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

Drichoutis, Andreas C. and Nayga, Rodolfo

Agricultural University of Athens, University of Arkansas

26 November 2020

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

Andreas C. Drichoutis*[1] and Rodolfo M. Nayga, Jr.†[2]

[1]Agricultural University of Athens
[2]University of Arkansas

Abstract: We elicited incentivized and stated measures of risk and time preferences from a sample of undergraduate students in Athens, Greece, as part of a battery of psychological, behavioral and economic measures and traits that could be later matched with data from laboratory experiments. Data collection for these measures was first initiated in 2017 and the exact same battery of measures was administered in 2019 and early 2020 to students of the university that had voluntarily enrolled to participate in surveys/experiments. About halfway through the 2020 wave, our study was re-designed because of the COVID-19 pandemic. We re-launched our study on March 23, 2020, coinciding with a general curfew imposed by the government, and invited back all subjects that had participated in the 2019 and the early 2020 wave. The exact same sets of incentivized and stated measures of risk and time preferences were administered to the invited subjects and the wave duration was extended until a few weeks after the opening up of the economy and restart of business activity that followed the curfew. We then estimated structural parameters for various theories of risk and time preferences from the incentivized tasks and find no effect between the different waves or other key events of the pandemic, despite the fact that we have about 1,000 responses across all waves. Similar conclusions come out of the stated preferences measures. Overall, our subjects exhibit intertemporal stability of risk and time preferences despite the very disruptive effect of the COVID-19 pandemic on the global economy.

Keywords: time preferences, risk preferences, pandemic, natural disaster.

JEL codes: C90, D12, D81, D91, Q54.

*Associate Professor, Department of Agricultural Economics & Rural Development, School of Applied Economics and Social Sciences, Agricultural University of Athens, Iera Odos 75, 11855, Greece, e-mail: adrihout@aua.gr.

†Distinguished Professor and Tyson Endowed Chair, Department of Agricultural Economics & Agribusiness, University of Arkansas, Fayetteville, AR 72701, USA, tel:+1-4795752299 e-mail: rnayga@uark.edu.

1 Introduction

Economic theory suggests that a broad set of decisions relating to important outcomes such as savings, investments, insurance, retirement plans, occupational choices, labor supply, health services purchase, health behaviors and other aspects of everyday life, can be explained by differences in agents' budget constraints as well as Risk and Time Preferences (RTPs). RTPs are at the crux of consumer behavior and in standard economic analysis, individual preferences are considered to be stable over time. Andersen et al. (2008b) argue that the assumption of stable preferences lies in the ability to assign causation between changing opportunity sets and choices in comparative statics exercises or, in Stigler and Becker's (1977) words, 'no significant behavior has been illuminated by assumptions of differences in tastes'.

The assumption of stability of RTPs has been challenged however by the empirical literature. For example, Chuang and Schechter (2015) find weak evidence of stability in experimental measures of time preferences, although they find strong evidence of non-stability of experimental measures of risk preferences over time. Schildberg-Hörisch (2018) take the view that the extent to which preferences are stable is ultimately an empirical question. It is therefore of great importance for the study of economic outcomes to understand whether RTPs are a stable individual characteristic, change over time, or whether they are affected by various negative shocks, such as financial crises, trauma from conflict, natural disasters or a pandemic.

Our study adds to a stream of literature that examines the effect of major negative shocks on peoples preferences.[1] 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.

[1]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 (2016). 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.

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.

Our study focuses on the negative shock of the COVID-19 pandemic (caused by SARS-CoV-2) which has been extremely disruptive to public health and the global economy. We originally set up our study in 2017 with the purpose of administering, on an annual basis, a battery of incentivized and unincentivized measures to the student population of the Agricultural University of Athens, Greece. Each year since 2017, we administered the exact same battery of measures to students of the university that had voluntarily enrolled to participate in surveys/experiments. Students were invited to participate online via Qualtrics and were invited to participate in batches in order to achieve a good spread of responses across the one and a half month that the elicitation took place. The original purpose of the study was to elicit a battery of psychological, behavioral and economic measures and traits that could be later matched with data from laboratory experiments conducted at the premises of the university. The study was initiated in 2017 and was then repeated annually at similar dates every year. About halfway the 2020 wave, our study was re-designed due to the COVID-19 pandemic. The first case of COVID-19 was confirmed on February 26 in the country and on March 12 the first death occurred which coincided with the end of the originally planned study for 2020.

We decided to re-launch our study and invite back all subjects that had participated in the 2019 and the early 2020 wave. The re-launch of the study on March 23, 2020 coincided with a general curfew imposed by the government banning all nonessential transport and movement across the country. We extended the duration of the study until a few weeks after the opening up of the economy and restart of business activity. Thus, for a considerable number of subjects (we have more than 1,000 responses over the three waves), we have their response before the pandemic, during the pandemic, and after successfully flattening the curve of cases/deaths.

Our study adds to the emerging stream of studies that examine how risk or time preferences have evolved over the course of the pandemic. Angrisani et al. (2020) study the stability of risk preferences by comparing choices in the Bomb Risk Elicitation Task (Crosetto and Filippin, 2012) from undergraduate students (60 subjects) as well as professional traders and portfolio managers (48 subjects) in London. They elicited subjects' choices before the pandemic in 2019 as well as on a specific 13-day time window in April 2020 when London was in a lock-down. They find no change in risk preferences during the pandemic.

Bu et al. (2020) recruited 257 graduate students from Wuhan University of Science and Technology in China (which was ground zero of the COVID-19 pandemic) before the pandemic. They then administered a follow up online survey, and captured precise geolocation information from subjects. Out of 225 subjects that responded in the follow up study, 106 were in provinces outside of Hubei, with lower infection cases than Hubei. Subjects in all waves responded to two general (hypothetical) risk preferences questions (that were used to form a composite scale) while subjects amidst the pandemic were asked to answer a different (hypothetical) question about how to allocate money to a *hypothetical* risky investment that had an equal probability of higher returns or a loss. They found that subjects who were quarantined in Wuhan, with greater exposure to the virus, allocated significantly less money to the risky investment option relative to those in other cities within the Hubei province and those in other provinces of China. With respect to the pre-pandemic period, subjects showed a large decrease in general preferences for risk albeit there was no difference between areas with different intensity of exposure to the pandemic.

Ikeda et al. (2020) administered a five-wave internet panel survey to Japanese respondents from March 13 to June 15, 2020 (4000 subjects/wave; N=14,470 for the balanced panel; N=19,737 across the five waves). In the same time period the number of infected individuals rose sharply in Japan. They elicited responses from two *hypothetical* questions where participants were asked to choose the highest acceptable insurance premium from a given multiple price list to cover the probabilistic risk of losing an amount of money. They used the stated insurance premiums to calculate two prospect theory parameters for risk and the probability weighting function and found that risk premiums decreased almost monotonically, implying that subjects became more risk tolerant on average.

Shachat et al. (2020) administered incentivized lottery choice tasks in the gain and loss domain in 396 students from the Wuhan University, that were equally split among five waves (79 subjects/wave). Data for each wave were collected right after key events starting in January

2020 and up to March 2020 (when WHO declared it a global pandemic) and were also contrasted to pre-pandemic data from May, 2019. They observed significant increases in risk tolerance (risk is measured based on the switching point) during the early stages of the COVID-19 crisis.

Lohmann et al. (2020) administered incentivized lottery choice tasks, incentivized convex time budgets and hypothetical investment games (investments that offered higher returns as well as chances of losing the investment) to student subjects from Beijing universities. Subjects participated in online surveys in October 2019 (wave 1), December 2019 (wave 2) and March 2020 (wave 3). In the third wave, subjects had been geographically scattered in various areas of China and Lohmann et al. (2020) use the balanced sample of 539 subjects along with information about virus exposure in the geographical region of subjects' area to examine potential effects on preferences. They find no significant changes in either risk or time preferences across waves.

Table 1 summarizes the attributes of the various studies in this literature and compares these with our study. One unique feature of our study is that in each wave, we collected responses for a period longer than one and a half months, allowing us to record multiple key events in the timeline of the pandemic. Moreover, our study is unique in that we jointly estimate the structural parameters for various theories of risk and time preferences. Given that most studies are focused on samples from China and only one of them measures time preferences, our study is the only one providing structural estimates for time preferences for subjects from Europe. Furthermore, our sample size is fairly large for an incentivized study, and using students as our workhorse is not at odds with what almost all other studies cited in Table 1 did. Snowberg and Yariv (2020) compare a sample from almost the entire undergraduate population of the California Institute of Technology with a representative sample of the U.S. population and an Amazon Mechanical Turk sample. They find that the student population exhibits less noise as compared to the other samples and while large differences in behaviors are observed, these differences had limited impacts on comparative statics and correlations between behaviors.

