Electronic Supplementary Material of

On the stability of risk and time preferences amid the COVID-19 pandemic

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A Experimental instructions

Instructions were provided in electronic form in Qualtrics. This is a translation of the original instructions written in Greek.

Instructions for time preferences task

In the next screens you will be asked to choose between monetary amounts that are paid in **vouchers** in **future dates**. In one option you will be shown **a monetary amount paid in one date** and in another option you will be shown **a larger monetary amount** paid in a **later date**. You will have to state which option you prefer. In addition, you will be given the opportunity to state if the options are equally attractive for you. In this case, the computer will randomly choose one option for you.

In total, you will see **30** different **screens** with different monetary amounts each time.

After making your choices, the computer will **randomly pick a number from 1 to 20**. **If number 1 is randomly drawn**, you will gain money from this stage. Otherwise, you receive nothing. That is, you have a **5% probability** (1 in 20) to **gain** an additional **monetary amount of money** from this stage. The computer will then randomly draw a number from 1 to 30. This number will determine which of the 30 screens will be binding and the choice you made in that choice set will be realized.

Reminder: The monetary amounts you gain in this stage will be given to you in vouchers that you can exchange with goods in a wide network of stores, restaurants, coffee places etc.: http://www.uphellas.gr/network/. The voucher will be given to you by Dr. Andreas Drichoutis, Associate Professor in the Department of Agricultural Economics and Rural Development in the exact future date that is listed under the binding option. More information will be provided to you at the end of the survey.

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Instructions for risk preferences task

Next, you will be shown 20 different screens. Each screen will give you the opportunity to choose between two lotteries that will be shown in a screen similar to the image below:

Each column represents a lottery where two different monetary amounts are displayed and right next to each amount, the respective probability to win the amount is displayed. You will have to choose one of the two alternatives shown, by clicking on the corresponding button. You will also have the option to indicate indifference between the two options. If you state indifference for the lotteries, that is, if you state that both lotteries are equally likeable, then the computer will randomly select one of the lotteries for you.

The screen will be shown 20 times with different monetary amounts and different probabilities assigned to each amount and **you will choose between the two different lotteries 20 times.**

At the end of the lottery selection stage, the computer will randomly draw a number from 1 to 20 and a number from 1 to 100. These numbers will determine the binding Screen (one of the 20 screens) and the probability which will determine the amount paid by the lottery you selected in the Screen that was drawn. The amount of money from this stage will be given to you in cash from the person in charge on this survey (more information on how to receive your money will be given at the end of the questionnaire).

You can win only one of the two amounts that appear on each lottery and only in one of the 20 lottery choices; in the one that will be randomly drawn. For this reason you should be very careful and make every choice as if it is the one that will be randomly drawn.

B Pre-registration material

ASPREDICTED

Wharton CREDIBILITY LAB UNIVERSITY of PENNSYLVANIA

The effect of the coronavirus pandemic on risk and time preferences (#38063)

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1) Have any data been collected for this study already?
It's complicated. We have already collected some data but explain in Question 8 why readers may consider this a valid pre-registration nevertheless.

2) What's the main question being asked or hypothesis being tested in this study?
We will examine whether risk/time preferences change during the outbreak of the coronavirus and at key points of the timeline of events as defined by response measures to slow the spread taken by the government.

3) Describe the key dependent variable(s) specifying how they will be measured.
Subjects make incentivized discrete choices between lottery options and sooner vs later amounts of money. We use these discrete choices as the dependent variable to estimate structural econometric models of risk and time preferences.

4) How many and which conditions will participants be assigned to?
Three conditions:
Condition 1: Subjects choices are elicited until a couple of days later after the occurrence of the first death (in March 12) from the coronavirus in the country in 2020 (January 29 - March 17).
Condition 2: Subjects are then re-invited to participate in the survey eliciting their risk/time measures after the onset of the curfew in the country (March 23).
Condition 3: Data will be also compared with a wave of subjects from last year (where no pandemic occurred). Data collection was for the period 30/1/2019 to 20/3/2019.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We will jointly estimate structural econometric models of risk and time preferences. We will try estimating competing models of EUT, RDU with various errors stories and hyperbolic/exponential discounting functions. We will select the best fitting model based on information criteria. The models will also be estimated with dummies indicating the major time events during the spread of the coronavirus epidemic (e.g., first reported case, first reported death, curfew initiated etc.). Results will also be compared with risk/time preferences estimates from last year's wave characterized by the absence of a pandemic.

Additional basic demographic controls will be introduced in the models to compare with models without controls.

6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
We will exclude subjects that chose the dominated option in the Holt and Laury task and subjects with no variation in their choices.

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
We will invite 501 subjects to participate in the wave after the onset of the curfew in the country. This is the overlap of subjects that participated in the 2019 wave and subjects that participated in the wave before the onset of the curfew.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
This study is pre-registered midway the data collection. This is because we had originally planned to collect data up to March 17, 2020 but then the coronavirus pandemic occurred halfway the project.

Data are collected annually for purposes of having a battery of measures for part of the student population in case these need to be matched later with other experimental data. The idea came when the coronavirus pandemic started in Greece and we thought it would be a good opportunity to re-invite subjects that had participated before the curfew due to the coronavirus. The start of the second wave in 2020, coincided with the curfew enforcement in the country. We have already collected incentivized data for risk and time preferences for subjects that participated in the 2019 wave (where no pandemic occurred) which will be used for comparison purposes.

C Literature on stability of preferences

Our study adds to a stream of literature that examines the effect of major negative shocks on people's preferences.[3] A large portion of the studies we are aware of examine the effect of *natural disasters* on RTPs. Results from these studies point to contradictory results with respect to risk. Some studies find an increase in risk seeking behavior due to a natural disaster. For example, Eckel et al. (2009) investigated risk preferences of a sample of hurricane Katrina evacuees shortly after evacuation, another sample of evacuees a year later, and a third sample of residents with demographics similar to the Katrina evacuees. Women in the Katrina sample shortly after evacuation were found to be significantly more risk loving than other samples. Page et al. (2014) found that homeowners, who were victims of the 2011 Australian floods in Brisbane and faced large losses in property values, were more likely to opt for risky gambles. Hanaoka et al. (2018) investigated individuals' risk preferences after experiencing the 2011 Great East Japan Earthquake and found no effect for females, while males that were exposed to higher intensities of the earthquake become more risk tolerant one year after the earthquake. Moreover, this effect was persistent even five years after the earthquake.

On the other hand, Cameron and Shah (2015) found that individuals who suffered a flood or earthquake in rural Indonesia exhibited *more* risk-aversion as a consequence of increased background risk perception of a future disaster. Similarly, Cassar et al. (2017) found that the 2004 tsunami in Thailand led to substantial and long-lasting increases in risk aversion as well as in impatience. More recently, Beine et al. (2020) examined how two large earthquakes that shook the Tirana area in Albania affected RTPs and found unambiguous effects towards more risk aversion and impatience for affected individuals. Moreover, the second earthquake amplified the effect of the first one, suggesting that experiences accumulate in their influence on RTPs. Finally, Callen (2015) found that exposure to the Indian Ocean Earthquake tsunami increased patience in a sample of Sri Lankan wage workers.

