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Time-varying risk and time preferences

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Abstract

Standard economic theory often treats preferences as time-invariant, yet little is known about their stability at high (daily) frequency in representative samples. The present study fills this gap by daily eliciting risk and time preferences simultaneously of 2266 individuals using a Convex Time Budgets design, alongside simpler measures. Our design allows us to study day-to-day dynamics within the same individuals and relate them to an exogenous, plausibly salient signal: the daily change in national COVID-19 hospitalizations during 2020. We find that risk aversion, time consistency, and patience move at a daily frequency and co-vary with this signal, while aggregate, wave-level comparisons imply stability and simpler elicitation methods do not detect any variation. Our findings are consistent with fear- and uncertainty-based mechanisms. Robustness checks address alternative mechanisms, controls, and specifications. We conclude that preferences can vary systematically over short horizons, and that fine-grained elicitation is essential to detect this variation.

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Risk and time preference parameters are crucial inputs for behavioral scientists and policymakers. These preferences determine respectively to what extent individuals are willing to take risks and to what extent individuals are willing to trade-off current benefits for future benefits. An individual's risk aversion and an individual's patience predict important aspects of labor market and health outcomes, addictive behaviors, investment and retirement planning, and migration decisions[1,2,3,4,5,6,7]. Over the recent years, methods have been developed by economists to measure risk and time preferences. Standard economic theory assumes that preferences are constant over time[8], but in recent years economists have empirically started to investigate the stability of risk and time preferences[9,10].

To date, relatively little is known about the temporal stability of risk preferences[11], even less so about the stability of risk preferences when assessed with quantitative economic measures, particularly involving stability on a daily frequency[9,10]. The literature on the temporal stability of time preferences is even more scarce[9]. There is a new emerging literature that studies how preferences are impacted by extreme events, such as violent conflicts, (natural) disasters, (economic) crises, and pandemics. While this literature is fascinating, researchers tend to face one main difficulty: data on preferences is typically only available after the event, and usually not before, let alone continuously throughout an event[9,12,13,14,15,16,17,18,19]. In addition, the data is usually not representative for the wider population or does not measure both types of preferences simultaneously.

Our research fills this important gap. We use online experimental survey evidence to simultaneously measure both risk and time preferences from a large representative sample of The Netherlands on a daily frequency *during* the COVID-19 crisis. Our main, simultaneous measure of risk and time preferences is based on a well-established method from experimental economics, known as the Convex Time Budgets (CTB) approach[20]. With this method, we estimate on an individual level risk aversion, present bias, and patience, while controlling for probability weighting[21,22]. Given the evidence that multiple elicitation methods can give rise to different levels of risk preferences[23,11], something to be expected for time preferences as well, and given the trade-offs between cognitive complexity and estimation precision of elicitation methods[24], we additionally measure risk and time preferences using cognitive simpler but coarser methods from the behavioral and experimental economics literature[25,26,27,28,29].

Our online survey experiments took place on a daily frequency between 2 March 2020 and 31 March 2020, and between 7 December 2020 and 29 December 2020. We can estimate risk and time preferences for 2266 individuals. We observe 2020 individuals during March 2020, of which we observe 246 individuals again during December 2020. The daily experiments 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 at the end of the month The Netherlands had 1.173 deaths, 13.614 contaminations, and a so-called intelligent lockdown. The daily experiments 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.

During the COVID-19 crisis, but especially in March and December 2020 due to the lockdowns in The Netherlands, national hospitalizations were salient and communicated daily on the news, radio, and phones via push notifications. Hospitalizations were especially salient, because there was a general concern that hospitals might reach full capacity with among others a potential health crisis. These are times in which fear and uncertainty could naturally arise, as there were growing concerns about the future state of the world. We measure the severity of the COVID-19 situation by the relative daily change in hospitalizations and we use this measure to study potential daily time variation in risk and time preferences.

Our results show that risk and time preferences strongly correlate with the severity of the COVID-19 crisis on a daily frequency, indicating instability of preferences during extreme events. Specifically, if daily national COVID-19 hospitalizations in The Netherlands increase, then individuals' risk aversion, time consistency, and long-term patience increase as well. Thus, individuals are less willing to take financial risks and prefer to save more for the future after an increase in the daily national COVID-19 hospitalizations. The time variation in risk and time preferences is consistent with the mechanisms of fear[30,31,32,33] and uncertainty[34,35,36,37]. Even if individuals do not experience the shock directly themselves (i.e., get infected, or hospitalized, by COVID-19), fear and uncertainty can be activated by watching and reading news about the extreme event. Our findings relate to short-term systematic but temporary variations in preferences[10].

Our results are robust to a battery of robustness checks, which excludes potential other mechanisms and alternative model specifications. Interestingly, risk and time preferences appear significantly stable when studied on an aggregated population level across both 'waves' of March and December 2020. This aggregating 'wave' approach, or 'before-after' analysis, which is typically taken in the literature, overlooks the important aspect of daily dynamics in preferences. We do not observe instability of preferences when using the simpler measures, which indicates that such measures are too coarse to capture the daily dynamics of risk and time preferences.

Results

Aggregated preferences

For each subject we estimate risk and time preferences using the CTB method, while controlling for probability weighting[21]. Risk preferences are modelled by the curvature of the power utility function, which is the most widely used parametric family for fitting utility functions to data[38]. The curvature parameter is denoted by γ and also known as the coefficient of relative risk aversion. With this functional form, $\gamma = 0$ denotes risk neutral behavior, $\gamma > 0$ denotes risk aversion and $\gamma < 0$ denotes risk seeking behavior.

Time preferences are modelled by quasi-hyperbolic discounting[39,40], which is able to capture a well-documented discounted utility anomaly[41]: empirically observed discount rates are not constant over time, i.e., individuals are time inconsistent. The quasi-hyperbolic discounting model features a long-term discount factor, δ, and a present-bias factor, β. $\delta < 1$ indicates impatience, $\beta < 1$ indicates present bias, and if $\beta = 1$ the model equals exponential discounting, i.e., time-consistent behavior. By design of our experiment, the present-bias factor and discount factor can be interpreted on an annual basis. For interpretation purposes, we transform the (annual) discount factor δ into an annual discount rate[21].

We compute the 25^{th}, 50^{th}, and 75^{th} percentiles of the population's distributions of preferences. Table 1 shows the estimated parameters for risk aversion, present bias, and impatience. Panel A displays the estimation results for our observed population when aggregating all observations from March and December in 2020. We estimate a median risk aversion parameter γ of 1.687. This result shows that individuals are risk averse, in line with the prior literature using CTB designs with individually varying background income and two-limit Tobit regressions[42].

We estimate a median (annual) present-bias factor, β, of 0.966, and a median (annual) discount factor δ of 0.977, which translates into an annual discount rate of 2.3%. The

Table 1: **Aggregated risk and time preferences in 2020.** Two-limit Tobit maximum likelihood estimates for risk preferences, as measured by the CRRA parameter γ in $U(x) = \frac{x^{1-\gamma}}{1-\gamma}$, and for time preferences, as measured by the (annual) present-bias factor β and (annual) discount factor δ in the quasi-hyperbolic discount model. For convenience, the (annual) discount factor is translated into an (annual) discount rate. Background consumption equals annual after-tax income, which varies across subjects.

	Median	25$^{\text{th}}$ Percentile	75$^{\text{th}}$ Percentile	N
Panel A: Aggregated				
Risk aversion $\hat{\gamma}$	1.687	1.276	2.343	2266
Present-bias factor $\hat{\beta}$	0.966	0.837	1.219	2266
Discount factor $\hat{\delta}$	0.977	0.912	1.050	2266
Discount rate	0.023	-0.048	0.097	2266
Panel B: Aggregated, March 2020				
Risk aversion $\hat{\gamma}$	1.687	1.266	2.350	2020
Present-bias factor $\hat{\beta}$	0.968	0.838	1.224	2020
Discount factor $\hat{\delta}$	0.977	0.911	1.050	2020
Discount rate	0.023	-0.048	0.097	2020
Panel C: Aggregated, December 2020				
Risk aversion $\hat{\gamma}$	1.688	1.342	2.241	246
Present-bias factor $\hat{\beta}$	0.947	0.833	1.172	246
Discount factor $\hat{\delta}$	0.976	0.914	1.046	246
Discount rate	0.024	-0.044	0.094	246

discount factor shows that individuals are impatient and they discount the future by about 2.3% annually. Our estimated annual discount rate is similar to prevailing market interest rates and lower than most previous studies[43,20,41]. A potential reason for our lower, but plausible, annual discount rate is the magnitude of the experimental budget and the long-term decision horizon. Discount rates can drop as the size of wealth increases or the length of time increases[44]. In our experiment, the endowment of €10,000 and a time delay of at most 6 years are both larger than in most previous studies[45,46,47,48,49,50,51]. The present-bias factor shows that individuals are present biased and, thus, display a form of time inconsistency. The present, which is by our experimental design somewhere between today and one year from now, is discounted by roughly an additional 3.4%. Our estimated present-bias factor is similar to previous studies estimating present-bias factors using a CTB design[52,45,41]. Overall, the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles reveal heterogeneity in risk and time preferences.