Table 1: Literature on risk and time preferences in relation to the COVID-19 pandemic

	Risk elicitation	Measure for risk	Incentives	Type of subjects	Sample size	Subjects' location	When and how	Results
Angrisani et al. (2020)	Bomb Risk Elicitation Task	Number of boxes opened in the BRET	Real incentives	Undergraduate students Professional traders/managers	Pre-pandemic: 79 students, 56 traders/managers Amidst pandemic: 60 students, 48 traders/managers (sub-sample of pre-pandemic subejcts)	London, UK	Pre-pandemic (February-March 2019; lab experiment) April 9-21, 2020 (online)	No change in risk preferences
Bu et al. (2020)	General Risk taking questions Allocate money in a 50:50 lottery with higher returns or losses	Weighted scale of two general risk taking measures (range from 1 to 5) Amount of money allocated to the investment	Hypothetical	Graduate students	Pre-pandemic: 257 students Amidst pandemic: 225 students (sub-sample of pre-pandemic sample)	Pre-pandemic: Wuhan, China Amidst pandemic: 47% of subjects are outside of Hubei	Pre-pandemic in 2019 (October 16- 18, 2019; paper and pencil) February 28 - March 3, 2020 (online)	Subjects reduce risk taking in the pandemic but no effect between areas with different intensity of exposure to the pandemic Subjects in Wuhan (vs. Subjects outside of Wuahn vs. Subjects outside of Hubei), with greater exposure to the pandemic, allocate significantly less to the risky gamble
Ikeda et al. (2020)	Choose the highest insurance premium that covers the probabilistic risk of losing an amount of money	Prospect theory parameters are calculated	Hypothetical	Stratified random sampling according to age and gender distribution of the Japanese census	4000 subjects/wave (N=14,470 for the balanced panel; N=19,737 across the five waves)	Japan	Five waves: March 13-16; March 27-30; April 10-13; May 8-11; June 12-15, 2020 (online)	As COVID-19 spreads, risk premiums decreased almost monotonically, implying that subjects became more risk tolerant on average
Shachat et al. (2020)	Lottery choice tasks in the gain and loss domain	The switching point for the pairwise lottery ranges	Real incentives	Students	Pre-pandemic: 206 subjects Amidst pandemic: 79 subjects/wave (N=396 subjects in total)	Wuhan, China	Pre-pandemic: 206 subjects, May 2019 (online) January 24-26; February 4-6; February 7-8; February 21-22; March 6-7, 2020 (online)	Increase in risk tolerance during the early stages of the pandemic
Lohmann et al. (2020)	Lottery choice task Convex time budget Investment game	Coefficient of relative risk aversion midpoints (CRRA) Percentage invested into a lottery Dummy for present biasedness parameter beta being greater than 1 Discount rate (parameter delta)	Real incentives except for the Investment game	Students	Pre-pandemic: 793 subjects (wave 1); 650 subjects (wave 2) Amidst pandemic: 539 subjects (wave 3)	Pre-pandemic: Beijing universities Amidst pandemic: geographically dispersed across country	Pre-pandemic: October 2019; December 2019 (online) Amidst pandemic: March 2020 (online)	No significant changes in either risk or time preferences across waves
This study	Lottery choice tasks Choices over time dated monetary amounts	Structural estimates of risk and time preferences	Real incentives	Students	Pre-pandemic: 304 subjects (wave 1) Amidst pandemic: 309 subjects (wave 2); 343 subjects (wave 3); N=359 for the balanced panel	Greece	Pre-pandemic: January 30 - March 20, 2019 (online) Amidst pandemic: January 29 - March 16, 2020; March 23 - May 28, 2020 (online)	No significant changes in risk or time preferences

Our paper is structured as follows. In Section 2 we provide details about the design of the study and elicitation of risk and time preferences. In the same section, we also provide information about how the COVID-19 pandemic evolved in the country of our study (Greece) as well as present how we go about with our structural econometric methods to model key parameters from the theory of RTPs. Results and various robustness checks specifications are presented in Section 3. We conclude and discuss our results in the last section.

2 Survey design

2.1 Sample and quality control

An online questionnaire was administered annually to the population of students registered in the online recruitment software (ORSEE) of the university (Greiner, 2015), using the Qualtrics platform. The first wave started in 2017 and invitations were sent out gradually on a rolling basis, starting from late January to mid March. Similar days and dates were selected for the next waves administered in years 2018, 2019 and 2020.[2]

Subjects could take the survey anytime they wanted once they received an invitation to participate, but had a limited time window to complete the survey once they started. Figure 1a shows the number of responses per day in the 2019 wave—one year before the outbreak of the pandemic in the country. Similarly, Figure 1b shows responses per day for the 2020A wave which was planned to conclude by March 17, 2020. As can be seen, halfway through the 2020A wave, the first case of COVID-19 was confirmed (February 26, 2020) and the first death occurred (March 12, 2020). Given the rapid development of subsequent cases and deaths, we decided to launch an additional wave (2020B wave) where we invited the union of subjects that had participated in the 2019 and 2020A waves to participate again. Our study was preregistered in AsPredicted and a copy of the publicly available file can be found in the Electronic Supplementary Material. The start of the 2020B wave coincided with the enactment of a general curfew (March 23, 2020) banning all nonessential transport and movement across the country. Invitations to participate in the 2020B wave were distributed throughout the period of the curfew (where cases and deaths increased) as well as for almost a month after the curfew was relaxed (relaxation started on May 4, 2020) when the curve of cases and deaths had been flattened.

The recruiting procedure was similar for every wave and worked as follows. First, a list of valid email addresses was compiled (along with names and surnames) using as source the list of the universe of active students that are voluntarily registered through the ORSEE recruiting system (Greiner, 2015). Email invitations were then sent in batches, scheduled for two times

[2]The start of the survey was selected to be exactly 50 days from the payment of the sooner option of the time preferences tasks that was always selected to be a working day (a Thursday) so that payments could be delivered.

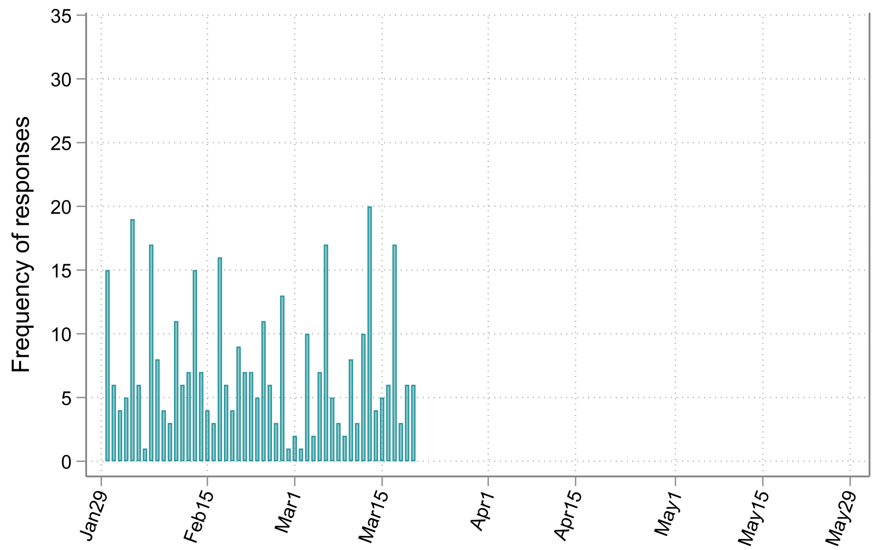
a week, covering a period of approximately one and a half months. A reminder email was sent two days after a batch of emails was first sent. Students are identified by their unique student ID number and at the conclusion of the survey, they were asked to upload a picture of their student ID for verification. Given that all waves included incentivized tasks of risk and time preferences (described momentarily), money transactions were ordered only when their ID was confirmed following a manual cross verification procedure by one of the investigators. Moreover, the invitation email emphasized several times that the invitation link is unique and that subjects must not forward their participation link to other subjects.[3] Given that the risk/time preferences tasks were part of a larger battery of questions and that subjects knew they would be asked for verifiable data in order to be paid, it is unlikely that other subjects but the intended recipients would answer a given questionnaire. Thus, we can be very confident that subjects with a given ID number are the same subjects answering the questionnaire throughout the different waves of the survey.

In total, we were able to collect 1103 responses over the three waves (2019, 2020A and 2020B). Two responses were excluded because they were from a different person than the intended recipient of the invitation email. Ninety responses were excluded because subjects stopped the questionnaire before reaching the risk/time preferences elicitation tasks which renders them useless for the purpose of the present paper. Three more persons were excluded because their age or household size contained implausible values and their responses were deemed of ambiguous quality. Table 2 shows the number of responses per wave as well as the number of unique subjects that participated across one, two or all three waves. In all, we have 1008 response that come from 495 unique subjects.

