33	0.75	1	0
10	3	0	1	10,000	20,000	2	100	0.75	1.5	50
11	3	0	1	10,000	33,300	3.33	233.33	0.75	2.5	150
12	3	0	1	10,000	60,000	6	500	0.75	4.5	350
13	4	0	5	10,000	10,000	1	0	1	1	0
14	4	0	5	10,000	15,000	1.5	8.45	1	1.5	8.45
15	4	0	5	10,000	45,000	4.5	35.1	1	4.5	35.1
16	4	0	5	10,000	80,000	8	58.49	1	8	58.49
17	5	1	5	10,000	10,000	1	0	1	1	0
18	5	1	5	10,000	15,000	1.5	8.45	1	1.5	8.45
19	5	1	5	10,000	45,000	4.5	35.1	1	4.5	35.1
20	5	1	5	10,000	80,000	8	58.49	1	8	58.49

Table 11: **Eckel-Grossman risk aversion task.** Subjects choose which gamble to play, all of which involve a 50/50 chance of a low or high payoff. The implied Coefficient of Relative Risk Aversion (CRRA) range is based on the power utility function $U(x)=\frac{x^{1-\gamma}}{1-\gamma}$. Each range is calculated by equalizing the gamble to its neighbors, and computing the value of γ that makes the individual indifferent in utility between each adjacent gamble.

Choice	Low payoff	High payoff	Exp. return	St. Dev.	Implied CRRA range
Gamble 1	5600	5600	5600	0	$\gamma > 3.46$
Gamble 2	4800	7200	6000	1200	$1.16 < \gamma < 3.46$
Gamble 3	4000	8800	6400	2400	$0.71 < \gamma < 1.16$
Gamble 4	3200	10400	6800	3600	$0.50 < \gamma < 0.71$
Gamble 5	2400	12000	7200	4800	$0 < \gamma < 0.50$
Gamble 6	400	14000	7200	7000	$\gamma < 0$

Table 12: **Time preferences (risk neutrality) and qualitative statements.** Panel A shows the matching task of Rieger et al. (2015) and Wang (2017), in which subjects fill in the amount X. Panel B displays the qualitative statements, and subjects answer the questions on a 7-point Likert scale.

Panel A: Time preferences (under the assumption of risk neutrality)
Assume for this question that prices in the future remain equal to the prices today (no inflation). Fill in an amount X_1 such that option B is as attractive as option A.
A. Receive €10.000 now
B. Receive $\mathbf{X_1}$ over 1 year
Assume for this question that prices in the future remain equal to the prices today (no inflation). Fill in an amount X_5 such that option B is as attractive as option A.
A. Receive €10.000 now
B. Receive $\mathbf{X_5}$ over 5 years
Panel B: Qualitative questions (7-point Likert scale: strongly disagree to strongly agree)
Risk taking
I am prepared to take the risk to lose money, when there is also a chance to gain money
Impulsiveness
I am impulsive and tend to buy things even when I can't
Patience
I am prepared to spend now and let the future take care of itself
Trust
I have trust in insurers

Table 13: **Products in disposition effect experiment.** This table shows for each product the win and loss outcomes, which follow from a coin toss (heads or tails).

Choice	Product	Win (Heads)	Lose (Tails)	Exp. return	St. Dev.
1.	A	+3000	-4000	-500	4950
	B	-4000	+3000	-500	4950
2.	C	+4000	-4000	0	5657
	D	-4000	+4000	0	5657
3.	E	+5000	-4000	+500	6364
	F	-4000	+5000	+500	6364
4.	X	+6000	-5000	+500	7778
	Y	-2000	+4000	+1000	4243