A related stream of research examines the effect of *conflict and violence* on RTPs. Voors et al. (2012) used a series of field experiments in rural Burundi to examine the impact of exposure to conflict on RTPs. They found that individuals exposed to violence were more risk-seeking and had higher discount rates. Callen et al. (2014) studied preferences in Afghanistan and found that individuals exposed to violence, when primed to recall fear, exhibited an increased preference for certainty. We are aware of only one study that examined the effect of a financial crisis on RTPs. Jetter et al. (2020) found that males (but not females) were systematically more sensitive to local economic conditions (e.g., their region's unemployment rate) since the global financial crisis of 2008.

[3] Our study is also related to the stream of research that examines the intertemporal stability of RTPs. A literature review of this research stream can be found in Drichoutis and Vassilopoulos (2021). Moreover, there is a strand of research that examines the effect of major early life experiences on risk preferences. For example, Bellucci et al. (2020) show that warfare exposure during childhood in the World War II was associated with lower financial risk taking in later life. Moreover, Bellucci et al. (2020) review the literature on similar studies that track and associate major early life experiences with preferences.

D Theory and econometrics of risk and time preferences: Details

Let the utility function be the constant relative risk aversion (CRRA) specification:

$$U(M) = \frac{M^{1-r}}{1-r} \tag{A.1}$$

where r is the relative risk aversion (RRA) coefficient, $r = 0$ denotes risk neutral behavior, $r > 0$ denotes risk averse behavior and $r < 0$ denotes risk loving behavior. If we assume that Expected Utility Theory (EUT) describes subjects' risk preferences, then the expected utility of lottery i can be written as:

$$EU_i = \sum_{j=1,2} p_i(M_j)U(M_j) \tag{A.2}$$

where $p(M_j)$ are the probabilities for each outcome M_j that are induced by the experimenter (shown in Tables 3 and 4). A popular alternative is Rank Dependent Utility (RDU) developed by Quiggin (1982). RDU extends the EUT model by allowing for non-linear probability weighting associated with lottery outcomes.[4] To calculate decision weights under RDU, we can replace expected utility in equation (A.2) with:

$$RDU_i = \sum_{j=1,2} w_i[p(M_j)]U(M_j) = \sum_{j=1,2} w_{ij}U(M_j) \tag{A.3}$$

where $w_{i2} = w_i(p_2 + p_1) - w_i(p_1) = 1 - w_i(p_1)$ and $w_{i1} = w_i(p_1)$ with outcomes ranked from worst to best and $w(\cdot)$ is the probability weighting function.

There are many probability weighting functions that have been used in the literature and here we consider Prelec's (1998) two parameter function: $w(p) = exp(-\beta_r(-lnp)^{a_r})$ where $a_r > 0, 0 < p < 1, \beta_r > 0$ (if $a_r = 1$ it collapses to the power function $w(p) = p^{\beta_r}$; if $a_r = \beta_r = 1$ it collapses to $w(p) = p$). a_r primarily controls curvature and β_r primarily controls elevation.[5]

We assume subjects have some latent preferences over risk which are linked to observed choices via a probabilistic model function of the general form:

$$Pr_B^{RA} = \Lambda\left(\frac{\frac{(V_B - V_A)}{C}}{\mu}\right) \tag{A.4}$$

[4]As in most experiments of choice under risk, our experiment involved multiple choices over lotteries for which subjects where randomly paid for one of these choices. This payoff mechanism, known as the Random Lottery Incentive Mechanism (RLIM), is incentive compatible if and only if the Independence Axiom holds (Holt, 1986). Given that RDU does not include the independence axiom, then RLIM is inappropriate for non-EUT theories on theoretical grounds. The use of the RLIM under non-EUT specifications either invokes the assumption of the isolation effect i.e., that a subject views each choice in an experiment as independent of other choices in the experiment or assumes two independence axioms as in Harrison and Swarthout (2021): one axiom that applies to the evaluation of a given prospect which is assumed to be violated by RDU, and another axiom that applies to the evaluation of the experimental payment protocol. Only the validity of the latter axiom is required to ensure incentive compatibility of the RLIM.

[5]Note, that the Prelec function is often applied with the constraint $0 < a_r < 1$ which requires that the probability weighting function exhibits subproportionality (weighting function exhibits an inverse-S shape form). We follow Andersen et al. (2018, 2014) and Harrison and Ng (2016) and use the more general specification from Prelec (1998, Proposition 1: (C)), which only requires $a_r > 0$ and nests the case where $0 < a_r < 1$.

where $Pr(B)$ is the probability of choosing lottery B (the right hand side lottery), μ is a structural 'noise parameter' associated with the Fechner error story (sometimes called a scale or precision parameter) used to allow some errors from the perspective of the deterministic model and V_A, V_B are the decision-theoretic representations of values associated with lotteries A and B i.e., $V_k = EU_k$ for $k = A, B$ if the theory is EU or $V_k = RDU_k$ for $k = A, B$ if the theory is RDU. $\Lambda(\cdot) : R \rightarrow [0, 1]$ is the standard logistic distribution function with $\Lambda(\zeta) = 1/(1 + e^{-\zeta})$, $\Lambda(0) = 0.5$ and $\Lambda(x) = 1 - \Lambda(-x)$, that is, Λ takes any argument between $\pm\infty$ and transforms it to a number between 0 and 1 i.e., a probability.

C is a normalizing term that defines the heteroskedastic class of models.[6] Wilcox (2008, 2011) proposed a 'contextual utility' error specification which adjusts the scale parameter by $C = V_{max} - V_{min}$ to account for the range of possible outcome utilities. C is defined as the maximum utility V_{max} over all prizes in a lottery pair minus the minimum utility V_{min} over all prizes in the same lottery pair. It changes from lottery pair to lottery pair, and thus it is said to be contextual. Contextual utility maintains that the error specification is mediated by the range of possible outcome utilities in a pair, so that $Pr(B) = \Lambda\left(\frac{\frac{(V_B - V_A)}{V_{max} - V_{min}}}{\mu}\right)$.

With respect to time preferences, assume that EUT holds for choices over risky alternatives and that discounting is exponential. Then a subject is indifferent between two income options M_t and $M_{t+\tau}$ if and only if:

$$U(M_t) = \frac{1}{(1+\delta)^\tau} U(M_{t+\tau}) \tag{A.5}$$

where $D^E(\tau) = \frac{1}{(1+\delta)^\tau}$ is the discount factor for $\tau \geq 0$ and where the discount rate is $d^E(\tau) = \delta$. The discount rate equalizes the present value of the two monetary outcomes in the indifference condition (A.5). Under exponential discounting, the discount rate is stable over time.