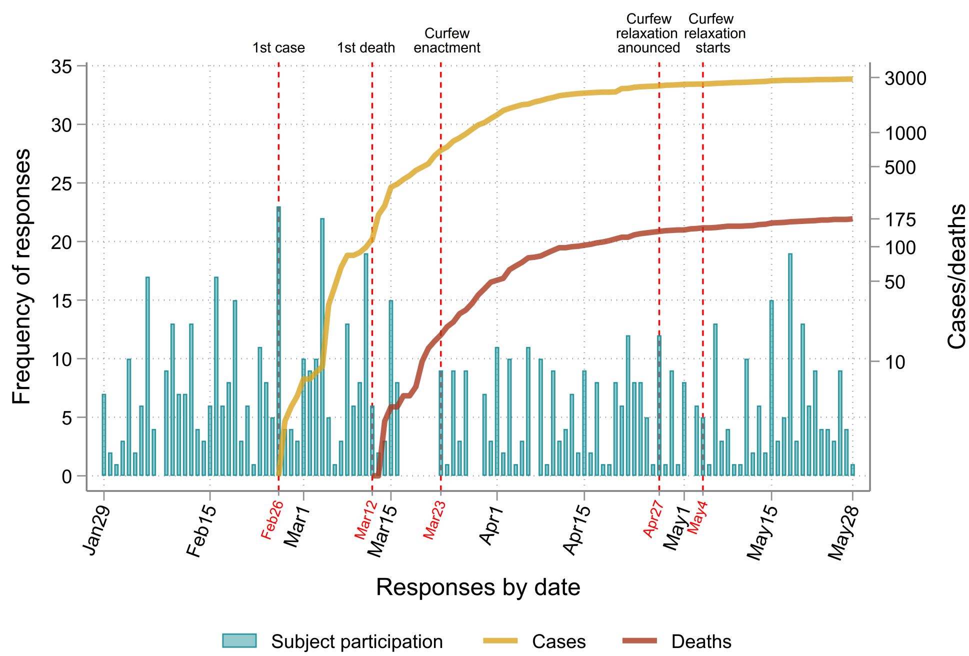
[3]The general principle was that we excluded and did not pay a subject if their ID listed a different person than the name we had sent the email to.

Figure 1: Number of subjects per wave and day of the waves

(a) 2019 wave



(b) 2020 waves



Notes: The number of cases/deaths from COVID-19 are depicted in log scale.

Table 2: Number of subjects per wave

	Wave			
Participated in ...	2019	2020A	2020B	Total
one wave	69	36	3	108
two waves	117	169	236	522
		25	144	
all three waves	126	126	126	378
Total	312	331	365	**1,008**

Notes: The numbers below the brackets indicate how subjects that participated in two waves are allocated to the waves. For example, while 117 subjects from the 2019 wave participated in two waves, 25 of them also responded in the 2020A wave. Similarly, of the 169 subjects that responded in two waves in the 2020A wave, 144 of them responded in the 2020B wave as well. It is implied that 92 subjects (=117-25 or =236-144) participated in both the 2019 and 2020B waves.

2.2 The COVID-19 pandemic in Greece

The COVID-19 pandemic in Greece started with the first confirmed case on February 26, 2020, when a 38-year-old woman who had recently visited Milan, Italy, was confirmed to be infected.[4] Subsequent cases in late February and early March were related to a group of pilgrims who had traveled to Israel and Egypt (and their contacts) as well as to persons who had traveled to Italy.

The first death from COVID-19 occurred on March 12 in Greece. With subsequent cases and deaths occurring at a faster rate, the government started imposing gradual restrictions on movements and gatherings: all educational institutions were closed starting on March 11, flights from Northern Italy (March 9) and the whole of Italy (March 14) were banned, borders with Albania and North Macedonia were closed (March 16), and nonessential transport and movement across the country was banned (March 23).[5] During this period many businesses and workplaces were also shutdown: theatres, hotels, courthouses, cinemas, shopping centres, cafes, restaurants, bars, museums and archaeological sites, with the exception of supermarkets, pharmacies and food outlets that were allowed to offer take-away and delivery only.

Following a successful flattening of the curve (see Figure 1b), the government announced on April 27 a plan for the gradual lifting of the restrictive measures and the restart of business activity. Starting on May 4, the curfew was relaxed and subjects did not need a special permit to commute within their regional unit while retail-shops, coffee-places and restaurants gradually

[4]The virus in Milan had spread through the Lombardy cluster of cases. The first cases were confirmed on February 21 (Anzolin and Amante, 2020), but had been circulating undetected much earlier. It was subsequently reported that the origin of these cases were connected to the first European local transmission that occurred in Munich, Germany as early as January 19, 2020 (Luna, 2020).

[5]Movement was permitted only for a pre-specified set of reasons: moving to and from work, grocery shopping, visiting a doctor or assisting a person in need of help, exercising etc.

Table 3: The Holt and Laury (2002) risk preference task

Lottery A				Lottery B				EV_A €	EV_B €	EV difference
p	€	p	€	p	€	p	€			
0.1	2	0.9	1.6	0.1	3.85	0.9	0.1	1.640	0.475	1.165
0.2	2	0.8	1.6	0.2	3.85	0.8	0.1	1.680	0.850	0.830
0.3	2	0.7	1.6	0.3	3.85	0.7	0.1	1.720	1.225	0.495
0.4	2	0.6	1.6	0.4	3.85	0.6	0.1	1.760	1.600	0.160
0.5	2	0.5	1.6	0.5	3.85	0.5	0.1	1.800	1.975	-0.175
0.6	2	0.4	1.6	0.6	3.85	0.4	0.1	1.840	2.350	-0.510
0.7	2	0.3	1.6	0.7	3.85	0.3	0.1	1.880	2.725	-0.845
0.8	2	0.2	1.6	0.8	3.85	0.2	0.1	1.920	3.100	-1.180
0.9	2	0.1	1.6	0.9	3.85	0.1	0.1	1.960	3.475	-1.515
1	2	0	1.6	1	3.85	0	0.1	2.000	3.850	-1.850

Notes: EV stands for Expected Value.

re-opened for business but with specific rules in place that they had to abide upon.

2.3 Incentivized elicitation of risk preferences

Subjects' risk preferences were elicited using the Holt and Laury (2002) task (HL) as well as a payoff varying task (PV). Drichoutis and Lusk (2016) have shown that greater predictive performance of choices from a hold-out task can be achieved by combining information from the HL task and a PV task. This is because the HL task varies the probabilities of the lottery choices and provides a better approximation of the curvature of the probability weighting function (given that subjects weigh probabilities non-linearly), while the PV task varies the monetary amounts and is better in approximating the curvature of the utility function. In the HL task, individuals are asked to make a series of 10 decisions between two lottery options (see Table 3). Table 4 shows a payoff varying task that keeps the probabilities constant across the 10 decision tasks and instead changes the monetary payoffs across the 10 tasks. Both tasks are constructed in a way that the expected value of lottery A exceeds the expected value of lottery B for the first four decision tasks. Thus, a risk neutral person under Expected Utilty Theory (EUT) should prefer lottery A for the first four decision tasks and then switch to lottery B for the remainder of the decision tasks.

Choices were not presented all together in a table form, but each choice was presented separately showing the probabilities and prizes as in Andersen et al. (2014).[6] Subjects could indicate whether they preferred lottery A, lottery B or whether they are indifferent between the lotteries, in which case they were told that the computer would randomly decide the binding

[6]It is likely that by presenting each pair of lotteries in a single screen allows subjects to focus more on a specific pair of lotteries while when presenting all pairs of lotteries arrayed in a table makes subjects to think the whole choice set as a single task.

Table 4: The payoff varying risk preference task

Lottery A				Lottery B				EV_A €	EV_B €	EV difference
p	€	p	€	p	€	p	€			
0.5	1	0.5	1	0.5	1.2	0.5	0.2	1.00	0.70	0.300
0.5	1.2	0.5	1	0.5	1.5	0.5	0.2	1.10	0.85	0.250
0.5	1.4	0.5	1	0.5	1.8	0.5	0.2	1.20	1.00	0.200
0.5	1.6	0.5	1	0.5	2.2	0.5	0.2	1.30	1.20	0.100
0.5	1.8	0.5	1	0.5	2.9	0.5	0.2	1.40	1.55	-0.150
0.5	2.0	0.5	1	0.5	3.5	0.5	0.2	1.50	1.85	-0.350
0.5	2.2	0.5	1	0.5	4.6	0.5	0.2	1.60	2.40	-0.800
0.5	2.4	0.5	1	0.5	6.8	0.5	0.2	1.70	3.50	-1.800
0.5	2.6	0.5	1	0.5	9.2	0.5	0.2	1.80	4.70	-2.900
0.5	2.8	0.5	1	0.5	15	0.5	0.2	1.90	7.60	-5.700

Notes: EV stands for Expected Value.

lottery to determine their payouts. The order of appearance of the HL and PV tasks were randomized across the subjects. An example of one of the decision tasks for the HL task is shown in Figure 2 and the instructions for this task can be found in the Electronic Supplementary Material in Section A.