Data

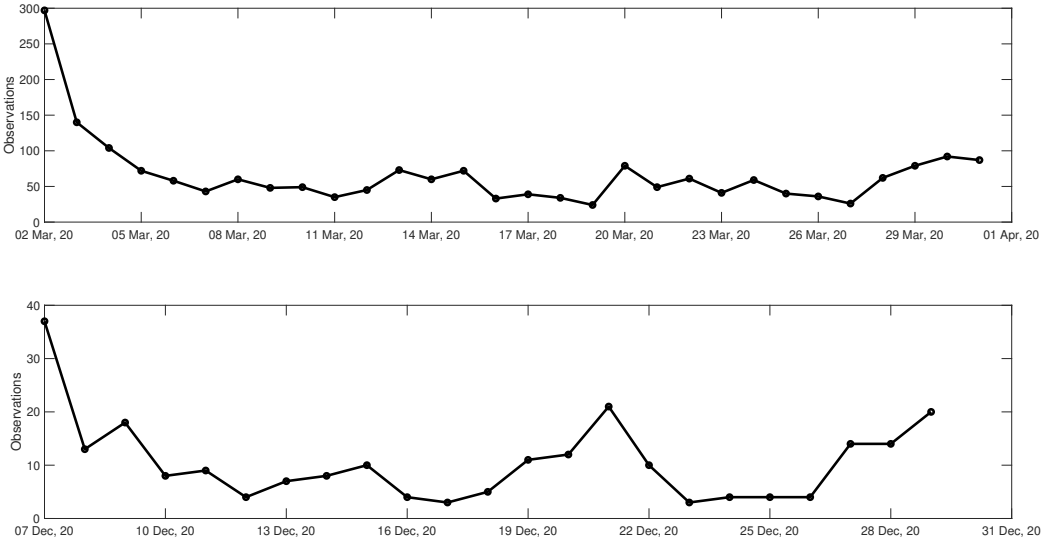

Figure 3: **Daily survey observations during March 2020 (top) and December 2020 (bottom).**

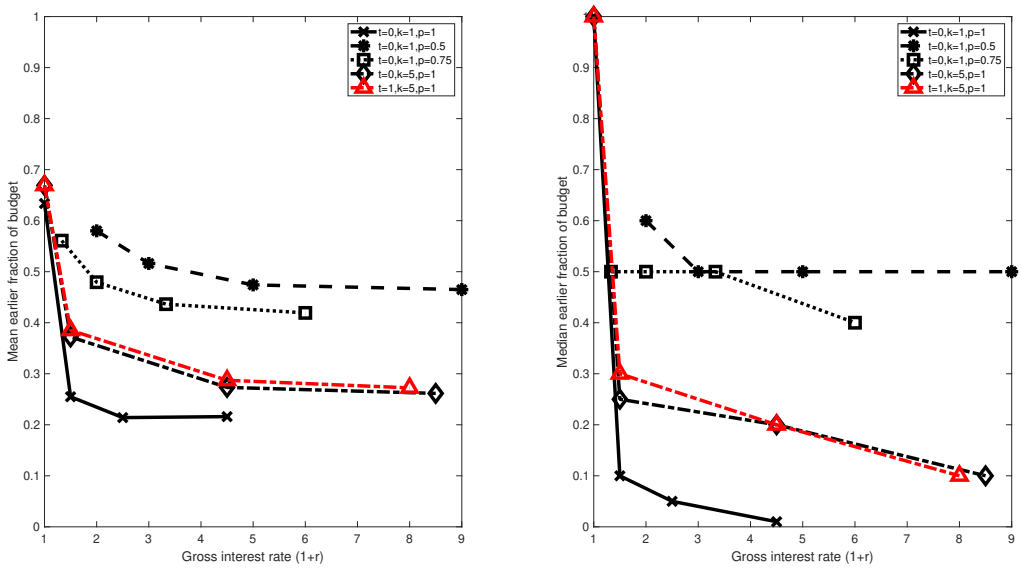

Figure 4: **Mean and median experimental allocated payments in the Convex Time Budgets.**

Table 14: **Aggregate risk and time preferences from Convex Time Budgets: Trading sample.** This table shows the preferences for the only sample that participated in the disposition effect experiment. Two-limit Tobit maximum likelihood estimates for quasi-hyperbolic β, δ discounting, CRRA utility $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$ and Prelec-weighting function $\pi(p) = p^{\eta}$. Background consumption equals annual after-tax income, which varies across subjects.