Panel B and Panel C in Table 1 show the estimated aggregated population's preferences in March 2020 (i.e., emergence of COVID-19 and first lockdown) and December 2020 (i.e., second lockdown), respectively. The main finding is that risk and time preferences are similar throughout the COVID-19 crisis when preferences are compared on the aggregated population level. That is, the aggregated preferences in March 2020 (Panel B) and the aggregated preferences in December 2020 (Panel C) are similar (in statistical terms and magnitudes) to the aggregated preferences of March and December 2020 (Panel A). More specifically, we cannot reject the hypothesis that the estimated preferences in March 2020 are equal to the estimated preferences in December 2020 (p-values for γ, β, and δ are respectively, 0.45, 0.21, and 0.81, using unmatched data Wilcoxon rank-sum tests). Overall, by studying preferences at aggregated population levels during the COVID-19 crisis, it appears that preferences remain remarkably stable, which is in line with studies on before-after analyses using the same parametric assumptions on preferences as ours[53,14].

Daily preferences

An important aspect is overlooked when aggregating preferences over time at the population level, namely the daily dynamics of preferences. Our study allows us to study this aspect, as we measure preferences on a daily frequency. Our unique contribution lies in the ability to measure, exploit, and analyze preferences at a daily level over a two-month period for the same individuals. We present evidence that risk and time preferences vary on a daily frequency and the variation is related to the severity of COVID-19.

To study how risk and time preferences are affected during extreme events, we use the daily percentage change in national COVID-19 hospitalizations in The Netherlands ($\Delta Hosp$). We take an increase in $\Delta Hosp$ as a proxy for an increase in the severity of the exogenous COVID-19 shock. If $\Delta Hosp > 0$, then the number of COVID-19 hospitalizations from day $t-1$ to day t is increasing. Daily COVID-19 hospitalizations are on average increasing by about 16 percentage points during March 2020 and December 2020, see Supplementary Table 12. The daily percentage change in hospitalizations ranges between roughly -53% and +144% during March and December 2020. The average increase in national COVID-19 hospitalizations is about 3 percentage points higher in March 2020 than December 2020, see Supplementary Table 13.

The hospitalization numbers include COVID-19 patients in both the ICU (Intensive Care

Unit) and the nursing wards, and only those individuals who are hospitalized due to COVID-19. In other words, the measure excludes patients who are in the hospital for reasons other or in addition to COVID-19. We do not use COVID-19 infected cases, because test capacity, especially during 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. We do not use COVID-19 deaths nor the reproduction number, because these measures lag behind the actual COVID-19 situation. We use the percentage change in hospitalizations rather than levels, since COVID-19 expanded exponentially. In early March 2020 the absolute level of hospital admissions was low, but the impact of relative changes in hospitalizations was large. Moreover, the daily percentage change in hospitalizations is temporarily uncorrelated, whereas the absolute levels violate the temporal uncorrelatedness.

Descriptive evidence

Figure 1 illustrates our main finding. The graphs show the estimated (normalized) risk and time preferences from the CTB experiment on a daily frequency throughout March 2020 together with the (normalized) daily changes in national COVID-19 hospitalizations throughout March 2020. From top to bottom, the panels display the risk aversion parameter γ, the present-bias factor β, and the long-term discount factor δ. To fit both the preference parameters and change in hospitalizations in a graph, we normalize both variables. Let $X = (X_1, X_2, ..., X_n)$ be a vector of n observations, then we normalize by $\frac{X_i - \min(X)}{\max(X) - \min(X)}$ such that both series in each graph lie in the interval of 0 and 1.

We make two observations. First, the preferences (solid lines) clearly vary on a daily frequency. Second, by eyeballing the graphs, we observe that the preference parameters have a positive correlation with the daily percentage change in national COVID-19 hospitalizations (dotted lines). That is, on a daily frequency, a rise in national COVID-19 hospitalizations correlates positively with an increase in the risk aversion parameter γ, an increase in the present-bias factor β, and an increase in the long-term discount factor δ. Stated differently, individuals in our sample, who are representative for the Dutch population, become more risk averse, less present biased, and more patient when national COVID-19 hospitalizations rise, all on a daily frequency. The unconditional rank correlation coefficient of the daily percentage change in COVID-19 hospitalizations (i) with the risk aversion parameter equals 0.3460 (p-value = 0.0611), (ii) with the present-bias factor equals 0.3625 (p-value = 0.0490),

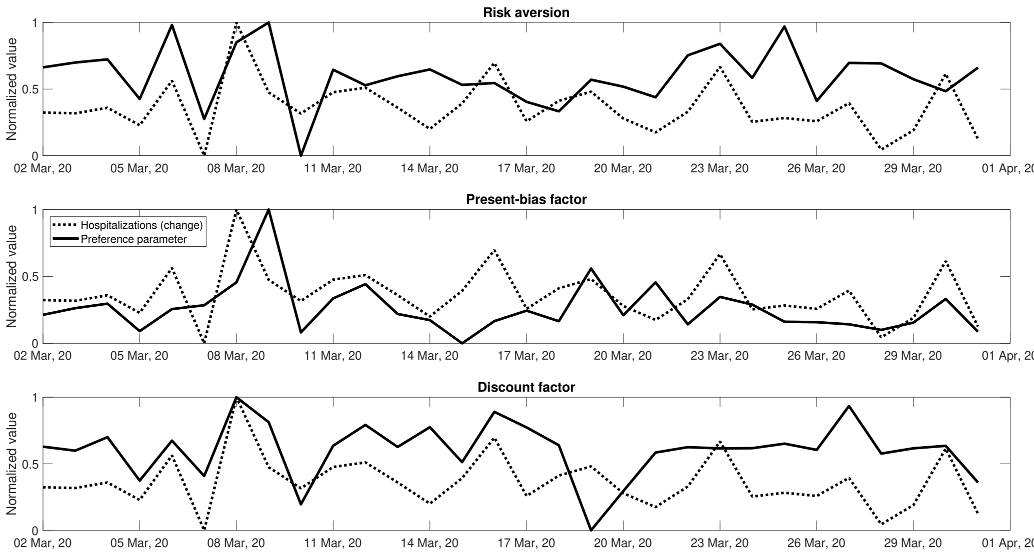

Figure 1: **Daily risk and time preferences during the COVID-19 crisis.** Risk aversion parameter γ (top), present-bias factor β (middle), and discount factor δ (bottom) throughout March 2020 on a daily basis. Preferences are depicted with solid lines and the dotted lines depict the daily percentage changes in COVID-19 hospitalizations on a national level.

and (iii) with the long-term discount factor equals 0.4192 (p-value $= 0.0211$). These results show that the correlation between preferences and $\Delta Hosp$ is significantly different from zero and positive.

Formalization

To formalize the above suggestive evidence, we regress the estimated preferences on the change in 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 regression 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., risk aversion parameter, present-bias factor, or discount factor) 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. We include control variables for individuals' gender, age, partner status, education level, income, and fixed effects for the month of the survey and days of the week. We include day fixed effects to address potential concerns regarding daily seasonality effects in hospitalizations. We use quantile regressions to estimate the conditional median of the preference parameters, as this is more robust to extreme observations. Since individuals' decisions are likely to be cross-sectionally correlated, we cluster standard errors at the individual level in all regressions.