For each subject, one of the choices was randomly chosen and paid out after we added a €2 participation fee and we cross validated their student ID. Monetary payouts were paid via bank transfer to subject's preferred bank account.[7] All transactions were ordered after cross validation of their IDs was performed, which was normally within a few minutes after they completed the questionnaire.

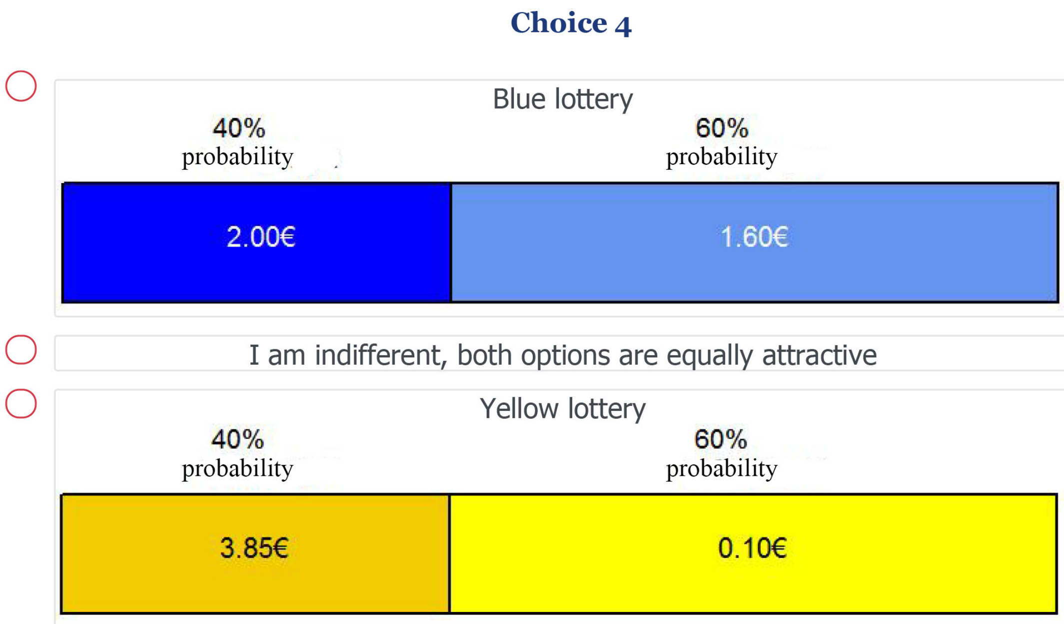
For a subset of observations (49 observations from 45 subjects), payments could not be completed because subjects failed to complete the questionnaire and provide us with a valid mobile phone number, although we do have their complete responses from the risk and time preferences tasks.[8] In addition, if a transaction would not go through, we would try to resend the money for a maximum of two times or until we resolved the problem with the transaction (in case the person would contact us to indicate there was a problem with the transaction). For 82 observations coming from 76 subjects, transactions were not completed even though we tried repeatedly to send the money. Finally, 877 transactions (87% of all observations) from 442 subjects were completed. Based on the 877 transactions, subjects were paid on average €4.4 (S.D.=2.62, min=2.1, max=17).[9] We should note beforehand that our results are invariant

[7]We used the 'Pay a friend' service of the bank 'Eurobank' which allows transferring money to subject's preferred bank account without knowing subject's account number, only by using an email address or a mobile phone number. The service is similar to the *Zelle* service operated by the Wells Fargo bank in the United States.

[8]For the same reason, we don't have complete demographic and attitudinal information for all subjects.

[9]Note that because subjects repeatedly participated in the three waves, many of them were paid for more than one time.

Figure 2: Example screen for lottery choices



when using the full sample or just the constrained sample of subjects that accepted the payment. Thus, this should alleviate any concerns that the subjects who did not accept the payment may have treated the tasks as hypothetical and thus behaved differently.

2.4 Incentivized elicitation of time preferences

The experimental design for eliciting time preferences is based on the experiments of Coller and Williams (1999), Harrison et al. (2002) and Andersen et al. (2008a). Subjects were confronted with the payoff options listed in Table 5. In Table 5, option A (the principal) offers either a €60 or a €90 sooner option. Option B offers an amount x 190 days later, where x ranged from annual interests rates of 5% to 50% on the principal, compounded semi-annualy. The sooner option (option A) was delivered on March 21 in the 2019 wave, March 19 in the 2020A wave, and June 1 on the 2020B wave.[10] The later option (option B) was delivered 190 days later. These choices also offered the option of stating indifference between options, in which case subjects knew that a random draw would decide the binding option. Another set of choices also included a middle option which split the 190 days interval in two halves. Consequently, the middle option was delivered 95 days later than option A. The purpose of the latter task was to construct a choice set with fewer choices (choices 21 to 30 in Table 5) that is similar to choice tasks 1 to 20 in Table 5. Comparison of these tasks is relegated to a different paper.

[10]All dates and days were carefully pre-selected to be working days so that the payments could be physically delivered to subjects.

The tasks always impose a front-end delay on the early payment (option A) which comes with two advantages. First, it avoids the passion for the present that decision makers exhibit when offered monetary amounts today or in the future by holding the transaction costs of future options constant (see Coller and Williams, 1999, for a discussion). Second, it allows us to equalize the credibility of future payments because of the uncertainty associated with the receipt of later rewards. Payments were promised to be paid with meal vouchers issued by an international company, redeemable in a wide network of supermarkets, restaurants, coffees shops etc in the country and all payments were guaranteed by a permanent faculty member (one of the authors). Moreover, the faculty member has a long history of performing experiments in this particular institution and is well known for paying students to participate in experiments. Therefore, mistrust issues are expected to be minimal, if any. Subjects knew beforehand how to contact the experimenter through telephone and email and where his office is located in the campus. In all, subjects provided 30 choices for the time preference task that are used to infer time preferences.

Financial constraints precluded us from paying every single subject; hence, subjects were given a 5% chance of receiving any money from this task and they knew this beforehand. If a subject was selected to receive money from this task, only one of their choices was selected as binding and their choice was realized. Subjects were subsequently contacted by the experimenter and were provided with details about when to receive their payment. All vouchers with the corresponding amount that they had won, were delivered to subjects on exactly the date the subject had selected for her respective choice.

Experimental instructions for this task can be found in the Electronic Supplementary Material in Section A. Figure 3 shows example screens for the times preferences choice task. Because Read et al. (2005) document a date/delay effect; i.e., choices to be more patient when they are described using calendar dates than when choices are characterized in terms of time delay from the current moment, we used both dates and time delay to frame choices. Each choice always displayed a calendar to illustrate the time delay and choices listed the delivery calendar dates along with the monetary amount.

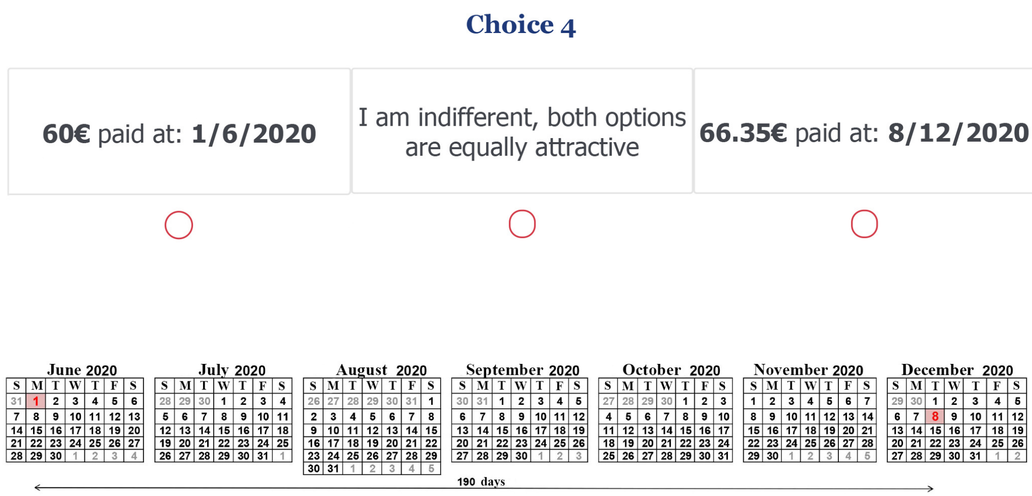
Table 5: Payoff table in discount rate tasks