Another class of discounting models is the family of hyperbolic specifications. A popular hyperbolic specification is due to Mazur (1984) which specifies the discount factor as $D^H(\tau) = \frac{1}{(1+K\tau)}$ for some parameter $K > 0$ and discount rates $d^H(\tau) = (1 + K\tau)^{(1/\tau)} - 1$.[7]

We can write the discounted utility of each option as:

$$PV_A = \frac{M_A^{1-r}}{1-r} \quad \text{and} \quad PV_B = D\frac{M_B^{1-r}}{1-r} \tag{A.6}$$

where D can be either the exponential D^E or the hyperbolic discount factor D^H. The probability of choosing one of the options is given by:

$$Pr_B^D = \Lambda\left(\frac{PV_B - PV_A}{\nu}\right) \tag{A.7}$$

[6]Note that this form of heteroskedasticity, refers to models where the standard deviation of utility differences is conditioned on lottery pairs. Econometrically this can be considered as pair- and subject-specific heteroskedasticity but one that requires no extra parameters into the model since the form of the heteroscedasticity is determined by outcome utilities. See Wilcox (2008) for a related discussion.

[7]The hyperbolic specification does not nest exponential discounting in the way RDU nests EUT and, therefore, other alternatives have been proposed. A two parameter specification based on the Weibull distribution from statistics, defines the discount factor as $D^W(\tau) = exp(-r_d t^{(1/s_d)})$ for $r_d, s_d > 0$. For $s_d = 1$ this collapses to the exponential discounting specification. Unfortunately, when we tried to fit this specification with our data, we run into severe numerical optimization problems and none of our efforts was fruitful.

Given that some choice sets in the time preferences task presented subjects with choices between three options i.e., a payment option A, a payment option B and a middle option C (see Table 5), we can model the probability of choosing any of the three options using a multinomial logit setup:

$$Pr_J^D = \frac{exp(PV_J/\nu)}{\sum_{j=A}^{C} exp(PV_j/\nu)} \text{ for } J = A, B, C \tag{A.8}$$

This is a particularly attractive form as it is comparable with Equation A.7 since for the case of two options it can easily be shown that $Pr_B^D = \Lambda\left(\frac{PV_B - PV_A}{\nu}\right) = \frac{exp(PV_B/\nu)}{exp(PV_A/\nu)+exp(PV_B/\nu)}$ given that $\Lambda(\zeta) = \frac{1}{1+e^{-\zeta}}$.

We can write the conditional log-likelihood for the risk preferences tasks as:

$$\begin{aligned} \ln L^{RA}(r, \mu; y, \mathbf{X}) = \sum_{i=1}^{N} \big[&(\ln(Pr_B^{RA})|y_i = 1) + (\ln(1 - Pr_B^{RA})|y_i = 0) \\ &+(\frac{1}{2}\ln(Pr_B^{RA}) + \frac{1}{2}\ln(1 - Pr_B^{RA})|y_i = -1)\big] \end{aligned} \tag{A.9}$$

where $y_i = 1$, 0 denotes the choice of lottery B or A in the ith risk preference task, respectively, and $y_i = -1$ denotes the choice of indifference. X is a vector of variables that are assumed to affect the estimated parameters. The conditional log-likelihood for the time preferences task can be written as:

$$\begin{aligned} \ln L^{D}(T, \nu; y, \mathbf{X}) = \sum_{i=1}^{N} \big[&(\ln(Pr_B^{D})|y_i = 1) + (\ln(Pr_A^{D})|y_i = 0) \\ +(\frac{1}{2}\ln(Pr_A^{D}) + \frac{1}{2}&\ln(Pr_B^{D})|y_i = -1) + (\ln(Pr_C^{D})|y_i = 2)\big] \end{aligned} \tag{A.10}$$

where $y_i = 1$, 0 denotes the choice of option B (the later option) or A (the sooner option) in the ith time preference task, respectively, $y_i = -1$ denotes the choice of indifference and $y_i = 2$ denotes the choice of the middle option C.[8] X is a vector of variables that are assumed to affect the estimated parameters. T is either δ under exponential discounting or K under the hyperbolic specification.

The joint likelihood of the risk aversion and discount rate responses can then be written as:

$$\ln L(r, T, \mu, \nu; y, \mathbf{X}) = \ln L^{RA} + \ln L^{D} \tag{A.11}$$

Equation (A.11) is maximized using standard numerical methods. The statistical specification also takes into account the multiple responses given by the same subject and allows for correlation between responses by clustering standard errors; i.e., it relaxes the independence assumption and requires only that the observations be independent across the clusters. The robust estimator of variance that relaxes the assumption of independent observations involves a slight modification of the robust (or sandwich) estimator of variance which requires independence across all observations (StataCorp, 2013, pp. 312).

[8] It is implied that for choice tasks 21 to 30, Pr_A^D and Pr_B^D are calculated based on Equation A.8 and not based Equation A.7.

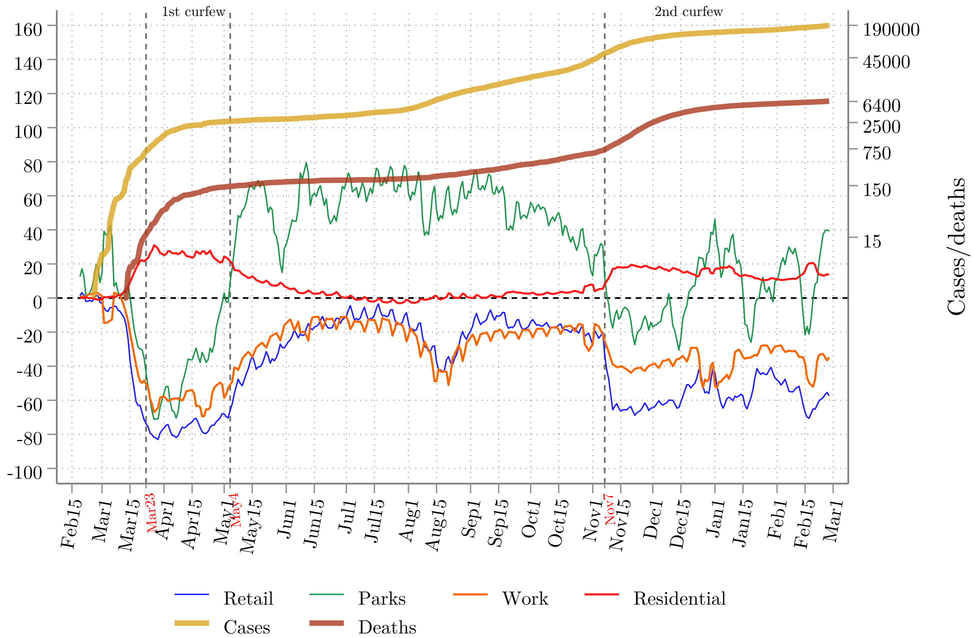
E Phases of the pandemic

The successful flattening of the curve was followed by a second phase of the pandemic that started building up during the summer of 2020 and received exploding dimensions in Autumn, leading to a second curfew that was imposed on November 7, 2020 and was in place until March 2021. Therefore, our study took place in the first phase of the pandemic, missing the next and deadlier phase. One might rightly wonder whether any effects of the pandemic on risk/time preferences would be more pronounced in a phase where there was a larger number of cases and deaths due to the coronavirus.