Our coefficient of main interest is a_1. Based on the descriptive evidence, we expect a_1 to be positive: a growth of national COVID-19 hospitalizations correlates positively with the risk aversion parameter, the present-bias factor, and the long-term discount factor. Table 2 shows that indeed our coefficient of interest, a_1, is positive and statistically significant for risk and time preferences. Hence, individuals are more risk averse, less present biased and more patient when observed during a rise in national COVID-19 hospitalizations.

In economic terms, a two-standard deviation increase in the change in COVID-19 hospitalizations (about 73 percentage points, see Supplementary Table 12) leads to an increase of about 0.087 in the risk-aversion parameter γ, 0.043 in the present-bias factor β, and 0.015 in the annual discount factor δ. Especially, the change in time preferences can be well interpreted and the change is economically sizeable. Regarding long-term discounting, when hospitalizations rise by two standard deviations, individuals are more patient as they discount the future *less* at the median; namely, individuals decrease their median annual discount rate of 2.3% (see Table 1) by about 1.5 percentage points (i.e., $2 \times \frac{36.51}{100} \times 0.021$) to an annual discount rate of 0.8%. Regarding present bias, when hospitalizations rise, individuals behave time consistent as they are no longer present biased at the median; namely, individuals increase their median present-bias factor β from 0.966 (see Table 1) to 1.009. Regarding risk aversion, when hospitalizations rise, individuals behave more risk averse as the median individuals' risk aversion parameter γ increases from 1.687 to 1.774.

Potential mechanisms

What could potentially drive the changes in preferences, as a result of changes in hospitalizations? In the event of extreme (negative) shocks, such as the COVID-19 pandemic, people may experience fear, specifically with regard to the uncertain future. Individuals become

Table 2: **Daily risk and time preferences during the COVID-19 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, (annual) present-bias factor β, (annual) discount factor δ, 1-year, and 5-years self-reported life expectancy. The unit of observations is at the individual level for a daily frequency. t-values are shown between parentheses, using robust standard errors and corrected for clustering of observations at the individual level.

	Risk aversion	Present-bias factor	Discount factor	1-year life exp.	5-years life exp.
$\Delta Hosp$ ($\times$100)	0.119	0.059	0.021	-0.826	-0.657
	(2.56)	(2.88)	(2.43)	(-0.70)	(-0.46)
December	-0.019	-0.024	-0.006	-2.204	-2.589
	(-0.42)	(-1.45)	(-1.02)	(-1.92)	(-2.09)
Male	-0.082	-0.015	-0.003	-0.490	-1.249
	(-2.30)	(-1.02)	(-0.60)	(-0.65)	(-1.41)
Age	0.013	0.002	0.000	0.042	-0.244
	(7.57)	(3.04)	(0.20)	(1.06)	(-5.36)
Partner	-0.090	-0.034	-0.006	-0.558	0.482
	(-2.55)	(-2.49)	(-1.02)	(-0.74)	(0.55)
Edu. medium	-0.068	-0.005	-0.010	2.467	2.681
	(-1.52)	(-0.22)	(-1.37)	(2.34)	(2.28)
Edu. high	-0.186	-0.040	-0.023	4.000	4.783
	(-3.85)	(-1.76)	(-3.11)	(3.81)	(4.00)
Income ($\times$1000)	0.429	-0.015	0.006	0.617	0.903
	(18.75)	(-3.15)	(2.73)	(1.90)	(2.35)
Constant	0.248	0.909	0.983	88.497	96.150
	(2.25)	(19.73)	(57.10)	(33.19)	(31.54)
Day FE	Yes	Yes	Yes	Yes	Yes
N	2266	2266	2266	2265	2265
R^2	0.039	0.007	0.007	0.019	0.038

more risk averse through fear during an extreme negative exogenous shock, such as the financial crisis of 2007-2008[32], a horror movie[32], and a primed financial burst[31]. Fear is identified as a significant correlate with within-person changes in risk aversion[33] and fear decreases the amount invested in risky assets[30]. Thus, individuals' risk aversion can be altered through a fearful negative 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 shock[32]. Our CTB experiments, reflecting intertemporal consumption-savings decisions under uncertainty, took place during the emergence of COVID-19 and lockdowns, times

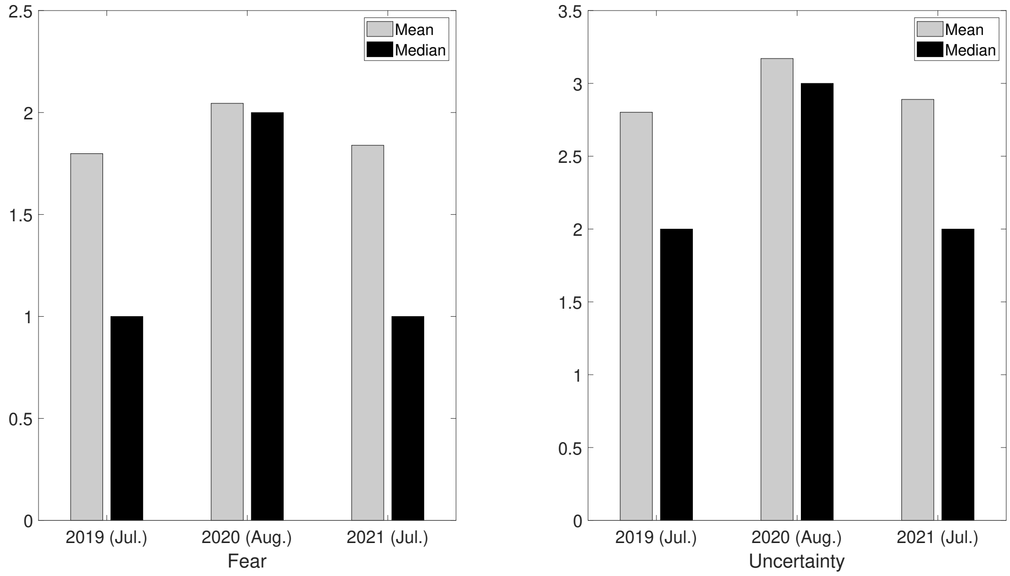

Figure 2: **Fear and uncertainty before, during, and after the emergence of COVID-19.** The left panel shows mean and median self-reported fear on a 7-point Likert scale (0 = 'not at all' and 6 = 'extremely') the year before, during, and after the emergence of COVID-19. Similarly, the right panel shows self-reported uncertainty, as proxied by self-reported distress.

in which fear could be born naturally. 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 fear that hospitals might reach full capacity resulting in a potential health crisis.

Thus, building upon earlier literature, fear may serve as a potential mechanism through which risk aversion increases as the severity of the COVID-19 crisis rises. That is, when national COVID-19 hospitalizations increase, individuals experience more fear when confronted with higher reported COVID-19 hospitalizations. Figure 2, left panel, shows that fear among our individuals during the COVID-19 crisis in 2020 is higher than the years before and after the crisis in 2020. Data on fear is only available on an annual basis, not on a daily basis. Overall, this provides suggestive evidence for the role of fear in explaining our results on the dynamics of risk preferences.

The literature on the connection between time preferences and emotions is limited[54]. Experimental settings, especially in an intertemporal consumption-savings context with uncertainty, regarding fear and time preferences are to the best of our knowledge absent. However, there are authors that study the connection between uncertainty and precautionary savings[34,35,36], also during the COVID-19 pandemic[37]. Albeit on a micro- or macroeconomic level, these studies find that precautionary savings increase during uncertain times, such as the Great Depression or the financial crisis of 2007-2008. Individuals want to insure themselves against bad states of the economy in the future and try to retain a smooth consumption path by precautionary savings and lower consumption in the current period. Thus, individuals saving behavior can be altered by uncertainty.

Our CTB experiments took place during uncertain times, namely the emergence of COVID-19 and lockdowns. We identify time preferences through consumption and savings decisions in our experiments, by definition. Individuals are elicited to be more patient when they delay consumption and increase savings in the current period. Thus, as a potential mechanism we propose that patience increases when national COVID-19 hospitalizations increase, i.e., when uncertainty increases. Individuals lower their time preference in uncertain times, leading to higher precautionary savings. Figure 2, right panel, shows that uncertainty among our individuals during the COVID-19 crisis in 2020 is higher than the years before and after the crisis in 2020. Data on uncertainty is only available on an annual basis, not on a daily basis. Overall, this provides suggestive evidence for the role of uncertainty in explaining our results on the dynamics of time preferences.