Payoff alternative	Payment option A	Middle payment option	Payment option B	Annual interest rate
1	60	A $\sim$ B	61.58	0.05
2	60	A $\sim$ B	63.17	0.10
3	60	A $\sim$ B	64.76	0.15
4	60	A $\sim$ B	66.35	0.20
5	60	A $\sim$ B	67.94	0.25
6	60	A $\sim$ B	69.54	0.30
7	60	A $\sim$ B	71.13	0.35
8	60	A $\sim$ B	72.73	0.40
9	60	A $\sim$ B	74.33	0.45
10	60	A $\sim$ B	75.94	0.50
11	90	A $\sim$ B	92.38	0.05
12	90	A $\sim$ B	94.76	0.10
13	90	A $\sim$ B	97.14	0.15
14	90	A $\sim$ B	99.53	0.20
15	90	A $\sim$ B	101.91	0.25
16	90	A $\sim$ B	104.31	0.30
17	90	A $\sim$ B	106.70	0.35
18	90	A $\sim$ B	109.10	0.40
19	90	A $\sim$ B	111.50	0.45
20	90	A $\sim$ B	113.90	0.50
21	60	60.79	63.17	0.05, 0.10
22	60	62.33	66.35	0.15, 0.20
23	60	63.85	69.54	0.25, 0.30
24	60	65.33	72.73	0.35, 0.40
25	60	66.78	75.94	0.45, 0.50
26	90	91.18	94.76	0.05, 0.10
27	90	93.50	99.53	0.15, 0.20
28	90	95.77	104.31	0.25, 0.30
29	90	98.00	109.10	0.35, 0.40
30	90	100.17	113.90	0.45, 0.50

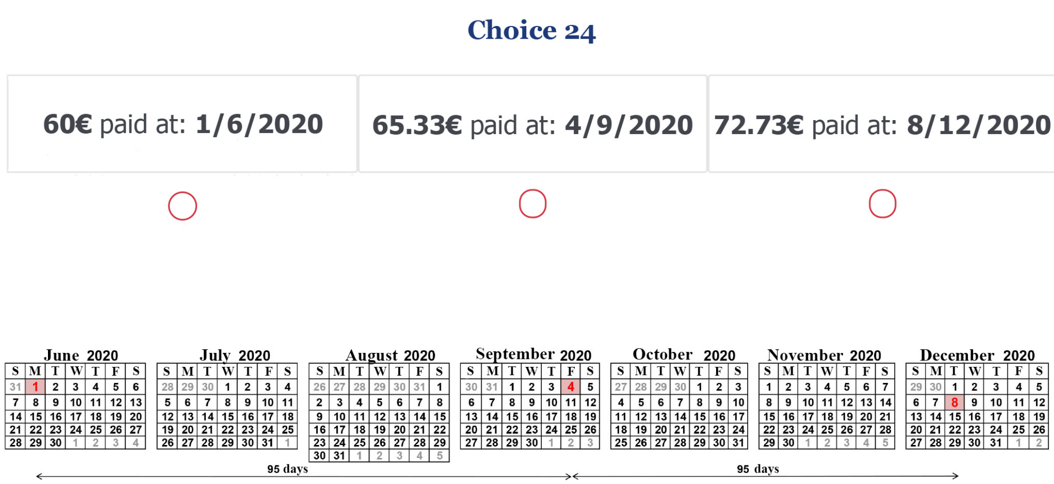
Notes: The sooner option (option A) was delivered on March 21 in the 2019 wave, March 19 in the 2020A wave and June 1 on the 2020B wave. The latter option (option B) was delivered 190 days later. The middle option for the payoff alternatives 1 to 20 was an option of stating indifference between payment option A and payment option B. The middle option monetary amount for the payoff alternatives 21 to 30, was delivered 95 days later than option A. In choices 21 to 30, the middle option is compounded with the smaller interest rate of the two rates listed in the last column and the latter option is compounded with the largest interest rate of the two rates listed in the last column.

Figure 3: Example screen for time dated monetary choices

(a) Two options



(b) Three options



2.5 Theory and econometrics of risk and time preferences

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

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

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:

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

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.[11] To calculate decision weights under RDU, we can replace expected utility in equation (2) with:

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

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 two of the more popular ones that nest linear probabilities: a) Tversky and Kahneman's (1992) (TK) function $w(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{\frac{1}{\gamma}}}$ (if $\gamma = 1$ it collapses to $w(p) = p$) and b) Prelec's (1998) probability weighting function $w(p) = exp(-(-lnp)^{a_r})$ where $0 < a_r$, $0 < p < 1$ (if $a_r = 1$ it collapses to $w(p) = p$).[12]

We assume subjects have some latent preferences over risk which are linked to observed

[11] 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.

[12] 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 $0 < a_r < 1$.

choices via a probabilistic model function of the general form:

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

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.[13] 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:

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

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 (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 $d^H(\tau) = (1 + K\tau)^{(1/\tau)} - 1$.

We can write the discounted utility of each option as:

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

[13]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.

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:

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

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:

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

This is a particularly attractive form as it is comparable with Equation 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:

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

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:

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

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.[14] 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.

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

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

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

Equation (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).

3 Results

Given competing theories of risk (EUT vs. RDU), the various probability weighting functions, and discount factors, we utilize a model selection criteria that allow us to select one model over another. We therefore estimated all possible combinations of risk and discount factors and calculated the associated information criteria such as Akaike's and Bayesian information criteria (AIC and BIC). AIC and BIC do not reveal how well a model fits the data in an absolute sense; i.e., there is no null hypothesis being tested. Nevertheless, these measures offer relative comparisons between models on the basis of information lost from using a model to represent the (unknown) true model.[15]

In order to explore the effect of the pandemic on risk and time preferences, we modeled the structural parameters as a function of either a) *wave dummies* defined as dummies for the waves 2019 (pre-pandemic wave), 2020A and 2020B (see also Table 2) or b) *event dummies* defined as key events that occurred in the timeline of the pandemic in the country. These events are: i) first reported case in the country (February 26; overlaps with the 2020A wave), ii) first reported death in the country (March 12; overlaps with the 2020A wave) iii) onset of curfew when all nonessential transport and movements across the country were banned (March 23; coincides with the beginning of the 2020B wave) iv) announcement of a plan for the gradual lifting of the restrictive measures and the restart of business activity (April 27; overlaps with the 2020B wave) and curfew relaxation and business re-openning (May 4; overlaps with the 2020B wave).[16] Figure 1b shows a timeline of these events as well.

[15] Drichoutis and Lusk (2016) have shown that AIC and BIC are in agreement in terms of model selection with more complex selection criteria such as Vuong's test (Vuong, 1989), Clarke's test (Clarke, 2003) or the out-of-sample log likelihood (OSLLF) criterion (Norwood et al., 2004).

[16] Because the time between announcement of relaxation of the restrictive measures and the actual relaxation was very short, we merged these two key events in one.

Table 6 shows the AIC and BIC values for the various estimated models combining the different risk and discount factor functions. The models are estimated with two different sets of dummies as described above; i.e., wave dummies and event dummies.[17] The two information criteria do not fully agree with each other but do point that the hyperbolic discount factor function performs better than the exponential. The disagreement between AIC and BIC is whether a model with linear probabilities for risk fits the data better than a model with Prelec's (1998) probability weighting function. In what follows, we present both EUT and RDU models (with Prelec's (1998) probability weighting function) with a hyperbolic discount function, since these are favored by the information criteria.

Table 6: Akaike's and Bayesian Information criteria

		with Wave dummies			with Event dummies		
Risk	Discount	Log-L	AIC	BIC	Log-L	AIC	BIC
Linear	Exponential	-28472.86	56961.73	57031.93	-28461.96	56951.92	57074.77
Linear	Hyperbolic	-28423.46	56862.93	**56933.13**	-28412.41	56852.81	**56975.66**
T&K	Exponential	-28469.95	56961.89	57058.41	-28457.31	56954.63	57130.12
T&K	Hyperbolic	-28419.24	56860.49	56957.01	-28406.23	56852.45	57027.95
Prelec	Exponential	-28467.34	56956.69	57053.21	-28455.01	56950.01	57125.51
Prelec	Hyperbolic	-28414.37	**56850.75**	56947.27	-28401.50	**56842.99**	57018.49

Notes: Linear stands for linear probabilities which is equivalent to EUT; T&K stands for Tversky and Kahneman's (1992) probability weighting function; Prelec stands for Prelec's (1998) probability weighting function; Bold numbers indicate the lowest number column-wise, highlighting which model performs better than other.