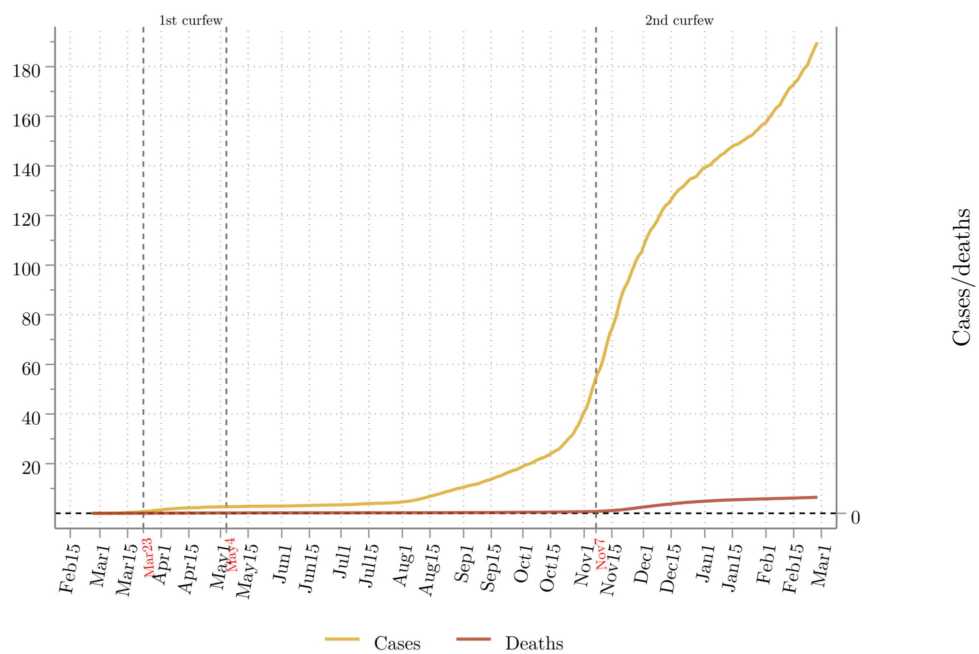
We believe that the first phase, although lower in number of cases/deaths, might had a larger measured impact on risk/time preferences. We base this on the likely adaptation in human behavior that comes after a large shock. We can find some support for this adaptive behavior by looking at Google's COVID-19 Community Mobility Reports. We downloaded the publicly available data for Greece for the whole period starting from February 2020 up to February 2021, and graphed the mobility trends for residential visits, visits at parks, retail and work. Graph A1b shows that cases and deaths in the 1st curfew were a very small part of what came later, before and during the 2nd curfew. Figure A1a shows mobility trends along with cases/deaths in log scale. A few things are noteworthy: a) retail mobility levels are similar under both curfews; this is to be expected given a strict enforcement by the state b) both park mobility and work mobility are negatively affected under both curfews with respect to the baseline but are less affected under the 2nd curfew despite the huge increase in cases/deaths during the 2nd curfew. We should note that the same restrictions were in place in both curfews for park and work mobility. We interpret this as evidence that some adaptation occurred with time and people have learned to cope with the pandemic. Thus, we believe that any effect on risk/time preferences might be stronger during the early phase of the pandemic where people came across an unprecedented shock.

Figure A1: Mobility trends and cases/deaths

(a) Mobility in percentage change from baseline (5-day rolling average) and case/deaths in log scale



(b) Case/deaths (in thousands)



F Stated preferences measures for risk and time preferences

In this section, we examine the potential effects of the pandemic on stated measures of risk and time preferences. Economists are typically skeptical about whether self-reported measures of attitudes and traits are meaningful measures of preferences. However, due to budget constrains (as well as due to unforeseen obstacles posed by a pandemic), conducting large scale laboratory experiments to elicit preferences from representative samples is usually infeasible. Furthermore, although incentivized measures of risk and time preferences have been found to perform fairly well in predicting real life financial decisions, there is doubt on whether they can be generalized to important domains of life other than financial decision-making (see discussions in Arslan et al., 2020; Drichoutis and Vassilopoulos, 2021). For the sake of completeness, we examine here potential effects on popular stated risk and time preference measures.

We included a battery of questions across all waves that elicited three measures of risk preferences and three measures of time preferences. For time preferences, we included self-reported general purpose measures for patience and impulsivity (Vischer et al., 2013) as well as the 15-item abbreviated form (Spinella, 2007) of the Barratt Impulsiveness Scale (BIS), designed to assess the personality trait of impulsiveness (Patton et al., 1995).

For risk preferences, we elicited a general measure of risk-taking propensity, asking respondents to state their risk perception of themselves on a 0-10 scale ('Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?', anchored by 'Not willing at all to take risk' and 'Very willing to take risk') (Dohmen et al., 2011). We also included a risk investment question that asks respondents to place themselves in a situation where they have won €100,000 in a lottery and they have to decide how much to invest in a 50/50 lottery with the potential to double the money or lose the investment.[9] Possible answers range from nothing to the full amount with steps of €20,000. A final measure of risk that we utilize is a 15-item version of Weber et al.'s (2002) Domain-Specific Risk-Taking (DOSPERT) scale (Drichoutis and Vassilopoulos, 2021).

Table A1 and Table A2 show the ordered logit coefficients for models (1), (2) and (4) that account for the ordinal nature of the dependent variables and OLS regressions for all other models. Table A1 uses the wave dummies and Table A2 uses the event dummies. Reported standard errors are clustered standard errors.[10] As evident, the only robust effect across all specifications is the gender dummy. With respect to time preferences, males are more likely to be patient than females and they tend to have lower scores on the BIS, indicating lower impulsiveness. With respect to risk preferences, males are more likely to state they are willing to take risks, invest a higher amount in the risky investment and score higher in the DOSPERT scale. Note that, despite the statistically significant effect of gender on stated measures of risk and time preferences, gender did not statistically significantly affect any of the structural

[9] The risk investment measure has been found to be a strong predictor for decisions in the financial domain (Dohmen et al., 2011) and has been reported to have a significant relationship with the incentivized Holt and Laury (2002) risk preferences elicitation task (Leuermann and Roth, 2012).

[10] We report only the coefficient estimates for ordered logit models instead of the marginal effects (which would take considerably more space to show) since statistical significance of marginal effects follows statistical significance of the raw coefficients and the sign of the marginal effects changes exactly once when one moves from the smallest to the highest category, a property known as the single crossing property (Drichoutis et al., 2006; Greene and Hensher, 2010).