Discussion

Other mechanisms

First, one might have the concern that our results are potentially driven by a change in beliefs regarding life expectancy. However, we can rule out this channel, since there is no statistically significant correlation between changes in national COVID-19 hospitalizations and individual self-reported life expectancy probabilities, as shown in the last two columns of Table 2.

Second, one might have the concern that our results are potentially driven by the particular functional form of the utility function and time-discounting function. For this reason, we regress the individuals' raw, untransformed experimentally allocated amounts in the CTB to the late payment, c_{t+k}, on the changes in national COVID-19 hospitalizations, $\Delta Hosp$ (see Supplementary Table 9). In line with our earlier observations on preference parameters, we find that the raw experimentally allocated amounts in the CTB to the late payments correlate statistically significantly and positively with changes in national COVID-19 hospitalizations. Stated differently, our results are not merely a result of the assumed parametric specification of risk and time preferences. Thus, our analysis also avoids the problem of making our results dependent on a particular functional form of the utility function (such as constant relative and absolute risk aversion) as well as the discount function (such as exponential and hyperbolic discounting)[55,41] .

Third, our results are similar when using national COVID-19 *ICU* hospitalizations as main independent variable, which excludes patients in the nursing wards. Although COVID-19 *ICU* hospitalizations were less salient than COVID-19 hospitalizations including ICU and nursing wards, especially during the emergence of the crisis, individuals' preferences react similarly (see Supplementary Table 11, Panel H).

Fourth, a potential concern might be that changes in preferences are related to changes in income, as individuals might have suffered labor market problems during COVID-19. Our results remain similar when we perform our main analysis only for the group of individuals with an equal income during February, March, and December 2020 (see Supplementary Table 11, Panel I). Thus, our findings are not driven by changes in income. A related concern might be that shifts in wealth or stock-market participation could influence preferences, particularly for risk. We find little evidence for such a mechanism. The share of stock-market participants remained remarkably stable over time: 16.44% on 31 December 2019 and 17.08% on 31 December 2021, and this difference is statistically insignificant (paired t-test, $p = 0.32$).

Fifth, one might have the concern that our results are driven by particular estimation choices. However, Supplementary Tables 10 and 11 show that our results are robust to estimating preferences with OLS rather than median regressions (Panel A), using OLS regressions rather than median regressions for estimating our main specification in equation (1) (Panel B), estimating preference parameters with monthly background income w rather than annual background income (Panel C), using only demographic variables as set of controls (Panel D), adding self-reported life expectancy to the standard set of controls (Panel E), adding financial literacy to the standard set of controls (Panel F), and the unbalanced panel test (Panel G)[56].

Finally, a potential concern might be that the observed increased patience in our experiments is not driven by uncertainty, but rather by the inability of households to spend income during the COVID-19 crisis as a result of shop closures and lockdowns. However, we find that risk and time preferences react similarly to changes in national COVID-19 hospitalizations during the beginning of March 2020 and the end of March 2020, when shops were closed as a result of an intelligent lockdown. Hence, this alleviates such concerns.

Alternative model specifications

Our main estimation model (see equation 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 relax this assumption, we separate within and between effects by estimating the following hybrid model

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

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[57,58]. Analyzing the within effect allows individual specific unobserved heterogeneity to be correlated with the explanatory variables. 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 3, Panel A, shows the results of the estimated hybrid model. When we compare the between and within estimates for each preference, we make two observations. First, we observe that the between and within effects are similar in size, although standard errors are larger for within effects (which are based on a smaller number of observations). The Wald test suggests, at any reasonable significance level, that we can not reject the null hypothesis of equality for between and within estimates ($H_0 : \tilde{a}_1 = \tilde{a}_2$). This suggests that individual specific unobserved variables are not correlated with hospitalizations. This is in favor of our main estimation model (see equation 1). Second, still, self-reported life expectancies are not affected by hospitalizations.

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. (A province in The Netherlands is very similar to a county in the U.S.). We hypothesize that province level COVID-19 hospitalizations matter less for time-varying preferences as the reported hospitalizations on TV, internet, and smartphones were 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. The results in Panel B, Table 3, indeed confirm that COVID-19 hospitalizations on a province level are unrelated to the time variation in preferences and self-reported life expectancy. Thus, this provides additional suggestive evidence that the salience of the reported national news induces time variation in risk and time preferences.

Table 3: **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 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 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 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. $y_{i,t}$ represents the preference parameter for individual i at day t, per column: risk aversion γ, (annual) present-bias factor β, (annual) discount factor δ, 1-year, and 5-years self-reported life expectancy. The unit of observations is at the individual level for a daily frequency. Controls $X_{i,t}$ include *December*, *Male*, *Age*, *Partner*, *Edu. medium*, *Edu. high*, and *Income*. The Wald test shows the null hypotheses between parentheses. t-values are shown between parentheses, using robust standard errors and corrected for clustering of observations at the individual level.

	Risk aversion	Present-bias factor	Discount factor	1-year life exp.	5-years life exp.
Panel A: Within and between					
$\Delta Hosp_{i,t} - \overline{\Delta Hosp_i}$ ($\times 100$)	0.091	0.012	0.034	-0.674	-0.240
	(0.92)	(0.25)	(1.92)	(-0.27)	(-0.09)
$\overline{\Delta Hosp_i}$ ($\times 100$)	0.121	0.063	0.020	-0.844	-0.705
	(2.50)	(2.82)	(2.18)	(-0.68)	(-0.47)
Constant	0.256	0.906	0.983	88.496	96.146
	(2.29)	(19.52)	(58.13)	(33.16)	(31.52)
Wald test ($\tilde{a}_1 = \tilde{a}_2$)	0.7679	0.3099	0.4671	0.9465	0.8687
Controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	2266	2266	2266	2265	2265
R^2	0.039	0.008	0.006	0.019	0.038
Panel B: Province					
$\Delta Hosp_p$ ($\times 100$)	0.025	0.019	0.005	-0.644	-0.300
	(1.26)	(1.79)	(1.49)	(-1.24)	(-0.47)
Constant	0.376	0.912	0.985	86.500	89.753
	(2.69)	(15.73)	(49.01)	(26.12)	(21.78)
Controls	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
N	2256	2256	2256	2255	2255
R^2	0.038	0.004	0.005	0.025	0.047

Simpler measures

Since different risk elicitation methods can give rise to considerably varying risk aversion levels[23], something which could also be expected for time preferences, we measure risk and time preferences not only with the CTB but also with other elicitation methods. We selected these other elicitation methods based on the criterion that they are simpler compared to the CTB method, in the sense that these other elicitation methods are cognitively less demanding, but as a result yield a coarser measurement of preferences. It is known that simpler, but coarser, elicitation methods may be preferred to more complex, but finer, methods (such as the CTB), depending on the level of numeracy of the individuals[24]. We use simple qualitative and quantitative measures of risk and time preferences.

The qualitative measures (see Supplementary Table 13) show moderate risk taking behavior and low impulsiveness, in line with our estimated risk aversion parameter and present-bias factor from the CTB. The quantitative risk aversion measure[26] confirms that our respondents are risk averse in the CTB. The quantitative measures for time preferences[28,29], assuming linear utility, yield somewhat higher discount rates for the present and the long term compared to the CTB experiment. This corroborates the observation in the literature that time preferences are upward biased if true utility is concave[59] and, therefore, simultaneous estimation of risk and time preferences might be preferred over independent measurements. Correlations between the CTB and qualitative measures are insignificant, but correlations between the CTB and quantitative measures are mostly significant, having the expected sign yet small in magnitude (see Supplementary Table 14).

We now take these simple qualitative and quantitative measures of risk and time preferences as the dependent variable in our main estimation model (see equation 1). Interestingly, as shown in Table 4, we find that the simpler qualitative and quantitative preference measures are unable to capture the time variation in preferences. That is, national COVID-19 hospitalizations are uncorrelated with the simple preference measures. A potential reason might be that the cognitive simpler tasks are too coarse to capture the daily dynamics in preferences, while the cognitive more complex CTB measure has overall superior accuracy as the measure is finer, potentially at the cost of more noisy behavior[24]. When studying the simpler measures with the hybrid model of within and between effects, results remain similar and, thus, insignificant. Using the simpler measures, we still observe no effects at the province level.