Table 7 shows the estimates of the structural parameters for EUT and RDU that are modeled as a function of two sets of dummy variables. Models (1) and (2) use the wave dummies while models (3) and (4) use the event dummies. As evident, none of the wave or event dummies are statistically significant, indicating remarkable stability of estimated risk and time preference parameters across time. The estimated parameters also allow us to test the RDU model versus the EUT by testing whether the parameter a_r in the probability weighting function $w(p) = exp(-(-lnp)^{a_r})$ is statistically different from 1.[18] A joint significance test with respect to the regressors of the a_r parameter that a) the wave dummies in model (2) are 0 and the constant is equal to 1, does not reject the null ($\chi^2 = 3.50$, p-value $= 0.321$), b) the event dummies in model (4) are 0 and the constant is equal to 1, does not reject the null ($\chi^2 = 4.97$, p-value $= 0.548$), indicating that EUT is a better descriptive model of subjects' risk preferences.

[17] Note that in the estimations of Table 6, we removed choices of 35 cases where subjects chose the dominated option (i.e., the lottery offering a lower amount of money over certainties) in the last choice of the Holt and Laury (2002) task. We also removed choices from 17 cases (associated with 11 unique subjects) where after geolocating their IP addresses, we found they responded in the 2020A or the 2020B wave from abroad. This is because living abroad at the time of the pandemic likely disassociates behavior with the key events that happened in this period inside the country.

[18] When $a_r = 1$ then $w(p) = p$.

Table 7: Structural estimates

	EUT		RDU		EUT		RDU	
	(1)		(2)		(3)		(4)	
r								
Constant	0.542***	(0.026)	0.506***	(0.034)	0.542***	(0.026)	0.506***	(0.034)
2020A wave	0.032	(0.038)	0.016	(0.049)				
2020B wave	-0.023	(0.039)	-0.027	(0.051)				
2020 events:								
Before first case					0.052	(0.045)	0.047	(0.057)
Before first death					0.024	(0.055)	-0.000	(0.069)
Before curfew					-0.056	(0.093)	-0.105	(0.123)
Curfew starts					0.016	(0.048)	-0.009	(0.061)
Curfew announced relaxation					-0.069	(0.049)	-0.050	(0.067)
α_r								
Constant			0.902***	(0.055)			0.901***	(0.055)
2020A wave			-0.044	(0.078)				
2020B wave			-0.011	(0.083)				
2020 events:								
Before first case							-0.013	(0.092)
Before first death							-0.064	(0.105)
Before curfew							-0.135	(0.179)
Curfew starts							-0.070	(0.095)
Curfew announced relaxation							0.052	(0.113)
K								
Constant	0.208***	(0.015)	0.225***	(0.018)	0.208***	(0.015)	0.225***	(0.018)
2020A wave	-0.016	(0.021)	-0.008	(0.026)				
2020B wave	0.030	(0.023)	0.034	(0.029)				
2020 events:								
Before first case					-0.028	(0.024)	-0.025	(0.029)
Before first death					-0.008	(0.030)	0.004	(0.037)
Before curfew					0.027	(0.053)	0.052	(0.074)
Curfew starts					0.011	(0.029)	0.028	(0.036)
Curfew announced relaxation					0.052*	(0.029)	0.043	(0.036)
μ	0.131***	(0.003)	0.128***	(0.003)	0.131***	(0.003)	0.128***	(0.003)
ν	0.067***	(0.002)	0.066***	(0.002)	0.067***	(0.002)	0.066***	(0.002)
N	47800		47800		47800		47800	
Log-likelihood	-28423.46		-28414.37		-28412.41		-28401.50	
AIC	56862.927		56850.745		56852.811		56842.994	
BIC	56933.125		56947.268		56975.658		57018.490	

Notes: Standard errors in parentheses. * 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.

The results are similar if we constrain the sample to only those for which we have their data for at least two waves (see Table A1 in the Electronic Supplementary Material) or to only those for which we have their data for all three waves (see Table A2 in the Electronic Supplementary Material) or to only those that the electronic payment transaction went through after the end of the experiment (see Table A3 in the Electronic Supplementary Material).

Another way to augment the models of Table 7 is by including variables related to the perception of the pandemic or attitudes, and coping with it. We first constructed measures of the number of deaths and cases at the level of administrative regions of the country, adjusted for the population size (i.e., number of deaths and cases were divided by the population size of the respective region). We achieved this by matching IP (Internet Protocol) address geolocation data with the number of recorded deaths and cases in the respective administrative region the day each subject responded.[19] Naturally, these measures take a value of zero for dates before the onset of the pandemic. Table A4 in the Electronic Supplementary Material shows that the vast majority of responses (> 90%) originated from the cities of Athens/Piraeus and Thessaloniki which account for roughly 40% of the population in the country.

Models (1) and (2) in Table 8 show the structural parameter estimates when adding a gender dummy and the cases/deaths variables in the models for EUT and RDU, respectively. Models (3) and (4) constrain the sample to the 2020B wave and augment the set of regressors for the structural parameters with a set of variables from questions that where included in the last wave, in order to capture attitudes and behavior with respect to the pandemic.[20]

As evident in Table 8, none of the variables of interest has a statistically significant effect. Although some variables are shown to be statistically significant in the RDU models, note that

[19]We queried the recorded IP addresses collected by Qualtrics with `http://ip-api.com` which is an application programming interface that allows to query IP addresses and returns back location data at the level of region/city in the country. The number of deaths/cases per day and per region is maintained and curated by iMEdD's (Incubator for Media Education and Development) content production division. iMEdD is a non profit organization founded with a donation of Stavros Niarchos Foundation with a mission to support and promote the transparency, credibility and independence in journalism on the grounds of securing meritocracy and excellence in the field. The data can be found in iMEdD's GitHub repository: `https://github.com/iMEdD-Lab/open-data`.

[20]The set of variables includes: a) dummies about perception of how effective social distancing is with possible answers being i) very inefficient or inefficient, ii) neither inefficient, nor efficient, iii) efficient iv) very efficient, b) a dummy about whether the respondent has family members or others in their inner circle considered a high risk group, c) a composite score variable capturing whether respondents are stressed about the pandemic situation. This composite score variable was constructed as the sum of five variables that respondents answered on a five Likert scale ranging from 'highly disagree' to 'highly agree': i) I'm nervous/stressed ii) I'm calm/relaxed (reverse coded) iii) I worry about my health iv) I worry about the health of members of my family v) I feel stressed when I have to leave home, d) a composite variable capturing whether respondents' tendency to attribute the virus or the pandemic in conspiracy theories or misconceptions about the virus. This composite score variable was constructed as the sum of five variables that respondents answered on a five Likert scale ranging from 'very unlikely' to 'very likely': i) Coronavirus was made in a lab in China, got out of control and transmitted to the population ii) Coronavirus was made in a US lab and US soldiers then infected the population in China iii) Coronavirus is a zoonosis that spread from animals to humans (reverse coded) iv) Coronavirus is no more dangerous than common flu v) Coronavirus was invented as a pretense for limiting personal liberties.

Table 8: Structural estimates with number of cases/deaths and other coronavirus related control variables