Table A1: OLS and ordered logit regressions

	Time preferences			Risk preferences		
	Patience	Impulsiveness	BIS	General risk taking	Risk investment	DOSPERT
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-	-	29.743***	-	26.648***	49.772***
	-	-	(0.359)	-	(1.436)	(0.928)
2020A wave	-0.005	0.106	0.407	-0.051	-1.525	-1.527
	(0.154)	(0.155)	(0.448)	(0.142)	(1.874)	(1.205)
2020B wave	-0.204	-0.103	0.739	-0.266	0.744	-0.074
	(0.209)	(0.202)	(0.720)	(0.237)	(3.153)	(1.927)
Males	0.362***	0.201	-0.745**	0.505***	5.327***	5.437***
	(0.124)	(0.122)	(0.376)	(0.128)	(1.674)	(1.047)
N of cases/100K population	0.005	0.005	-0.048	0.014	-0.149	-0.036
	(0.012)	(0.009)	(0.039)	(0.012)	(0.164)	(0.084)
N of deaths/100K population	0.061	0.088	0.764	-0.336	2.427	-0.752
	(0.241)	(0.186)	(0.812)	(0.243)	(3.307)	(1.818)
N	986	986	986	986	986	986
Log-likelihood	-2196.566	-2184.522	-	-1982.754	-	-
R^2	-	-	0.007	-	0.013	0.035
R^2-adjusted	-	-	0.002	-	0.008	0.030

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave. BIS stands for the Barratt Impulsiveness Scale (Patton et al., 1995). DOSPERT stands for the Domain-Specific Risk-Taking scale (Weber et al., 2002).

parameters reported in the previous section.

Lastly, Table A3 shows estimates when the sample is constrained to the 2020B wave (robust standard errors are reported) and includes the same set of coronavirus related variables as in Table 10. An additional result that comes out of this table is that perceiving social distancing measures as more efficient, is related to a higher likelihood of the subject being patient and a lower score in the BIS, showing lower impulsivity. In addition, the stress score variable related to coronavirus is associated with a lower BIS score (indicating lower impulsivity), a lower likelihood of willingness to take risks and a lower score in the DOSPERT scale (indicating lower risk taking).

Overall, we conclude that the stated measures of risk and time preferences reported in this section also show stability across time and during the pandemic period. This corroborates well with the null effect reported on the structural parameters of risk and time preferences from the incentivized tasks.

Table A2: OLS and ordered logit regressions with event dummies

	Patience	Impulsiveness	BIS	General risk taking	Risk investment	DOSPERT
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-	-	29.739***	-	26.614***	49.766***
	-	-	(0.359)	-	(1.438)	(0.929)
Before first case	0.101	0.153	0.677	0.030	-0.093	-0.758
	(0.181)	(0.192)	(0.524)	(0.164)	(2.216)	(1.425)
Before first death	-0.306	0.147	0.048	-0.220	-5.151**	-2.009
	(0.210)	(0.205)	(0.598)	(0.206)	(2.520)	(1.730)
Before curfew	0.526	-0.342	0.146	0.059	3.677	-4.302*
	(0.371)	(0.363)	(1.279)	(0.270)	(4.900)	(2.300)
Curfew starts	-0.193	-0.114	0.740	-0.261	0.823	-0.072
	(0.211)	(0.203)	(0.727)	(0.239)	(3.145)	(1.946)
Curfew announced relaxation	-0.213	-0.110	0.242	-0.366	1.826	-3.428
	(0.278)	(0.287)	(0.961)	(0.339)	(4.909)	(3.182)
Males	0.370***	0.203*	-0.734*	0.511***	5.422***	5.454***
	(0.124)	(0.122)	(0.376)	(0.128)	(1.675)	(1.046)
N of cases/100K population	0.003	0.007	-0.052	0.013	-0.151	-0.060
	(0.012)	(0.009)	(0.040)	(0.012)	(0.162)	(0.087)
N of deaths/100K population	0.099	0.063	1.027	-0.273	2.061	1.018
	(0.274)	(0.217)	(0.908)	(0.277)	(3.668)	(2.295)
N	986	986	986	986	986	986
Log-likelihood	-2193.420	-2183.530	-	-1981.908	-	-
R^2	-	-	0.008	-	0.018	0.039
R^2-adjusted	-	-	-0.000	-	0.010	0.031

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave. BIS stands for the Barratt Impulsiveness Scale (Patton et al., 1995). DOSPERT stands for the Domain-Specific Risk-Taking scale (Weber et al., 2002).

Table A3: OLS and ordered logit regressions with coronavirus related control variables (sample constrained to the 2020B wave)

	Patience	Impulsiveness	BIS	General risk taking	Risk investment	DOSPERT
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-	-	33.983***	-	33.633***	61.431***
	-	-	(2.069)	-	(8.159)	(4.853)
Males	0.285	0.233	-0.724	0.414*	2.904	5.356***
	(0.230)	(0.256)	(0.675)	(0.240)	(2.919)	(1.775)
N of cases/100K population	0.006	0.007	-0.047	0.014	-0.161	-0.006
	(0.015)	(0.011)	(0.038)	(0.012)	(0.166)	(0.080)
N of deaths/100K population	0.181	0.130	0.573	-0.362	2.132	-1.120
	(0.300)	(0.234)	(0.790)	(0.250)	(3.311)	(1.698)
Neither inefficient, nor efficient	0.253	0.315	-0.013	0.356	-1.250	0.902
	(0.387)	(0.395)	(1.136)	(0.385)	(4.338)	(3.012)
Efficient	0.469	0.611*	-1.722*	-0.379	-1.289	-2.008
	(0.349)	(0.325)	(1.016)	(0.344)	(3.316)	(2.559)
Very efficient	1.351***	0.627	-2.541**	-0.054	-1.386	-1.751
	(0.421)	(0.391)	(1.231)	(0.407)	(4.335)	(2.953)
Close ones in high risk group	-0.242	-0.290	1.214	0.488*	4.133	1.541
	(0.265)	(0.243)	(0.776)	(0.257)	(3.055)	(1.934)
Coronavirus stress score	-0.034	0.057*	-0.175**	-0.070***	-0.358	-1.151***
	(0.029)	(0.029)	(0.086)	(0.027)	(0.350)	(0.206)
Conspiracy theories score	-0.002	-0.015	-0.045	0.035	-0.177	0.272
	(0.025)	(0.027)	(0.083)	(0.026)	(0.318)	(0.203)
N	347	347	347	347	347	347
Log-likelihood	-728.986	-710.426	-	-678.238	-	-
R^2	-	-	0.054	-	0.018	0.154
R^2-adjusted	-	-	0.029	-	-0.009	0.131

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave. BIS stands for the Barratt Impulsiveness Scale (Patton et al., 1995). DOSPERT stands for the Domain-Specific Risk-Taking scale (Weber et al., 2002).