Table 4: **Daily risk and time preferences during the COVID-19 crisis with simpler measures.** This table reports the estimated coefficients of the pooled regressions $\bar{y}_{i,t} = \bar{a}_0 + \bar{a}_1 \Delta Hosp_{i,t} + \bar{a}_2 Dec + \bar{b} X_{i,t} + \bar{\varepsilon}_{i,t}$. Columns (1) till (3) use the qualitative statements for the dependent variable, and columns (4) till (7) use the quantitative statements for the dependent variable. In columns (1), (2), and (3) the dependent variable is a dummy variable which equals 1 if the individual is respectively risk taking, impulsive, and impatient (Likert scale 4 or higher), and 0 otherwise. In column (4) the dependent variable is the risk tolerance category. In columns (5) and (6) the dependent variable is respectively the discount rate over a 1-year horizon and a 5-years horizon, and in column (7) the dependent variable is a dummy variable which equals 1 if the 1-year discount rate exceeds the 5-years discount rate, and 0 otherwise. Columns (1), (2), (3), (4), and (7) feature (ordered) logistic regressions, and columns (5) and (6) feature OLS regressions. Controls $X_{i,t}$ include $Male$, Age, $Partner$, $Edu.\ medium$, $Edu.\ high$, and $Income$. t-values are shown between parentheses, using robust standard errors and corrected for clustering of observations at the individual level.

	Qualitative			Quantitative			
	Risk	Time		Risk	Time		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Hosp$ ($\times 100$)	-0.128	-0.467	-0.163	-0.175	-10.735	0.330	-0.092
	(-0.85)	(-1.87)	(-1.05)	(-1.23)	(-1.06)	(0.18)	(-0.63)
December	0.122	0.055	-0.028	-0.145	-14.882	0.913	0.005
	(0.92)	(0.27)	(-0.20)	(-1.09)	(-2.69)	(0.63)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2179	2236	2229	2266	2266	2266	2266

Conclusion

Research on the stability of preferences is conceptually at the heart of economics. Typically, individuals' preferences are assumed to be stable and persistent over time[8]. However, we show that preferences vary on a daily frequency during an extreme event, i.e., the COVID-19 pandemic, in a systematic but temporary fashion. Using well-established methods from behavioral and experimental economics, we elicit and estimate risk and time preferences on a daily frequency during the COVID-19 crisis for 2266 individuals representative of the Dutch population. We find a strong statistically significant and sizable correlation between preferences and the daily severity of the COVID-19 situation. In particular, we show that risk aversion, time consistency, and patience correlate positively with daily changes in national COVID-19 hospitalizations when preferences are simultaneously measured with the CTB[20]. Individuals become more risk averse, more time consistent, and more patient when hospitalizations increase. Especially, the effect on time preferences is sizable: individuals decrease their long-term annual discount rate from 2.3% to 0.8% when COVID-19 hospitalizations increase by two standard deviations. A potential mechanism for the time variation in risk preferences is fear, while a potential mechanism for the time variation in time preferences is uncertainty. Extensive robustness checks on other mechanisms and alternative specifications confirm our findings. Aggregated preferences remain remarkably stable and cognitive simpler measures show no association with COVID-19 hospitalizations, possibly because these measures are too coarse[24]. Overall, our findings cast doubt on the perfect stability of preferences, specifically during extreme events on a high frequency. Changes in the stability of preferences have vital real-world consequences for policy making and welfare analyses.

Methods

We adopt an experimental approach in an online survey to elicit risk and time preferences. Our main measure simultaneously elicits and estimates risk and time preferences, based on the well-known existing experimental method of convex time budgets (CTB)[20]. Our survey also features simpler, but coarser, quantitative and qualitative methods to elicit risk and time preferences independently of each other. To control for order effects, we randomize the order of presentation of the elicitation methods at the individual level as well as the order of choices within the CTB. The complete survey can be found in the Online Additional Information.

Simultaneous: Risk and time preferences

We measure risk aversion, present bias, and patience simultaneously with the CTB, while controlling for probability weighting[21]. 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[59].

We ask 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 350% (risk-adjusted) 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, which is in line with the average amount of CTB questions asked in the literature[52]. Our method consists of five different decision sets, and within each set we have four different interest rate scenarios. In the first three choice sets, individuals distribute the endowment between today ($t = 0$) and one year later ($k = 1$); the three choice sets differ in the payment probability one year later, i.e., $p_{t+k} = \{0.5, 0.75, 1\}$. In the fourth choice set, individuals distribute the endowment between today ($t = 0$) and five years later ($k = 5$). In the fifth choice set, individuals distribute the endowment between one year later ($t = 1$) and six years later ($k = 5$). Both the fourth and fifth choice sets have certain early and late payment probabilities. Supplementary Table 5 presents an overview of the CTB experimental design.

Sensitivity towards the early payment dates t elicit present bias, while sensitivity towards the delayed payment dates $t + k$ elicit long-term patience. Sensitivity to variation in the interest rates identifies curvature of the utility function. Sensitivity towards variation in the payment probabilities allows us to control for probability weighting.

Supplementary 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 individuals respond to changing interest rates and payment probabilities in an intuitive predicted way.

To estimate risk and time preferences, we identify the experimental allocated payments as solutions to standard intertemporal optimization problems. These solutions are functions of our parameters of interest (present bias, discounting, risk aversion and probability weighting), and experimentally varied parameters (interest rates, front- and back-end delays, 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 preference parameters. For details on the estimation, see 'Estimation risk and time preferences' in Supplementary Information.

Independent: Risk and time preferences

We also measure risk aversion, present bias, and patience in isolation of each other, using quantitative and qualitative measures. These methods are arguably cognitively less demanding than the CTB, but yield coarser measures of preferences[24].

Risk preferences, quantitative — We measure risk aversion with an adapted version of the well-known single choice list lottery task[25,26]. Supplementary Table 6 presents the task.

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 allows categorization of individuals into six risk tolerance categories, whereas the more complex, but finer, CTB allow categorization of individuals' risk aversion on a continuous scale.

Time preferences, quantitative — We measure present bias and patience using a matching task[60,28,29]. Supplementary Table 7 presents the task.

The task asks individuals to state 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. The task elicits the 1-year subjective discount rate and the 5-years subjective discount rate. The discount rate over a 1-year horizon is a proxy for the degree of present bias, while the discount rate over a 5-years horizon is a proxy for long-term patience. Suggestive evidence for present bias, i.e., time inconsistency, is found when the 1-year discount rate exceeds the 5-years discount rate[44].

Qualitative — We use three qualitative statements to measure financial risk-taking behavior, financial impulsiveness, and financial impatience. These statements proxy for the degree of risk aversion, present bias, and patience, respectively. Individuals answer three statements on a 7-points Likert scale from ‘strongly disagree’ to ‘strongly agree’. The risk-taking statement comes from the Dutch Central Bank Household Survey, and the impulsiveness and impatience statements are taken from the academic literature[27]. Supplementary Table 8 shows the qualitative risk and time preferences task.

Experimental procedure

Upon starting the online survey experiment, subjects read through the instructions for the CTB experiment. The instructions indicate that a budget should be distributed between an early payment and 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[61,45].

Supplementary Figure 3 shows a decision screen in the CTB. Individuals are told to divide an amount of €10,000 between the early payment today and a late payment next year. In this particular decision screen, the likelihood that the early and late payments are received equals 100%. Individuals make four budget decisions for gross interest rates from 1.00 to 4.50. In subsequent decision screens, the varying early and later payment dates are emphasized by underlining the dates, and probabilities of uncertain late payment were underlined as well. Individuals face a total of five such decision screen sets, such that they complete 20 decisions. Additionally, subjects complete the three other tasks that elicit risk and time preferences in independently. Finally, individuals respond to questions about their estimated life expectancy and financial literacy.

Sample

We directed the survey to a representative sample of Dutch households through the LISS (Longitudinal Internet Study in the Social Sciences) in The Netherlands. The panel is widely considered as one of the most comprehensive, reliable, and representative samples used in the household finance literature[62,63,64]. The LISS panel is based on a probability-address based sample of households (no self selection) drawn from the population register of The Netherlands and administered by CentERdata (Tilburg University). CentERdata is a non-profit research institute focused on academic, social, and policy-related research. The institute is a prominent player in conducting surveys, policy analysis, and consumer research. Households without a computer and/or internet connection receive a computer and/or internet connection free of charge. This household panel receives online questionnaires each month on different topics. When respondents complete a questionnaire, they receive a monthly incentive.