	All waves				Constrained to 3rd wave			
	EUT		RDU		EUT		RDU	
	(1)		(2)		(3)		(4)	
r								
Constant	0.573***	(0.033)	0.502***	(0.056)	0.139	(0.559)	0.259	(0.192)
Before first case	0.037	(0.049)	0.052	(0.080)				
Before first death	0.014	(0.055)	-0.007	(0.071)				
Before curfew	-0.066	(0.096)	-0.097	(0.134)				
Curfew starts	-0.037	(0.078)	-0.146	(0.115)				
Curfew announced relaxation	-0.192	(0.125)	-0.358*	(0.203)				
Males	-0.064	(0.045)	0.015	(0.084)	0.133	(0.383)	0.027	(0.059)
N of cases/100K population	0.000	(0.005)	0.001	(0.005)	0.001	(0.015)	-0.000	(0.002)
N of deaths/100K population	0.048	(0.137)	0.146	(0.188)	-0.008	(0.342)	0.212***	(0.068)
Is social distancing effective?								
Neither inefficient, nor efficient					0.074	(0.898)	0.077	(0.174)
Efficient					0.088	(0.785)	0.006	(0.209)
Very efficient					0.026	(0.741)	0.069	(0.195)
Close ones in high risk group					0.012	(0.301)	0.149	(0.114)
Coronavirus stress score					0.009	(0.025)	-0.006	(0.008)
Conspiracy theories score					0.012	(0.035)	-0.006	(0.010)
α_r								
Constant			0.825***	(0.079)			1.167**	(0.485)
Before first case			0.011	(0.114)				
Before first death			-0.067	(0.097)				
Before curfew			-0.109	(0.182)				
Curfew starts			-0.252**	(0.127)				
Curfew announced relaxation			-0.328*	(0.189)				
Males			0.214	(0.130)			-0.031	(0.164)
N of cases/100K population			0.006	(0.008)			0.002	(0.009)
N of deaths/100K population			0.137	(0.328)			0.589	(0.381)
Is social distancing effective?								
Neither inefficient, nor efficient							-0.248	(0.354)
Efficient							-0.355	(0.350)
Very efficient							-0.422	(0.358)
Close ones in high risk group							0.359	(0.311)
Coronavirus stress score							-0.034	(0.032)
Conspiracy theories score							-0.024	(0.027)
K								
Constant	0.191***	(0.020)	0.228***	(0.035)	0.390	(0.323)	0.363***	(0.089)
Before first case	-0.017	(0.027)	-0.028	(0.044)				
Before first death	-0.003	(0.030)	0.007	(0.039)				
Before curfew	0.025	(0.054)	0.039	(0.081)				
Curfew starts	0.004	(0.047)	0.068	(0.075)				
Curfew announced relaxation	0.072	(0.079)	0.176	(0.145)				
Males	0.033	(0.028)	-0.011	(0.050)	-0.079	(0.204)	-0.011	(0.023)
N of cases/100K population	0.002	(0.003)	0.003	(0.002)	0.002	(0.007)	0.002**	(0.001)
N of deaths/100K population	-0.060	(0.087)	-0.132	(0.108)	-0.039	(0.203)	-0.146***	(0.020)
Is social distancing effective?								
Neither inefficient, nor efficient					-0.011	(0.470)	-0.031	(0.063)
Efficient					-0.015	(0.407)	0.013	(0.081)
Very efficient					0.007	(0.382)	-0.027	(0.071)
Close ones in high risk group					0.006	(0.181)	-0.085	(0.054)
Coronavirus stress score					-0.007	(0.014)	0.001	(0.003)
Conspiracy theories score					-0.005	(0.021)	0.004	(0.005)
μ	0.130***	(0.003)	0.127***	(0.003)	0.133***	(0.012)	0.131***	(0.006)
ν	0.067***	(0.002)	0.066***	(0.002)	0.064***	(0.004)	0.063***	(0.004)
N	47250		47250		16650		16650	
Log-likelihood	-27998.79		-27973.346		-9658.032		-9590.938	
AIC	56037.587		56004.692		19360.064		19245.876	
BIC	56212.852		56258.825		19529.908		19492.921	

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01. For all models, the base category is the 2019 wave.

a joint significance test that the coefficients of the regressors of the a_r parameter are equal to 0 and the constant equal to 1, fails to reject the null for model (2) ($\chi^2 = 4.97$, p-value = 0.548) and model (4) ($\chi^2 = 8.69$, p-value = 0.562).

One could also be tempted to use the cases/deaths variables as an intensity of exposure to treatment variable by exploiting the geographical dispersion of students after the curfew. Although the strategy of exploiting the geographical dispersion of students after a lockdown has been used in the literature (Lohmann et al., 2020), the vast majority of our sample of students are located inside the Athens/Piraeus metropolitan area and the percentage of them are virtually similar in the pre-pandemic wave in 2019 and in the 2020B wave after the curfew (82.3% vs 83.2%). Thus, we don't observe widespread dispersion of students out of the university's region after the lockdown. Nevertheless, we also estimated a generalized difference-in-difference model (DID) where the continuous treatment variable is the number of coronavirus cases in the area where the subject is taking the survey and interacted this treatment intensity variable with the wave dummies. However, none of the interaction terms was statistically significant and did not pursue this strategy further.

4 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, 2016). Therefore, it may be important for completeness to examine popular stated risk and time preference measures along side incentivized 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.[21] 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, 2016).

Table 9: 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	-	-
AIC	4423.132	4399.044	-	3995.508	-	-
BIC	4496.537	4472.449	-	4068.913	-	-
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).

Table 9 and Table 10 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 9 uses the wave dummies and Table 10 uses the event dummies. Reported standard errors are clustered standard errors.[22] As evident, the only robust effect across all

[21]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).

[22]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.,

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 parameters reported in the previous section.

Table 10: OLS and ordered logit regressions with event dummies

	Patience (1)	Impulsiveness (2)	BIS (3)	General risk taking (4)	Risk investment (5)	DOSPERT (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	-	-
AIC	4422.840	4403.060	-	3999.817	-	-
BIC	4510.926	4491.146	-	4087.903	-	-
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).

Lastly, Table 11 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 8. 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

2006; Greene and Hensher, 2010).

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).

Table 11: 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	-	-
AIC	1495.972	1458.852	-	1392.475	-	-
BIC	1569.109	1531.989	-	1461.763	-	-
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).

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.

5 Conclusions

Risk and time preferences are key factors considered in many economic models since they have important impacts on a variety of outcomes. A growing debate in the literature is about the assumption of stability of RTPs. This is an important issue since it can have significant implications and consequences for human behavior and economic decision making. For example, RTPs can affect an individual's valuation of the future and willingness to take risks, which can then influence, among others, health and labor outcomes. Our study adds to a stream of literature that examines the effect of major negative shocks on peoples RTPs. We specifically focus on undoubtedly one of the biggest negative shocks that the world has experienced, the COVID-19 pandemic.

While there has been an emerging set of studies that examine how risk or time preferences have evolved over the course of the pandemic (Angrisani et al., 2020; Bu et al., 2020; Ikeda et al., 2020; Lohmann et al., 2020; Shachat et al., 2020), this study offers several advancements. First, unlike other studies, we jointly elicited and estimated the structural parameters for various theories of risk and time preferences from a fairly large sample of more than 300 subjects per wave (for a total of about 1,000 responses). Given that most studies are focused on samples from China and only one of them measures time preferences, our study is the only one providing structural estimates for time preferences for subjects from Europe. Furthermore, our study is unique in that we spread data collection in each wave over a relatively long period which allowed us to record multiple key events in the timeline of the pandemic.

Using estimated structural parameters for various theories of risk and time preferences from the incentivized tasks, our results clearly indicate that there are no significant differences in RTPs across the different waves of our data, before and during the pandemic. We also get similar conclusions coming out of the stated preferences measures. Overall, our subjects exhibit intertemporal stability of risk and time preferences despite the very disruptive effect of the COVID-19 pandemic on people's lives and the global economy.

This finding is important since it suggests that RTPs may not be that malleable even amid catastrophic events such as pandemics. This can significantly simplify and help policy and welfare analyses given that these are typically conducted under the assumption that preferences are stable. A worry among economists is that instability of preferences over time could deprive economics of a clean analytical foundation for welfare analysis and policy development (Schildberg-Hörisch, 2018). Our study provides evidence about the stability of preferences that will further help us in our understanding of individual decision-making and outcomes. At the very least, it tells us that RTPs are critical characteristics of human beings that can be stable over a period of time (e.g., few years) despite an exogenous shock in the form of a pandemic. Future studies should examine, however, if this stability persists in the longer term, way after an exogenous shock. It is possible that the last wave of our data has not incorporated the full impact of the financial crisis brought about by the pandemic. Hence, it is important to know the longer term effect of an exogenous shock since it can help new policies predict behavioral responses more adequately.

References

Andersen, S., G. W. Harrison, M. Lau, and E. E. Rutström (2018). Multiattribute utility theory, intertemporal utility and correlation aversion. *International Economic Review 59*(2), 537–555.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2008a). Eliciting risk and time preferences. *Econometrica 76*(3), 583–618.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2008b). Lost in state space: Are preferences stable? *International Economic Review 49*(3), 1091–1112.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2014). Discounting behavior: A reconsideration. *European Economic Review 71*, 15–33.

Angrisani, M., M. Cipriani, A. Guarino, R. Kendall, and J. Ortiz de Zarate Pina (2020). Risk preferences at the time of covid-19: An experiment with professional traders and students. *CEPR Discussion Paper No. 15108*.

Anzolin, E. and A. Amante (2020, February 21). Coronavirus outbreak grows in northern italy, 16 cases reported in one day. Available at https://web.archive.org/web/20200816091931/https://www.reuters.com/article/us-china-health-italy/coronavirus-outbreak-grows-in-northern-italy-16-cases-reported-in-one-day-idUSKBN20F0UI. Last accessed on August 16, 2020.

Arslan, R. C., M. Brómmer, T. Dohmen, J. Drewelies, R. Hertwig, and G. G. Wagner (2020). How people know their risk preference. *CESifo Working Paper Series No. 8586*.

Beine, M., G. Charness, A. Dupuy, and M. Joxhe (2020). Shaking things up: On the stability of risk and time preferences. *IZA Discussion Papers No. 13084*.