	Median	25th Percentile	75th Percentile	N
Panel A: All, trading experiment				
Risk aversion $\hat{\gamma}$	1.590	1.215	2.111	537
Present-bias factor $\hat{\beta}$	0.961	0.835	1.203	537
Discount factor $\hat{\delta}$	0.958	0.875	1.043	537
Annual discount rate	0.044	-0.041	0.143	537
Probability weighting $\hat{\eta}$	1.192	-0.007	2.309	537
Panel B: March, trading experiment				
Risk aversion $\hat{\gamma}$	1.599	1.232	2.316	294
Present-bias factor $\hat{\beta}$	0.962	0.784	1.203	294
Discount factor $\hat{\delta}$	0.961	0.869	1.055	294
Annual discount rate	0.041	-0.052	0.150	294
Probability weighting $\hat{\eta}$	1.085	-0.083	2.331	294

Table 15: **Aggregate preferences from independent measures.** *Risk taking*, *Impulsiveness* and *Impatience* measure qualitatively self-stated risk and time preferences on a 7-points Likert scale. *Trust* measures the trust in insurance companies with a 7-points Likert scale. *Risk aversion* (EG) measures quantitatively risk aversion following Eckel and Grossman (2008), while $Present-bias\ factor$ ($Wang$) and $Discount\ factor$ ($Wang$) measure quantitatively time preferences (assuming risk neutrality) following Rieger et al. (2015) and Wang (2017).

	Mean	St. Dev.	Min.	Max.	N
Panel A: Aggregate					
Qualitative measures					
Risk taking	3.52	1.76	1.00	7.00	2154
Impulsiveness	1.94	1.30	1.00	7.00	2210
Impatience	3.03	1.75	1.00	7.00	2203
Trust	3.35	1.49	1.00	7.00	2172
Quantitative measures					
Risk aversion (EG)	2.01	1.44	1.00	6.00	2240
Present-bias factor (RN)	0.93	0.21	0.10	1.78	1764
Discount factor (RN)	0.92	0.09	0.56	1.00	1764
Panel B: March					
$\Delta Hosp$	16.37	36.70	-52.63	144.44	1997
1-year life expectancy	93.25	15.26	0.00	100.00	1996
5-year life expectancy	85.70	18.14	0.00	100.00	1996
Qualitative measures					
Risk taking	3.50	1.76	1.00	7.00	1917
Impulsiveness	1.93	1.31	1.00	7.00	1969
Impatience	3.03	1.76	1.00	7.00	1963
Trust	3.33	1.49	1.00	7.00	1937
Quantitative measures					
Risk aversion (EG)	2.02	1.44	1.00	6.00	1997
Present-bias factor (RN)	0.93	0.21	0.10	1.78	1556
Discount factor (RN)	0.92	0.09	0.56	1.00	1556
Panel C: December					
$\Delta Hosp$	13.15	34.64	-44.73	74.16	243
1-year life expectancy	91.13	18.18	0.00	100.00	243
5-year life expectancy	82.63	19.92	0.00	100.00	243
Qualitative measures					
Risk taking	3.62	1.80	1.00	7.00	237
Impulsiveness	1.98	1.24	1.00	7.00	241
Impatience	3.00	1.66	1.00	7.00	24
Trust	3.54	1.48	1.00	7.00	235.00
Quantitative measures					
Risk aversion (EG)	1.95	1.45	1.00	6.00	243
Present-bias factor (RN)	0.95	0.17	0.38	1.50	208
Discount factor (RN)	0.92	0.08	0.67	1.00	208