We invite a total of 2998 LISS panel members between the ages of 40 and 70 in March 2020 and December 2020. We have chosen 70 years as an upper cutoff point to minimize potential issues regarding effects of mortality risk in the CTB decisions, which have a maximum horizon of 6 years. Our choice yields a late payment at the age of 76 at most, well within the average Dutch life expectancy at the time of the experiment. A total of 2631 panel members responded during both months, so we have a response rate of about 88% across both months. We can estimate preference parameters for 2266 panel members.

For 136 panel members we have no data on income and for 7 panel members we have no data on gender, age, partner status, or education. We require to have income, because we use it as a proxy for background consumption in the estimation of the CTB preference parameters. We require to have data on gender, age, partner status, and education as these variables are the main controls in our analyses. 75 panel members did not fully complete the CTB task, which yields preference parameter issues. 147 panel members never altered their decisions from a specific corner solution in all the CTB questions and thus provide insufficient variation for the calculation of preference parameters. Following the literature[65], we drop these panel members. Overall, this procedure yields a final sample of 2266 individuals, of which we observe 2020 individuals in March 2020 (invited 2676) and 246 individuals in December 2020 (invited 322). The observations in December 2020 are lower, because we invited the household heads that participated in March 2020 as well. Supplementary Figure 5 shows the number of daily observations throughout March and December in 2020.

Supplementary Table 12 reports the socio-demographic information. The male to female ratio is nearly 50%, and the average age is about 57 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 €1889. Participants on average estimate that they have about 93% chance of surviving one more year and about

85% chance of surviving the next five years.

The respective local ethics committee (Ethics Assessment Committee Faculty of Law and Nijmegen School of Management) approved the study under the following approval number: EACLM-LT-027. LISS ensures that the study is clear to its panel members and ensures consent. The median time to complete the online survey is 15 minutes. Using a 5-point Likert scale ('1 = definitely not' to '5 = definitely yes'), participants at the end of the survey answer the question "Did you find the questions clear?" at the median with a 4.0. This indicates that it was clear to the participants what was expected from them and that they understood their tasks. Analyses were conducted in MATLAB (9.6.0.1072779, R2019a)(`www.mathworks.com`) and STATA (17.0) (`https://www.stata.com/`).

COVID-19 data

We download the national hospitalizations from the website of the National Institute for Public Health and the Environment, based on the Osiris database which uses the data reported by the Public Health Services (GGD). Until 16$^{\text{th}}$ December 2020 the official COVID-19 hospitalization numbers on the governmental corona-dashboard were based on the Osiris database. The hospitalization numbers include COVID-19 patients on the ICU and the nursing wards, and only those individuals that are in the hospital because of COVID-19. That is, the measure excludes patients with additional reasons, besides COVID-19, for being in the hospital. To download the hospitalizations on a province level, we need the National Intensive Care Evaluation (NICE) reported numbers. These provincial COVID-19 numbers include patients on the ICU and nursing wards for individuals being in the hospital for at least having COVID-19, including possibly other reasons for being in the hospital. For the analysis using only ICU hospitalizations in the main independent variable, we downloaded the national COVID-19 ICU hospitalizations from the website of the National Institute for Public Health and the Environment, and they are based on the NICE reported numbers.

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Author contributions

J.G. and M.K. designed the research, managed the survey experiments, analysed the data, and wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper in the Online Appendix.

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Supplementary information

A. Experimental design

Table 5: **Risk and time preferences task[20].** Overview of the Convex Time Budgets method. 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 $((1+r)^{1/k}-1)\times 100$. Following by multiplication, 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	0	1.0	1.0	0
2	1	0	1	10,000	15,000	1.5	50	1.0	1.5	50
3	1	0	1	10,000	25,000	2.5	150	1.0	2.5	150
4	1	0	1	10,000	45,000	4.5	350	1.0	4.5	350
5	2	0	1	10,000	20,000	2.0	100	0.5	1.0	0
6	2	0	1	10,000	30,000	3.0	200	0.5	1.5	50
7	2	0	1	10,000	50,000	5.0	400	0.5	2.5	150
8	2	0	1	10,000	90,000	9.0	800	0.5	4.5	350
9	3	0	1	10,000	13,300	1.33	33.33	0.75	1.0	0
10	3	0	1	10,000	20,000	2.0	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	6.0	500	0.75	4.5	350
13	4	0	5	10,000	10,000	1.0	0	1.0	1.0	0
14	4	0	5	10,000	15,000	1.5	8.45	1.0	1.5	8.45
15	4	0	5	10,000	45,000	4.5	35.1	1.0	4.5	35.1
16	4	0	5	10,000	85,000	8.5	53.42	1.0	8.5	53.42
17	5	1	5	10,000	10,000	1.0	0	1.0	1.0	0
18	5	1	5	10,000	15,000	1.5	8.45	1.0	1.5	8.45
19	5	1	5	10,000	45,000	4.5	35.1	1.0	4.5	35.1
20	5	1	5	10,000	80,000	8.0	51.57	1.0	8.0	51.57

Divide €10,000 below each time between today and 1 year later.

	Euros today (with certainty)	Euros that you receive in 1 year with certainty
Suppose you receive an extra €0.00 per euro that you have paid out in 1 year	0 … 10000	
Suppose you receive an extra €0.50 per euro that you have paid out in 1 year	0 … 10000	
Suppose you receive an extra €1.50 per euro that you have paid out in 1 year	0 … 10000	
Suppose you receive an extra €3.50 per euro that you have paid out in 1 year	0 … 10000	

Figure 3: **Decision screen risk and time preferences task.** In this Convex Time Budgets decision screen, the individual 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 amounts to today are for illustration purposes only, the default values were blanks (subjects must actively allocate). The text is translated from Dutch to English.

Table 6: **Risk preferences task[25,26].** Individuals 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 7: **Time preferences task[28,29].** Individuals state the amount X that makes them indifferent between receiving options A. and B. The 1-year discount rate proxies the (annual) degree of present bias, the 5-years discount rate proxies the (annual) degree of long-term patience. If the 1-year rate exceeds the 5-years rate, then this is suggestive evidence for present bias, i.e., time-inconsistent discounting.

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

Table 8: **Qualitative risk and time preferences.** Individuals rate the statements on a 7-points Likert scale, ranging from 'strongly disagree' to 'strongly agree'. The statement for risk preferences is taken from the Dutch Central Bank Household Survey, and the statements for impulsiveness and impatience are taken from the academic literature[27].

Risk preferences
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

B. Estimation risk and time preferences

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, while controlling for probability weighting η. In the CTB experiment, individuals 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

$$c_t + \frac{c_{t+k}}{1+r} = m, \tag{3}$$

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

Assuming the seminal quasi-hyperbolic discounting model of intertemporal decision making[39,40], the individual maximizes discounted expected utility over the early payment c_t and late payment c_{t+k} (including interest)

$$\begin{aligned} \max_{c_t, c_{t+k}} \delta^t & \left[\pi(p_t)U(c_t + w_t) + (1 - \pi(p_t))U(w_t)\right] \\ & + \beta\delta^{t+k} \left[\pi(p_{t+k})U(c_{t+k} + w_{t+k}) + (1 - \pi(p_{t+k}))U(w_{t+k})\right], \end{aligned} \tag{4}$$

where δ is the (annual) discount factor and β is the (annual) 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 are interpreted as background consumption or income.

"Background consumption is the optimized consumption stream based on wealth and income that is perfectly anticipated before allowing for the effects of the money offered in the experimental tasks"[66]. We set background consumption w for each individual exogenously as (i) this limits the number of estimated parameters and (ii) this facilitates comparison with the previous literature since about 90% of the CTB studies set background consumption exogenously[52]. Specifically, in our main analyses, we set background consumption equal to the individual's annual after-tax income, i.e., $w_{t,i} = w_{t+k,i} = income_i$. Overall, we treat the experimental endowments as a prospect viewed in combination with the individual's personal income.