G Additional Tables

Table A4: Structural estimates with exponential discounting (sample restricted to those that participated to at least two waves)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.542***	(0.031)	0.699***	(0.060)	0.542***	(0.031)	0.706***	(0.059)
2020A wave	0.031	(0.043)	-0.008	(0.071)				
2020B wave	-0.022	(0.042)	0.026	(0.058)				
2020 events:								
Before first case					0.048	(0.050)	-0.050	(0.090)
Before first death					0.035	(0.059)	0.053	(0.090)
Before curfew					-0.090	(0.104)	0.013	(0.174)
Curfew starts					0.020	(0.051)	0.062	(0.066)
Curfew announced relaxation					-0.071	(0.053)	-0.021	(0.075)
a_r								
Constant			0.815***	(0.059)			0.811***	(0.058)
2020A wave			-0.009	(0.081)				
2020B wave			-0.037	(0.078)				
2020 events:								
Before first case							0.022	(0.100)
Before first death							-0.017	(0.104)
Before curfew							-0.120	(0.161)
Curfew starts							-0.054	(0.089)
Curfew announced relaxation							-0.016	(0.098)
β_r								
Constant			0.729***	(0.067)			0.720***	(0.065)
2020A wave			0.040	(0.075)				
2020B wave			-0.060	(0.061)				
2020 events:								
Before first case							0.118	(0.093)
Before first death							-0.024	(0.100)
Before curfew							-0.117	(0.153)
Curfew starts							-0.065	(0.072)
Curfew announced relaxation							-0.047	(0.073)
δ								
Constant	0.214***	(0.018)	0.137***	(0.028)	0.214***	(0.018)	0.134***	(0.028)
2020A wave	-0.013	(0.024)	0.006	(0.036)				
2020B wave	0.029	(0.026)	-0.005	(0.029)				
2020 events:								
Before first case					-0.022	(0.029)	0.028	(0.045)
Before first death					-0.013	(0.033)	-0.023	(0.045)
Before curfew					0.045	(0.067)	-0.009	(0.085)
Curfew starts					0.006	(0.030)	-0.023	(0.033)
Curfew announced relaxation					0.054	(0.033)	0.019	(0.039)
μ	0.129***	(0.003)	0.108***	(0.006)	0.129***	(0.003)	0.107***	(0.006)
ν	0.065***	(0.002)	0.071***	(0.003)	0.065***	(0.003)	0.071***	(0.003)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 2.34$	(0.674)	$\chi^2 = 1.77$	(0.987)	$\chi^2 = 7.96$	(0.633)	$\chi^2 = 7.48$	(0.995)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 27.77$	(0.0001)			$\chi^2 = 33.43$	(0.0008)
N	40700		40700		40700		40700	
Log-likelihood	-23965.13		-23939.04		-23952.72		-23922.71	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; δ is the discount rate of the exponential function.

Table A5: Structural estimates with hyperbolic discounting (sample restricted to those that participated to at least two waves)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.537***	(0.030)	0.581***	(0.058)	0.537***	(0.030)	0.580***	(0.056)
2020A wave	0.031	(0.043)	-0.038	(0.087)				
2020B wave	-0.022	(0.042)	0.030	(0.065)				
2020 events:								
Before first case					0.048	(0.050)	-0.085	(0.107)
Before first death					0.034	(0.058)	0.018	(0.114)
Before curfew					-0.089	(0.104)	-0.001	(0.195)
Curfew starts					0.018	(0.050)	0.052	(0.075)
Curfew announced relaxation					-0.070	(0.052)	-0.014	(0.084)
a_r								
Constant			0.844***	(0.063)			0.843***	(0.062)
2020A wave			-0.019	(0.085)				
2020B wave			-0.035	(0.083)				
2020 events:								
Before first case							0.010	(0.104)
Before first death							-0.031	(0.110)
Before curfew							-0.125	(0.176)
Curfew starts							-0.061	(0.095)
Curfew announced relaxation							-0.008	(0.105)
β_r								
Constant			0.949***	(0.076)			0.941***	(0.075)
2020A wave			0.123	(0.113)				
2020B wave			-0.059	(0.084)				
2020 events:								
Before first case							0.210*	(0.127)
Before first death							0.007	(0.155)
Before curfew							0.008	(0.321)
Curfew starts							-0.061	(0.100)
Curfew announced relaxation							-0.039	(0.103)
K								
Constant			0.871***	(0.076)			0.871***	(0.073)
2020A wave			0.079	(0.105)				
2020B wave			-0.074	(0.077)				
2020 events:								
Before first case							0.179	(0.127)
Before first death							0.006	(0.145)
Before curfew							-0.132	(0.202)
Curfew starts							-0.067	(0.094)
Curfew announced relaxation							-0.064	(0.093)
μ	0.129***	(0.003)	0.118***	(0.005)	0.129***	(0.003)	0.118***	(0.005)
ν	0.065***	(0.002)	0.066***	(0.003)	0.065***	(0.002)	0.066***	(0.003)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 2.48$	(0.648)	$\chi^2 = 2.43$	(0.965)	$\chi^2 = 7.71$	(0.657)	$\chi^2 = 6.62$	(0.998)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 10.77$	(0.096)			$\chi^2 = 13.95$	(0.304)
N	40700		40700		40700		40700	
Log-likelihood	-23924.70		-23906.66		-23909.66		-23888.83	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; K is the parameter of the hyperbolic function.

Table A6: Structural estimates with exponential discounting (sample restricted to those that participated to all three waves)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.594***	(0.039)	0.669***	(0.099)	0.593***	(0.039)	0.659***	(0.097)
2020A wave	-0.075	(0.061)	-0.023	(0.114)				
2020B wave	-0.044	(0.065)	0.108	(0.087)				
2020 events:								
Before first case					-0.014	(0.077)	-0.032	(0.149)
Before first death					-0.148*	(0.086)	-0.115	(0.192)
Before curfew					-0.120	(0.130)	0.149	(0.191)
Curfew starts					0.032	(0.078)	0.073	(0.111)
Curfew announced relaxation					-0.142	(0.088)	0.122	(0.108)
a_r								
Constant			0.879***	(0.094)			0.880***	(0.094)
2020A wave			0.065	(0.133)				
2020B wave			-0.060	(0.131)				
2020 events:								
Before first case							0.047	(0.162)
Before first death							0.070	(0.196)
Before curfew							0.149	(0.249)
Curfew starts							0.031	(0.183)
Curfew announced relaxation							-0.119	(0.149)
β_r								
Constant			0.843***	(0.124)			0.855***	(0.122)
2020A wave			-0.025	(0.126)				
2020B wave			-0.187*	(0.100)				
2020 events:								
Before first case							0.049	(0.175)
Before first death							0.004	(0.231)
Before curfew							-0.230	(0.178)
Curfew starts							-0.042	(0.149)
Curfew announced relaxation							-0.297***	(0.110)
δ								
Constant	0.186***	(0.022)	0.151***	(0.047)	0.187***	(0.022)	0.156***	(0.046)
2020A wave	0.029	(0.034)	0.004	(0.055)				
2020B wave	0.029	(0.037)	-0.050	(0.043)				
2020 events:								
Before first case					-0.000	(0.043)	0.010	(0.070)
Before first death					0.060	(0.046)	0.044	(0.096)
Before curfew					0.061	(0.080)	-0.073	(0.090)
Curfew starts					0.003	(0.047)	-0.023	(0.058)
Curfew announced relaxation					0.059	(0.048)	-0.066	(0.051)
μ	0.127***	(0.005)	0.111***	(0.010)	0.126***	(0.005)	0.111***	(0.009)
ν	0.061***	(0.003)	0.065***	(0.004)	0.061***	(0.003)	0.064***	(0.004)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 3.31$	(0.508)	$\chi^2 = 6.96$	(0.541)	$\chi^2 = 10.43$	(0.404)	$\chi^2 = 15.87$	(0.724)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 7.28$	(0.296)			$\chi^2 = 13.48$	(0.335)
N	16850		16850		16850		16850	
Log-likelihood	-9879.54		-9869.65		-9849.15		-9833.57	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; δ is the discount rate of the exponential function.