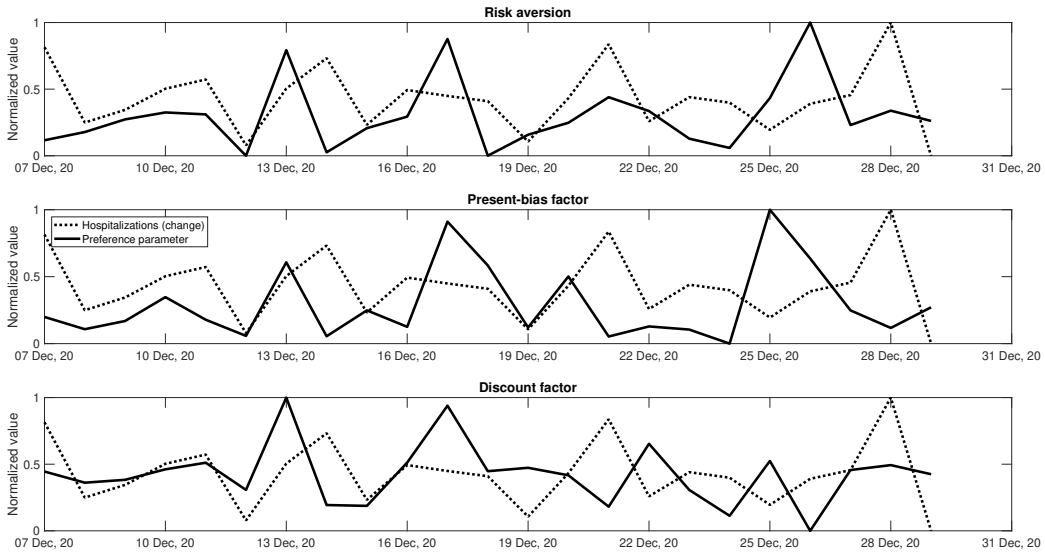

Figure 5: **Time-varying risk and time preferences with COVID-19 hospitalizations during December 2020.**

Results

Table 16: **Time-varying Convex Time Budget allocations**. This table reports the coefficients of the regressions $y_{i,t} = a_0 + a_1 \Delta Hosp_{i,t} + bX_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the average per individual i over the allocated amounts to the late payment at time t. Controls $X_{i,t}$ include *Dec*, *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, *Income* and day fixed effects. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Median regression	OLS
$\Delta Hosp$ ($\times$100)	1759.414***	971.356*
	(659.977)	(556.944)
December	-33.117	85.591
	(507.393)	(508.178)
Constant	26887.068***	26342.921***
	(1422.588)	(1290.979)
Observations	2240	2240
Controls	Yes	Yes
Day FE	Yes	Yes

Table 17: **Robustness time-varying preferences.** This table reports the coefficients of the regressions $y_{i,t} = a_0 + a_1 \Delta Hosp_{i,t} + bX_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ represents the preference parameter for individual i at day t (per column): risk aversion γ, present-bias factor β and annual discount factor δ. Controls $X_{i,t}$ include *Dec*, *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, *Income* and day fixed effects. Panel A uses OLS rather than median regressions to estimate our main regression equation, while Panels B-F use median regressions. Panel B uses the preference parameter estimates based on monthly background income rather than annual background income. Panel C only uses the set of controls $X_{i,t}$: *Dec*, *Male*, *Age*, and day fixed effects. Panel D controls for life expectancy, added to the standard set of controls. Panel E controls for financial literacy, added to the standard set of controls. Panel F tests for unbalancedness of the panel dataset using the test of Verbeek and Nijman (1992). Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Risk aversion	Present-bias factor	Discount factor
Panel A: OLS			
$\Delta Hosp$ (×100)	0.390**	1.362**	0.052***
	(0.160)	(0.554)	(0.019)
Observations	2240	2240	2240
Panel B: Monthly background income			
$\Delta Hosp$ (×100)	0.046*	0.081***	0.025**
	(0.027)	(0.030)	(0.013)
Observations	2240	2240	2240
Panel C: Controlling for demographics only			
$\Delta Hosp$ (×100)	0.098*	0.056***	0.025***
	(0.055)	(0.020)	(0.010)
Observations	2246	2246	2246
Panel D: Controlling for life expectancy			
$\Delta Hosp$ (×100)	0.147***	0.066***	0.025**
	(0.047)	(0.021)	(0.010)
1-year life expectancy	-0.001	-0.000	-0.000
	(0.002)	(0.001)	(0.000)
5-year life expectancy	-0.002	-0.001	-0.000
	(0.002)	(0.001)	(0.000)
Observations	2239	2239	2239
Panel E: Controlling for financial literacy			
$\Delta Hosp$ (×100)	0.083**	0.069***	0.022**
	(0.038)	(0.024)	(0.009)
Financial literacy	-0.319***	-0.058**	-0.041***
	(0.032)	(0.024)	(0.010)
Observations	2240	2240	2240
Panel F: Unbalanced panel test			
$\Delta Hosp$ (×100)	0.156***	0.065**	0.023**
	(0.048)	(0.025)	(0.010)
Times observed	-0.030	-0.002	-0.008
	(0.041)	(0.015)	(0.009)
Observations	2240	2240	2240