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

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}, \tag{5}$$

with γ the curvature parameter, also known as the coefficient of relative risk aversion. With this functional form, $\gamma = 0$ denotes risk neutral behavior, $\gamma > 0$ denotes risk aversion and $\gamma < 0$ denotes risk seeking behavior. Money allocated to the early payment has a value of c_t, while money allocated to the late payment has a present value of $c_{t+k}/(1+r)$. 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%.

and that the agent distorts probabilities according to a simple Prelec weighting function with parameter η.

Given the evidence regarding probability distortions[67,22], we assume that individuals distort probabilities according to a simple Prelec weighting function with parameter η such that

$$\pi(p) = p^{\eta}, \tag{6}$$

where p is the objective probability and $\pi(p)$ is the subjective (distorted) probability.

Solving the individual's maximization problem (4) subject to her budget constraint (3) yields the first-order condition

$$\frac{c_t + w_t}{c_{t+k} + w_{t+k}} = \begin{cases} \left(\beta\delta^k(1+r)\pi(p_{t+k})\right)^{-\frac{1}{\gamma}}, & \text{if } t = 0 \\ \left(\delta^k(1+r)\pi(p_{t+k})\right)^{-\frac{1}{\gamma}}, & \text{if } t > 0 \end{cases} \tag{7}$$

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

Taking the natural logarithm and using the Prelec weighting function, we find

$$\begin{aligned}\ln\left(\frac{c_t + w_t}{c_{t+k} + w_{t+k}}\right) = &\left(\frac{\ln\beta}{-\gamma}\right)\cdot \mathbb{1}_{t=0} + \left(\frac{\ln\delta}{-\gamma}\right)\cdot k \\ &+ \left(\frac{1}{-\gamma}\right)\cdot \ln(1+r) + \left(\frac{\eta}{-\gamma}\right)\cdot \ln(p_{t+k}).\end{aligned} \tag{8}$$

Given an additive error structure, such an equation is easily estimated with parameter estimates for β, δ, and γ obtained via non-linear combinations of coefficient estimates. The equation shows that the (annual) present-bias factor β is identified through sensitivity towards an early payment ($t = 0$), the long-term (annual) discount factor is identified through the delay in payments (via k), and the CRRA risk aversion follows from sensitivities towards the gross interest rate $(1 + r)$. Controlling for probability weighting is done via sensitivity towards the probability of a late payment p_{t+k}.

In our main analyses, we estimate the preference parameters per individual using two-limit Tobit maximum likelihood regressions to account for corner solutions. After the estimation, we winsorize the individually estimated parameters at the 1% level of the bottom and top of the overall distribution. Regarding probability weighting, aggregated for 2020, we find that 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of η are -0.0831575 and 1.829716, respectively.

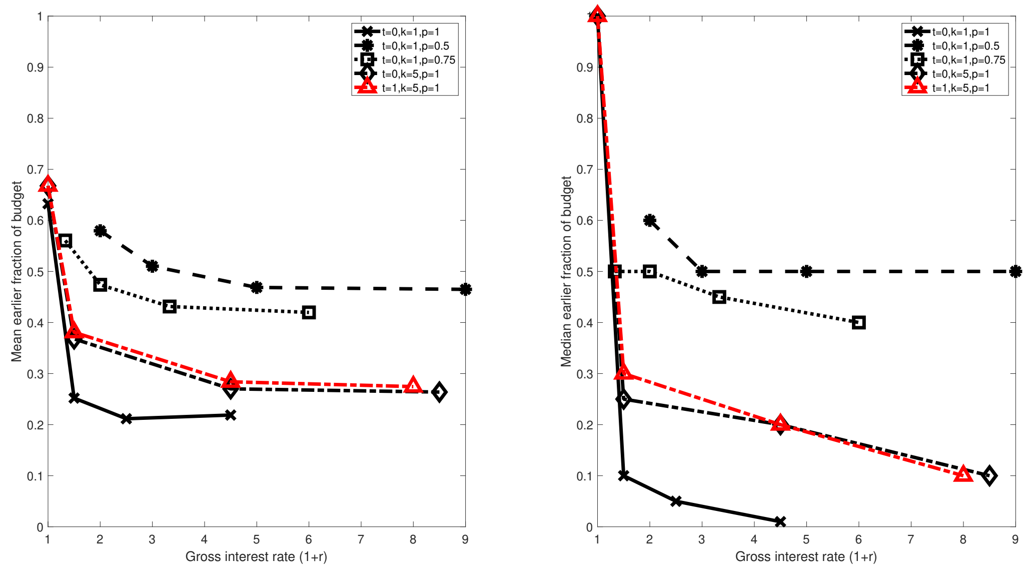

Figure 4: **Distribution of experimentally allocated payments in the risk and time preferences task.** On the horizontal axis the gross interest rate $1 + r$ as offered in the Convex Time Budgets, and on the vertical axis the mean (left) and median (right) allocated payments towards the earlier date, c_t, expressed as fraction of the total endowment m.

C. Robustness tests

Table 9: **Daily consumption-savings allocations (€) during the COVID-19 crisis.** 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, $Partner$, $Edu.\ medium$, $Edu.\ high$, $Income$. Column (1) uses a median regression and column (2) uses OLS. The unit of observations is at the individual level for a daily frequency. t-values are shown between parentheses, using robust standard errors and corrected for clustering of observations at the individual level.

	(1)	(2)
$\Delta Hosp$ ($\times$100)	1767.914	937.868
	(2.75)	(1.70)
December	-32.687	99.766
	(-0.06)	(0.20)
Constant	26775.932	26352.786
	(18.88)	(20.50)
Controls	Yes	Yes
Day FE	Yes	Yes
N	2266	2266
R^2	0.036	0.040

Table 10: **Robustness tests for main result.** 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, (annual) 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. In Panel A, risk and time preferences are estimated with OLS rather than TOBIT regressions. In Panel B, the main regression equation is estimated with OLS rather than median regressions. In Panel C, risk and time preferences are estimated with monthly background income rather than annual background income. In Panel D, the set of controls is confined to exogeneous variables only, i.e., $X_{i,t}$: Dec, $Male$, Age, and day fixed effects.

	Risk aversion	Present-bias factor	Discount factor
Panel A: Preferences estimated with OLS			
$\Delta Hosp$ ($\times 100$)	0.119	0.059	0.021
	(2.56)	(2.88)	(2.43)
N	2266	2266	2266
Panel B: OLS regression			
$\Delta Hosp$ ($\times 100$)	0.281	3.014	0.053
	(1.37)	(2.32)	(3.10)
N	2266	2266	2266
Panel C: Preferences estimated with monthly background income			
$\Delta Hosp$ ($\times 100$)	0.033	0.061	0.028
	(1.19)	(1.89)	(2.10)
N	2266	2266	2266
Panel D: Controlling for demographics only			
$\Delta Hosp$ ($\times 100$)	0.033	0.070	0.022
	(0.54)	(3.10)	(2.54)
N	2266	2266	2266

Table 11: **Robustness tests for main result (continued).** In Panel E, controls for life expectancy are added to the standard set of controls. In Panel F, controls for financial literacy are added to the standard set of controls. In Panel G, we test for unbalancedness of the panel dataset[56]. In Panel H, we use the daily percentage change in national COVID-19 *ICU* hospitalizations. In Panel I, we only use the individuals that have an equal salary during February, March, and December 2020. The unit of observations is at the individual level for a daily frequency. t-values are shown between parentheses, using robust standard errors and corrected for clustering of observations at the individual level.