Table A7: Structural estimates with hyperbolic discounting (sample restricted to those that participated to all three waves)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.589***	(0.038)	0.561***	(0.091)	0.589***	(0.038)	0.533***	(0.084)
2020A wave	-0.075	(0.061)	-0.041	(0.135)				
2020B wave	-0.042	(0.064)	0.131	(0.096)				
2020 events:								
Before first case					-0.013	(0.076)	-0.066	(0.175)
Before first death					-0.150*	(0.086)	-0.158	(0.225)
Before curfew					-0.118	(0.130)	0.164	(0.207)
Curfew starts					0.026	(0.078)	0.044	(0.135)
Curfew announced relaxation					-0.142	(0.088)	0.153	(0.111)
a_r								
Constant			0.903***	(0.097)			0.912***	(0.096)
2020A wave			0.065	(0.138)				
2020B wave			-0.062	(0.136)				
2020 events:								
Before first case							0.029	(0.172)
Before first death							0.097	(0.215)
Before curfew							0.151	(0.264)
Curfew starts							0.010	(0.187)
Curfew announced relaxation							-0.126	(0.155)
β_r								
Constant			0.990***	(0.130)			1.032***	(0.120)
2020A wave			-0.011	(0.168)				
2020B wave			-0.240**	(0.119)				
2020 events:								
Before first case							0.092	(0.238)
Before first death							0.059	(0.327)
Before curfew							-0.289	(0.217)
Curfew starts							-0.019	(0.193)
Curfew announced relaxation							-0.386***	(0.126)
K								
Constant	0.184***	(0.021)	0.199***	(0.043)	0.184***	(0.021)	0.211***	(0.040)
2020A wave	0.026	(0.032)	0.010	(0.064)				
2020B wave	0.028	(0.035)	-0.060	(0.047)				
2020 events:								
Before first case					0.000	(0.041)	0.026	(0.082)
Before first death					0.055	(0.043)	0.058	(0.113)
Before curfew					0.052	(0.073)	-0.083	(0.099)
Curfew starts					0.009	(0.046)	0.003	(0.076)
Curfew announced relaxation					0.053	(0.045)	-0.084	(0.052)
μ	0.127***	(0.005)	0.119***	(0.009)	0.126***	(0.005)	0.122***	(0.007)
ν	0.061***	(0.003)	0.062***	(0.004)	0.060***	(0.003)	0.060***	(0.004)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 3.24$	(0.518)	$\chi^2 = 8.08$	(0.425)	$\chi^2 = 10.25$	(0.419)	$\chi^2 = 19.53$	(0.489)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 5.48$	(0.484)			$\chi^2 = 13.46$	(0.337)
N	16850		16850		16850		16850	
Log-likelihood	-9865.63		-9857.95		-9830.79		-9817.01	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; K is the parameter of the hyperbolic function.

Table A8: Structural estimates with exponential discounting (sample constrained to only those that accepted electronic bank transfer)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.551***	(0.029)	0.653***	(0.060)	0.551***	(0.029)	0.659***	(0.059)
2020A wave	0.028	(0.042)	-0.065	(0.086)				
2020B wave	-0.027	(0.043)	-0.003	(0.062)				
2020 events:								
Before first case					0.035	(0.050)	-0.099	(0.104)
Before first death					0.048	(0.059)	0.017	(0.106)
Before curfew					-0.090	(0.097)	-0.139	(0.243)
Curfew starts					0.010	(0.052)	0.005	(0.073)
Curfew announced relaxation					-0.068	(0.053)	-0.019	(0.080)
a_r								
Constant			0.850***	(0.062)			0.846***	(0.061)
2020A wave			-0.003	(0.084)				
2020B wave			-0.024	(0.083)				
2020 events:								
Before first case							0.052	(0.105)
Before first death							-0.047	(0.110)
Before curfew							-0.098	(0.180)
Curfew starts							-0.064	(0.095)
Curfew announced relaxation							0.021	(0.109)
β_r								
Constant			0.802***	(0.076)			0.794***	(0.074)
2020A wave			0.113	(0.104)				
2020B wave			-0.033	(0.072)				
2020 events:								
Before first case							0.190	(0.125)
Before first death							0.017	(0.127)
Before curfew							0.033	(0.276)
Curfew starts							-0.019	(0.087)
Curfew announced relaxation							-0.041	(0.087)
δ								
Constant	0.208***	(0.017)	0.157***	(0.028)	0.208***	(0.017)	0.154***	(0.028)
2020A wave	-0.013	(0.023)	0.035	(0.044)				
2020B wave	0.034	(0.026)	0.015	(0.032)				
2020 events:								
Before first case					-0.019	(0.027)	0.051	(0.052)
Before first death					-0.018	(0.032)	-0.003	(0.056)
Before curfew					0.037	(0.059)	0.063	(0.128)
Curfew starts					0.016	(0.032)	0.013	(0.038)
Curfew announced relaxation					0.054*	(0.032)	0.020	(0.042)
μ	0.133***	(0.003)	0.119***	(0.006)	0.133***	(0.003)	0.118***	(0.006)
ν	0.067***	(0.003)	0.069***	(0.003)	0.067***	(0.003)	0.070***	(0.003)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 2.85$	(0.583)	$\chi^2 = 2.88$	(0.942)	$\chi^2 = 7.87$	(0.641)	$\chi^2 = 6.71$	(0.997)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 14.30$	(0.027)			$\chi^2 = 18.07$	(0.113)
N	41850		41850		41850		41850	
Log-likelihood	-24963.22		-24946.98		-24950.53		-24931.10	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; δ is the discount rate of the exponential function.