Table 18: **Within and between analyses for simpler measures.** This table reports the coefficients of OLS regressions from within and between analyses for the qualitative and quantitative preference measures. Panel A shows the qualitatively-measured binary dependent variable $y_{i,t}$. Panel B shows the quantitatively-measured dependent variable $y_{i,t}$. Subpanel 1 estimates $y_{i,t} = a_0 + a_1(\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}) + a_2\overline{\Delta Hosp_i} + bX_{i,t} + \varepsilon_{i,t}$. Subpanel 2 estimates $y_{i,t} = a_0 + a_1(\Delta Hosp_{i,t} \times Dec) + a_2\Delta Hosp_{i,t} + a_3 Dec + bX_{i,t} + \varepsilon_{i,t}$. Subpanel 3 estimates $y_{i,t,p} = a_0 + a_1\Delta Hosp_{t,p} + bX_{i,t} + \varepsilon_{i,t,p}$, in which $\Delta Hosp_{t,p}$ is measured on a province level. Controls $X_{i,t}$ include *Dec*, *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, and *Income*. The Hausman and Wald tests show the null hypothesis between parentheses. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Qualitative				
	Risk taking	Impulsiveness	Impatience	Trust
Panel A.1: Individuals				
$\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}$ (×100)	-0.093	-0.033	-0.123**	-0.180***
	(0.058)	(0.034)	(0.060)	(0.062)
$\overline{\Delta Hosp_i}$ (×100)	-0.027	-0.022	-0.052	-0.005
	(0.035)	(0.019)	(0.034)	(0.032)
Observations	2154	2210	2203	2172
Controls	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Wald test ($a_1 = a_2$)	0.2903	0.7549	0.2684	0.0083
Panel A.2: March and December				
$\Delta Hosp \times Dec$ (×100)	-0.122	0.027	-0.003	-0.251***
	(0.097)	(0.048)	(0.076)	(0.090)
$\Delta Hosp$ (×100)	-0.026	-0.026	-0.060*	-0.008
	(0.034)	(0.019)	(0.032)	(0.030)
December	0.050	-0.004	-0.008	0.106***
	(0.033)	(0.017)	(0.030)	(0.033)
Observations	2154	2210	2203	2172
Controls	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Wald test ($a_1 = a_3 = 0$)	0.2361	0.8497	0.9540	0.0018
Panel A.3: Province				
$\Delta Hosp_{t,p}$ (×100)	0.002	-0.006	-0.028**	-0.029**
	(0.014)	(0.006)	(0.013)	(0.013)
Observations	2144	2200	2193	2162
Controls	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes

Table continued.

Panel B: Quantitative			
	Risk aversion (EG)	Present-bias factor (RN)	Discount factor (RN)
Panel B.1: Individuals			
$\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}$ ($\times$100)	0.031	0.017	-0.001
	(0.204)	(0.034)	(0.012)
$\overline{\Delta Hosp_i}$ ($\times$100)	-0.099	-0.009	-0.002
	(0.112)	(0.019)	(0.008)
Observations	2240	1764	1764
Controls	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Wald test ($a_1 = a_2$)	0.5311	0.4534	0.9524
Panel B.2: March and December			
$\Delta Hosp \times Dec$ ($\times$100)	0.089	0.061	0.009
	(0.285)	(0.039)	(0.017)
$\Delta Hosp$ ($\times$100)	-0.091	-0.011	-0.002
	(0.111)	(0.019)	(0.007)
December	-0.081	0.007	0.000
	(0.100)	(0.013)	(0.006)
Observations	2240	1764	1764
Controls	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Wald test ($a_1 = a_3 = 0$)	0.7211	0.1532	0.8588
Panel B.3: Province			
$\Delta Hosp_{t,p}$ ($\times$100)	-0.024	-0.011	0.002
	(0.046)	(0.008)	(0.003)
Observations	2230	1756	1756
Controls	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Province FE	Yes	Yes	Yes

Table 19: **Correlations between preference measures.** This table reports the Spearman rank correlations between preference measures. Symbol * indicates significance at the 5% level.