	Risk aversion	Present-bias factor	Discount factor
Panel E: Controlling for life expectancy			
$\Delta Hosp$ ($\times$100)	0.119	0.056	0.022
	(2.86)	(2.70)	(2.54)
1-year life expectancy	-0.000	-0.002	-0.000
	(-0.00)	(-1.77)	(-0.54)
5-years life expectancy	-0.002	-0.001	-0.000
	(-1.44)	(-1.04)	(-0.86)
N	2265	2265	2265
Panel F: Controlling for financial literacy			
$\Delta Hosp$ ($\times$100)	0.077	0.056	0.024
	(1.94)	(2.59)	(2.70)
Financial literacy	-0.253	-0.066	-0.032
	(-7.41)	(-2.28)	(-4.16)
N	2266	2266	2266
Panel G: Unbalanced panel test			
$\Delta Hosp$ ($\times$100)	0.108	0.056	0.020
	(2.46)	(2.72)	(2.37)
Times observed	0.023	-0.018	-0.002
	(0.50)	(-0.98)	(-0.22)
N	2266	2266	2266
Panel H: ICU hospitalizations			
ΔICU ($\times$100)	0.241	0.199	0.040
	(1.46)	(2.91)	(1.67)
N	2266	2266	2266
Panel I: Constant income during 2020			
$\Delta Hosp$ ($\times$100)	0.157	0.079	0.028
	(2.73)	(2.64)	(2.30)
N	1406	1406	1406

D. Supplementary tables and figures

Table 12: **Socio-demographic and related variables.** *Partner* equals 1 if the participant lives together with a partner (either 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 $5 - years\ life\ expectancy$ 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	0.49	0.50	0.00	1.00	2266
Age (years)	56.59	8.54	40.00	70.00	2266
Partner	0.71	0.45	0.00	1.00	2266
Education low	0.25	0.43	0.00	1.00	2266
Education medium	0.37	0.48	0.00	1.00	2266
Education high	0.38	0.49	0.00	1.00	2266
Income (€)	1889	1145	0.00	10000	2266
$\Delta Hosp$	16.02	36.51	-52.63	144.44	2266
1-year life expectancy	93.02	15.59	0.00	100.00	2265
5-years life expectancy	85.38	18.33	0.00	100.00	2265

Table 13: **Preferences from simpler measures and other related variables.** *Risk taking*, *Impulsive* and *Impatient* measure qualitatively self-stated risk and time preferences on a 7-points Likert scale. *Risk tolerance category* measures quantitatively risk tolerance according to six categories[25,26], while $1 - year\ discount\ rate$ and $5 - years\ discount\ rate$ measure quantitatively time preferences[28,29] and $1 - year\ rate\ > \ 5 - years\ rate$ is a dummy variable equal to 1 if the 1-year discount rate exceeds the 5-years discount rate. $\Delta Hosp$ is the daily percentage change in national hospitalizations. $1 - year\ life\ expectancy$ and $5 - years\ life\ expectancy$ are self-reported probabilities for reaching at least your current *age* plus 1 year and your current *age* plus 5 years, respectively.

	Mean	St. Dev.	Min.	Max.	N
Panel A: Aggregated					
Qualitative					
Risk taking	3.52	1.77	1.00	7.00	2179
Impulsive	1.93	1.30	1.00	7.00	2236
Impatient	3.03	1.75	1.00	7.00	2229
Quantitative					
Risk tolerance category	2.02	1.45	1.00	6.00	2266
1-year discount rate	27.14	131.88	-100.00	900.00	2266
5-years discount rate	4.77	25.36	-100.00	58.49	2266
1-year rate > 5-years rate	0.55	0.50	0.00	1.00	2266
Panel B: Aggregated, March 2020					
Other					
$\Delta Hosp$	16.34	36.72	-52.63	144.44	2020
1-year life expectancy	93.23	15.25	0.00	100.00	2019
5-years life expectancy	85.69	18.12	0.00	100.00	2019
Qualitative					
Risk taking	3.51	1.76	1.00	7.00	1939
Impulsive	1.93	1.31	1.00	7.00	1992
Impatient	3.03	1.76	1.00	7.00	1986
Quantitative					
Risk tolerance category	2.03	1.44	1.00	6.00	2020
1-year discount rate	28.77	137.09	-100.00	900.00	2020
5-years discount rate	4.67	25.77	-100.00	58.49	2020
1-year rate > 5-years rate	0.55	0.50	0.00	1.00	2020
Panel C: Aggregated, December 2020					
Other					
$\Delta Hosp$	13.36	34.68	-44.73	74.16	246
1-year life expectancy	91.24	18.09	0.00	100.00	246
5-years life expectancy	82.78	19.86	0.00	100.00	246
Qualitative					
Risk taking	3.61	1.81	1.00	7.00	240
Impulsive	1.97	1.23	1.00	7.00	244
Impatient	2.99	1.67	1.00	7.00	243
Quantitative					
Risk tolerance category	1.95	1.46	1.00	6.00	246
1-year discount rate	13.72	75.51	-100.00	900.00	246
5-years discount rate	5.56	21.79	-100.00	43.10	246
1-year rate > 5-years rate	0.54	0.50	0.00	1.00	246

Table 14: **Correlations between preference measures.** This table reports the Spearman rank correlations between the CTB and simpler preference measures. Panel A correlates the CTB estimated preferences with the simpler qualitative measures, and Panel B correlates the CTB estimated preferences with the simpler quantitative measures. In Panels A and B, the variables of interest in (1), (2), and (3) are the CTB estimated risk aversion parameter γ, (annual) present-bias factor β, and (annual) discount factor δ, respectively. In Panel A, in (4), (5), and (6) each variable of interest is the simple qualitative measure translated into a dummy variable which equals 1 if the individual is respectively risk taking, impulsive, and impatient (i.e., equal to 4 or higher on the 7-points Likert scales), and 0 otherwise. In Panel B, in (4) the variable of interest is the risk tolerance category. In (5) and (6) the variables of interest are respectively the discount rate over a 1-year horizon and a 5-years horizon, and in (7) the variable of interest is a dummy variable which equals 1 if the 1-year discount rate exceeds the 5-years discount rate, and 0 otherwise. Symbol * indicates significance at the 1% level.

Panel A: CTB and qualitative measures

	CTB			Qualitative		
	(1)	(2)	(3)	(4)	(5)	(6)
(1)	1					
(2)	0.1810*	1				
(3)	0.2584*	0.2796*	1			
(4)	-0.0055	-0.0291	-0.0546	1		
(5)	-0.0143	-0.003	0.0169	0.1149*	1	
(6)	0.0147	-0.046	-0.038	0.2408*	0.2606*	1

Panel B: CTB and quantitative measures

	CTB			Quantitative			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1						
(2)	0.1716*	1					
(3)	0.2569*	0.2926*	1				
(4)	-0.0135	0.0184	0.0536	1			
(5)	-0.0247	-0.0618*	-0.0913*	0.0356	1		
(6)	-0.0374	-0.0638*	-0.0756*	-0.0024	0.7002*	1	
(7)	-0.0242	-0.0483	-0.0637*	0.0149	0.7737*	0.3987*	1

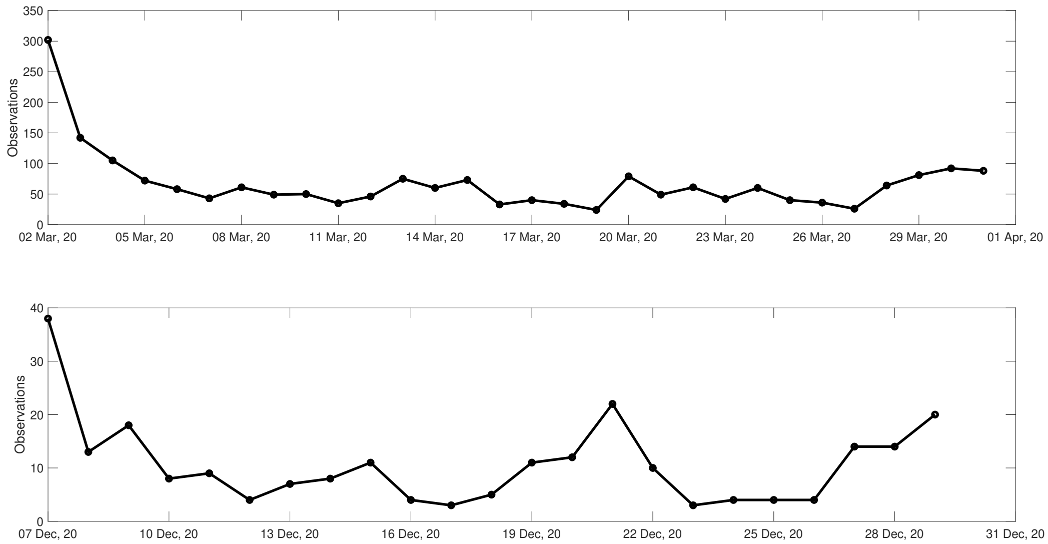

Figure 5: **Daily survey observations during March 2020 (top) and December 2020 (bottom).** The average amount of respondents per day during March is 67 and during December it is 11.