Table A9: Structural estimates with hyperbolic discounting (sample constrained to only those that accepted electronic bank transfer)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.546***	(0.029)	0.548***	(0.055)	0.546***	(0.029)	0.547***	(0.054)
2020A wave	0.027	(0.042)	-0.113	(0.099)				
2020B wave	-0.026	(0.042)	-0.000	(0.069)				
2020 events:								
Before first case					0.034	(0.050)	-0.141	(0.114)
Before first death					0.047	(0.059)	-0.044	(0.140)
Before curfew					-0.088	(0.097)	-0.176	(0.271)
Curfew starts					0.007	(0.052)	-0.016	(0.082)
Curfew announced relaxation					-0.067	(0.053)	-0.010	(0.087)
a_r								
Constant			0.877***	(0.064)			0.876***	(0.063)
2020A wave			-0.006	(0.089)				
2020B wave			-0.018	(0.088)				
2020 events:								
Before first case							0.050	(0.109)
Before first death							-0.060	(0.116)
Before curfew							-0.085	(0.202)
Curfew starts							-0.068	(0.102)
Curfew announced relaxation							0.035	(0.118)
β_r								
Constant			0.937***	(0.079)			0.939***	(0.077)
2020A wave			0.190	(0.136)				
2020B wave			-0.040	(0.089)				
2020 events:								
Before first case							0.278*	(0.155)
Before first death							0.091	(0.192)
Before curfew							0.078	(0.363)
Curfew starts							-0.000	(0.111)
Curfew announced relaxation							-0.055	(0.108)
K								
Constant	0.204***	(0.016)	0.202***	(0.026)	0.204***	(0.016)	0.202***	(0.025)
2020A wave	-0.012	(0.022)	0.060	(0.051)				
2020B wave	0.033	(0.024)	0.018	(0.035)				
2020 events:								
Before first case					-0.017	(0.026)	0.075	(0.057)
Before first death					-0.017	(0.030)	0.030	(0.076)
Before curfew					0.031	(0.054)	0.074	(0.137)
Curfew starts					0.020	(0.031)	0.034	(0.045)
Curfew announced relaxation					0.049	(0.030)	0.017	(0.045)
μ	0.133***	(0.003)	0.128***	(0.005)	0.132***	(0.003)	0.128***	(0.005)
ν	0.067***	(0.003)	0.065***	(0.003)	0.066***	(0.003)	0.065***	(0.003)
Wald tests (joint significance):								
Wave/event dummies = 0	$\chi^2 = 2.98$	(0.561)	$\chi^2 = 5.15$	(0.741)	$\chi^2 = 7.68$	(0.660)	$\chi^2 = 9.96$	(0.969)
Wald test $a_r = \beta_r = 1$			$\chi^2 = 6.56$	(0.364)			$\chi^2 = 9.41$	(0.668)
N	41850		41850		41850		41850	
Log-likelihood	-24922.90		-24908.23		-24908.08		-24890.44	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave which is captured by the constant for each parameter. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; K is the parameter of the hyperbolic function.

Table A10: Structural estimates with coronavirus related control variables (RDU with balanced set of covariates)

	Exponential (1)		Hyperbolic (2)	
r				
Constant	0.970***	(0.256)	0.954***	(0.333)
Males	0.137	(0.102)	0.179	(0.126)
Age	-0.014	(0.017)	-0.019	(0.020)
Not smoking	0.002	(0.017)	0.001	(0.023)
Is social distancing effective?				
Neither inefficient, nor efficient	0.064	(0.069)	0.085	(0.083)
Efficient	0.081	(0.077)	0.107	(0.087)
Very efficient	0.088	(0.090)	0.115	(0.102)
Close ones in high risk group	0.099	(0.186)	0.146	(0.246)
Coronavirus stress score	0.000	(0.007)	0.000	(0.009)
Conspiracy theories score	-0.007	(0.004)	-0.009	(0.006)
a_r				
Constant	0.595	(0.616)	0.668	(0.734)
Males	-0.063	(0.128)	-0.071	(0.154)
Age	0.020*	(0.011)	0.021	(0.013)
Not smoking	0.222	(0.278)	0.269	(0.355)
Is social distancing effective?				
Neither inefficient, nor efficient	-0.156	(0.251)	-0.191	(0.321)
Efficient	-0.095	(0.193)	-0.125	(0.250)
Very efficient	-0.259	(0.308)	-0.304	(0.386)
Close ones in high risk group	-0.031	(0.135)	-0.034	(0.165)
Coronavirus stress score	-0.003	(0.011)	-0.004	(0.013)
Conspiracy theories score	-0.018	(0.024)	-0.021	(0.030)
β_r				
Constant	0.309	(0.216)	0.334	(0.257)
Males	-0.049	(0.059)	-0.067	(0.078)
Age	0.007	(0.006)	0.010	(0.007)
Not smoking	0.096	(0.078)	0.108	(0.097)
Is social distancing effective?				
Neither inefficient, nor efficient	-0.003	(0.062)	-0.014	(0.075)
Efficient	0.012	(0.060)	-0.000	(0.069)
Very efficient	-0.037	(0.072)	-0.053	(0.087)
Close ones in high risk group	-0.052	(0.080)	-0.070	(0.109)
Coronavirus stress score	0.004	(0.005)	0.004	(0.006)
Conspiracy theories score	0.001	(0.004)	0.001	(0.005)
δ, K				
Constant	0.020	(0.029)	0.027	(0.037)
Males	-0.012	(0.020)	-0.015	(0.026)
Age	0.002	(0.002)	0.003	(0.002)
Not smoking	0.002	(0.004)	0.003	(0.005)
Is social distancing effective?				
Neither inefficient, nor efficient	-0.004	(0.006)	-0.005	(0.008)
Efficient	-0.005	(0.008)	-0.007	(0.010)
Very efficient	-0.007	(0.008)	-0.009	(0.010)
Close ones in high risk group	-0.007	(0.014)	-0.011	(0.019)
Coronavirus stress score	-0.000	(0.001)	-0.000	(0.001)
Conspiracy theories score	0.001	(0.001)	0.001	(0.001)
μ	0.101***	(0.008)	0.108***	(0.008)
ν	0.072***	(0.005)	0.069***	(0.005)
Wald test (joint significance):				
$a_r = \beta_r = 1$	$\chi^2 = 21.42$	(0.314)	$\chi^2 = 17.14$	(0.581)
N	16650		16650	
Log-likelihood	-9575.97		-9566.11	

Notes: Standard errors in parentheses for coefficient estimates. P-values in parenthesis for Wald tests. * p<0.1, ** p<0.05 *** p<0.01. r is the CRRA coefficient; a_r, β_r are the parameters of the Prelec probability weighting function; δ, K are the parameters of the exponential and hyperbolic functions, respectively.

Table A11: Responses per region

Region	N	%
Athens	811	84.83
Thessaloniki	39	4.08
Piraeus	14	1.46
Achaea	8	0.84
Heraklion	7	0.73
West Attica	7	0.73
Cyclades	5	0.52
Dodecanese	5	0.52
Euboea	5	0.52
Argolis	4	0.42
Corinthia	4	0.42
Zakynthos	4	0.42
East Attica	3	0.31
Laconia	3	0.31
Larissa	3	0.31
Aetolia-Acarnania	2	0.21
Boeotia	2	0.21
Chania	2	0.21
Grevena	2	0.21
Imathia	2	0.21
Kozani	2	0.21
Magnesia	2	0.21
Messenia	2	0.21
Rethymno	2	0.21
Trikala	2	0.21
Arcadia	1	0.1
Chios	1	0.1
Karditsa	1	0.1
Kastoria	1	0.1
Lesbos	1	0.1
Phthiotis	1	0.1
Pieria	1	0.1
Abroad	7	0.73
Total	956	