Panel A: Convex Time Budgets and qualitative measures

	Risk taking	Impulsiveness	Impatience	Risk aversion $\hat{\gamma}$	Present-bias factor $\hat{\beta}$	Discount factor $\hat{\beta}$
Risk taking	1					
Impulsiveness	0.0918*	1				
Impatience	0.1825*	0.2692*	1			
Risk aversion $\hat{\gamma}$	0.038	-0.0422	0.0387	1		
Present-bias factor $\hat{\beta}$	-0.0618*	0.008	-0.0351	0.2611*	1	
Discount factor $\hat{\delta}$	-0.0136	-0.0027	-0.0281	0.4211*	0.3157*	1

Panel B: Convex Time Budgets and quantitative measures

	Risk aversion (EG)	Present-bias factor (Wang)	Discount factor (Wang)	Risk aversion $\hat{\gamma}$	Present-bias factor $\hat{\beta}$	Discount factor $\hat{\beta}$
Risk aversion (EG)	1					
Present-bias factor (Wang)	-0.0618*	1				
Discount factor (Wang)	-0.0363	0.1282*	1			
Risk aversion $\hat{\gamma}$	0.0168	0.0119	0.0367	1		
Present-bias factor $\hat{\beta}$	-0.0013	0.0433	0.0107	0.2656*	1	
Discount factor $\hat{\delta}$	0.0272	0.0708*	0.0816*	0.4168*	0.3159*	1

Table 20: **Aggregate disposition effect, conditional on gains and losses.** This table reports all coefficients of the panel OLS regressions $Sell_{i,t} = d_0 + fX_{i,t} + e_{i,t}$. The dependent variable $Sell_{i,t}$ is a dummy variable equal to one if the investor sells an asset. Columns (1) - (4) contain all assets trading at a gain (i.e., $Gain_{i,t} = 1$), and Columns (5) - (8) contain all assets trading at a loss. The columns use different sets of control variables. Demographics include Dec, $Male$, Age, and Controls additionally include $Partner$, $Edu.\ medium$, $Edu.\ high$, and $Income$. Robust standard errors, corrected for clustering of observations at the individual level, are in parentheses. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Gains				Losses			
Dependent variable: Sell	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
December		-0.045	-0.045	-0.044		0.000	-0.002	-0.002
		(0.033)	(0.033)	(0.033)		(0.036)	(0.036)	(0.036)
Male		-0.053	-0.028	-0.026		-0.046	-0.045	-0.043
		(0.036)	(0.040)	(0.040)		(0.043)	(0.047)	(0.046)
Age (years)		0.005**	0.004*	0.004*		-0.004	-0.003	-0.003
		(0.002)	(0.002)	(0.002)		(0.003)	(0.003)	(0.003)
Partner			0.046	0.048			0.014	0.013
			(0.037)	(0.037)			(0.045)	(0.045)
Edu. medium			-0.023	-0.022			0.051	0.050
			(0.046)	(0.045)			(0.062)	(0.061)
Edu. high			-0.024	-0.023			0.029	0.027
			(0.050)	(0.050)			(0.064)	(0.064)
Income (× 1000)			-0.034*	-0.034*			0.001	0.000
			(0.019)	(0.019)			(0.024)	(0.024)
Constant	0.763***	106.553**	89.025*	86.433*	0.513***	-84.857	-75.778	-70.898
	(0.018)	(50.686)	(51.593)	(51.561)	(0.022)	(59.018)	(58.964)	(58.744)
Observations	1040	1040	1040	1040	1088	1088	1088	1088
Demographics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Asset FE	No	No	No	Yes	No	No	No	Yes
Day FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Appendix B

This section shows how we estimate risk and time preferences from the CTB. In the CTB experiment, subjects choose a payment c_t, available at time t, and a payment c_{t+k} available after delay k, continuously along a convex budget constraint

$$c_t + \frac{c_{t+k}}{1+r} = m, \tag{5}$$

where $(1+r)$ is the experimental gross interest rate and m is the experimental budget.

Using the quasi-hyperbolic model of intertemporal decision making (Phelps and Pollak, 1968; Laibson, 1997), the subject maximizes discounted expected utility over the early payment c_t and late payment c_{t+k} (including interest)

$$\begin{aligned} \max_{c_t, c_{t+k}} \delta^t \left[\pi(p_t)U(c_t + w_t) + (1 - \pi(p_t))U(w_t)\right] \\ + \beta\delta^{t+k} \left[\pi(p_{t+k})U(c_{t+k} + w_{t+k}) + (1 - \pi(p_{t+k}))U(w_{t+k})\right], \end{aligned} \tag{6}$$

where δ is the one period discount factor and β is the present-bias factor. The quasi-hyperbolic form is able to capture time-inconsistent behavior. $\beta < 1$ indicates present bias, and if $\beta = 1$ the model equals exponential discounting (i.e., standard time-consistent behavior). p_t and p_{t+k} are the corresponding probabilities of payment. The terms w_t and w_{t+k} are additional utility parameters which could be interpreted as background consumption or income (Andersen, Harrison, Lau, et al., 2008).

Hence, the CTB method asks subjects to maximize a utility function $U(c_t, c_{t+k})$. We assume that subjects have a time-separable Constant Relative Risk Aversion (CRRA) utility function of the form

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}, \tag{7}$$

with γ the coefficient of relative risk aversion.[15] Money allocated to the early payment has a value of c_t, while money allocated to the late payment has a present value of $c_{t+k}/(1+r)$.[16]

[15] With this functional form, $\gamma = 0$ denotes risk neutral behavior, $\gamma > 0$ denotes risk aversion and $\gamma < 0$ denotes risk seeking behavior.

[16] c_{t+k}/c_t defines the gross interest rate $(1+r)$ over k years, so $(1+r)^{1/k} - 1$ gives the standardized annual interest rate r. Multiplication by the payment probability p_{t+k} denotes the risk-adjusted interest rates.

Since early payments are always certain, it holds that $p_t = 1$. In some decision sets, the late payment is uncertain with probability p_{t+k}. For instance, when p_{t+k} is 0.7, the late payment is paid with a chance of 70%, and nothing is paid with a chance of 30%.

Given the evidence regarding probability distortions (Kahneman and A.Tversky, 1979; Tversky and Kahneman, 1992), we use $\pi(p_{t+k})$ as the subjective probabilities of a late payment. We use a simple Prelec probability weighting function

$$\pi(p) = p^{\eta}, \tag{8}$$

where p is the objective probability and $\pi(p)$ is the subjective (distorted) probability. Since our experimental setup contains late payment probabilities of 50% or larger, it is sufficient to identify the underweighting of high probabilities as there is no need to capture both the over- and underweighting of low and high probabilities, respectively.

Solving the subject's maximization problem (6) subject to her budget constraint (5) yields the first-order condition

$$\frac{c_t + w_t}{c_{t+k} + w_{t+k}} = \begin{cases} \left(\beta\delta^k(1+r)\pi(p_{t+k})\right)^{-\frac{1}{\gamma}}, & \text{if } t = 0 \\ \left(\delta^k(1+r)\pi(p_{t+k})\right)^{-\frac{1}{\gamma}}, & \text{if } t > 0 \end{cases} \tag{9}$$

which shows that the experimentally allocated payments depend on the preference parameters and the experimentally varied parameters.

Taking the logarithm and using the Prelec weighting function (8), we find

$$\begin{aligned} \ln\left(\frac{c_t + w_t}{c_{t+k} + w_{t+k}}\right) = &\left(\frac{\ln\beta}{-\gamma}\right) \cdot \mathbb{1}_{t=0,\ p_{t+k}=1} + \left(\frac{\ln\delta}{-\gamma}\right) \cdot k \\ &+ \left(\frac{1}{-\gamma}\right) \cdot \ln(1+r) + \left(\frac{\eta}{-\gamma}\right) \cdot \ln(p_{t+k}), \end{aligned} \tag{10}$$

where $\mathbb{1}_{t=0,\ p_{t+k}=1}$ is an indicator function for the time period $t = 0$ and a sure probability of late payment. In other words, we presume that present bias enters after today and to avoid interference between present bias and probability weighting, we estimate present bias only in the scenarios where late payment is guaranteed.

Given an additive error structure and assumptions on background income w_t, w_{t+k}, such an equation is easily estimated with parameter estimates for β, δ, γ and η obtained via non-

linear combinations of coefficient estimates. The equation shows indeed that the present-bias factor β is identified through the front-end delay in t, the long-term annual discount factor is identified through the back-end delay via k, the CRRA risk aversion follows from changes in the gross interest rate $(1 + r)$ and probability weighting follows from changes in the late payment probability p_{t+k}. We estimate the preference parameters per individual using two-limit Tobit maximum likelihood regressions to account for corner solutions. To limit the number of estimated parameters, we set background income for each individual to her annual after-tax income and we assume that $w_t = w_{t+k}$. After the estimation, we winsorize the individually estimated parameters at the 1% level of the bottom and top of the overall distribution.