Bellucci, D., G. Fuochi, and P. Conzo (2020). Childhood exposure to the second world war and financial risk taking in adult life. *Journal of Economic Psychology 79*, 102196.

Bu, D., T. Hanspal, Y. Liao, and Y. Liu (2020). Risk taking during a global crisis: Evidence from Wuhan. *Available at SSRN: https://ssrn.com/abstract=3559870*.

Callen, M. (2015). Catastrophes and time preference: Evidence from the indian ocean earthquake. *Journal of Economic Behavior & Organization 118*, 199 – 214.

Callen, M., M. Isaqzadeh, J. D. Long, and C. Sprenger (2014, January). Violence and risk preference: Experimental evidence from afghanistan. *American Economic Review 104*(1), 123–48.

Cameron, L. and M. Shah (2015). Risk-taking behavior in the wake of natural disasters. *Journal of Human Resources 50*(2), 484–515.

Cassar, A., A. Healy, and C. von Kessler (2017). Trust, risk, and time preferences after a natural disaster: Experimental evidence from thailand. *World Development 94*, 90 – 105.

Chuang, Y. and L. Schechter (2015). Stability of experimental and survey measures of risk, time, and social preferences: A review and some new results. *Journal of Development Economics 117*, 151 – 170.

Clarke, K. A. (2003). Nonparametric model discrimination in international relations. *Journal of Conflict Resolution 47*(1), 72–93.

Coller, M. and M. Williams (1999). Eliciting individual discount rates. *Experimental Economics 2*(2), 107–127.

Crosetto, P. and A. Filippin (2012). The "bomb" risk elicitation task. *SOEPpapers on Multidisciplinary Panel Data Research No 517*.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9*(3), 522–550.

Drichoutis, A. and A. Vassilopoulos (2016). Intertemporal stability of survey-based measures of risk and time preferences over a three-year course. Working Papers 2016-3, Agricultural University of Athens, Department Of Agricultural Economics.

Drichoutis, A. C., P. Lazaridis, and J. R. M. Nayga (2006). Heteroskedasticity, the single crossing property and ordered response models. *Economics Bulletin 3*(31), 1–6.

Drichoutis, A. C. and J. L. Lusk (2016). What can multiple price lists really tell us about risk preferences? *Journal of Risk and Uncertainty 53*(2), 89–106.

Eckel, C. C., M. A. El-Gamal, and R. K. Wilson (2009). Risk loving after the storm: A bayesian-network study of hurricane Katrina evacuees. *Journal of Economic Behavior & Organization 69*(2), 110 – 124.

Greene, W. H. and D. A. Hensher (2010). *Modeling ordered choices: A primer*. Cambridge, UK: Cambridge University Press.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with ORSEE. *Journal of the Economic Science Association 1*(1), 114–125.

Hanaoka, C., H. Shigeoka, and Y. Watanabe (2018, April). Do risk preferences change? evidence from the great east japan earthquake. *American Economic Journal: Applied Economics 10*(2), 298–330.

Harrison, G. W., M. I. Lau, and M. B. Williams (2002). Estimating individual discount rates in denmark: A field experiment. *The American Economic Review 92*(5), 1606–1617.

Harrison, G. W. and J. M. Ng (2016). Evaluating the expected welfare gain from insurance. *Journal of Risk and Insurance 83*(1), 91–120.

Harrison, G. W. and J. T. Swarthout (2021). Cumulative prospect theory in the laboratory: A reconsideration. In G. W. Harrison and D. Ross (Eds.), *Models of Risk Preferences: Descriptive and Normative Challenges*. Bingley, Emerald, UK.

Holt, C. A. (1986). Preference reversals and the independence axiom. *The American Economic Review 76*(3), 508–515.

Holt, C. A. and S. K. Laury (2002). Risk aversion and incentive effects. *The American Economic Review 92*(5), 1644–1655.

Ikeda, S., E. Yamamura, and Y. Tsutsui (2020). COVID-19 enhanced diminishing sensitivity in prospect-theory risk preferences: A panel analysis. *Discussion Paper No. 1106, The Institute of Social and Economic Research, Osaka University*.

Jetter, M., L. M. Magnusson, and S. Roth (2020). Becoming sensitive: Males risk and time preferences after the 2008 financial crisis. *European Economic Review 128*, 103512.

Leuermann, A. and B. Roth (2012). Does good advice come cheap? - on the assessment of risk preferences in the lab and the field. *SOEPpapers on Multidisciplinary Panel Data Research No 475*.

Lohmann, P., E. Gsottbauer, J. You, and A. Kontoleon (2020). Social preferences and economic decision-making in the wake of COVID-19: Experimental evidence from China. *Available at SSRN: https://ssrn.com/abstract=3705264*.

Luna, R. (2020, March 5). Coronavirus: il paziente tedesco. Available at https://web.archive.org/web/20200816091422/https://rep.repubblica.it/pwa/generale/2020/03/05/news/coronavirus-250377117/. Last accessed on August 16, 2020.

Mazur, J. E. (1984). Tests of an equivalence rule for fixed and variable reinforcer delays. *Journal of Experimental Psychology: Animal Behavior Processes 10*(4), 426–436.

Norwood, B. F., M. C. Roberts, and J. L. Lusk (2004). Ranking crop yield models using out-of-sample likelihood functions. *American Journal of Agricultural Economics 86*(4), 1032–1043.

Page, L., D. A. Savage, and B. Torgler (2014). Variation in risk seeking behaviour following large losses: A natural experiment. *European Economic Review 71*, 121 – 131.

Patton, J. H., M. S. Stanford, and E. S. Barratt (1995). Factor structure of the barratt impulsiveness scale. *Journal of Clinical Psychology 51*(6), 768–774.

Prelec, D. (1998). The probability weighting function. *Econometrica 66*(3), 497–528.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization 3*(4), 323–343.

Read, D., S. Frederick, B. Orsel, and J. Rahman (2005). Four score and seven years from now: The date/delay effect in temporal discounting. *Management Science 51*(9), 1326–1335.

Schildberg-Hörisch, H. (2018, May). Are risk preferences stable? *Journal of Economic Perspectives 32*(2), 135–54.

Shachat, J., M. J. Walker, and L. Wei (2020). The impact of the Covid-19 pandemic on economic behaviours and preferences: Experimental evidence from Wuhan. *Economic Science Institute Working Paper 20-33 available at: https://digitalcommons.chapman.edu/esi_working_papers/328/*.

Snowberg, E. and L. Yariv (2020). Testing the waters: Behavior across participant pools. *American Economic Review* (forthcoming).

Spinella, M. (2007). Normative data and a short form of the barratt impulsiveness scale. *International Journal of Neuroscience 117*(3), 359–368.

StataCorp (2013). *Stata user's guide release 13.* College Station, Texas, USA: Stata Press.

Stigler, G. J. and G. S. Becker (1977). De Gustibus Non Est Disputandum. *The American Economic Review 67*(2), 76–90.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Vischer, T., T. Dohmen, A. Falk, D. Huffman, J. Schupp, U. Sunde, and G. G. Wagner (2013). Validating an ultra-short survey measure of patience. *Economics Letters 120*(2), 142–145.

Voors, M. J., E. E. M. Nillesen, P. Verwimp, E. H. Bulte, R. Lensink, and D. P. Van Soest (2012). Violent conflict and behavior: A field experiment in Burundi. *American Economic Review 102*(2), 941–64.

Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica 57*(2), 307–333.

Weber, E. U., A.-R. Blais, and N. E. Betz (2002). A domain-specific risk-attitude scale: measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making 15*(4), 263–290.

Wilcox, N. (2008). Stochastic models for binary discrete choice under risk: A critical primer and econometric comparison. In J. C. Cox and G. W. Harrison (Eds.), *Research in Experimental Economics Vol 12: Risk Aversion in Experiments*, pp. 197–292. Bingley, UK: Emerald Group Publishing Limited.

Wilcox, N. T. (2011). 'Stochastically more risk averse:' A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics 162*(1), 89–104.

Electronic Supplementary Material of

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

Andreas C. Drichoutis* and Rodolfo M. Nayga†

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.

*Corresponding author: Associate Professor, Department of Agricultural Economics & Rural Development, Agricultural University of Athens, Iera Odos 75, 11855, Greece, e-mail: adrihout@aua.gr.

†Distinguished Professor and Tyson Endowed Chair, Department of Agricultural Economics & Agribusiness, University of Arkansas, Fayetteville, AR 72701, USA, tel:+1-4795752299 e-mail: rnayga@uark.edu.

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)

Created: 03/26/2020 03:53 PM (PT)
Public: 11/20/2020 12:06 PM (PT)

Author(s)
Andreas Drichoutis (Agricultural University of Athens) - adrihout@gmail.com
Rodolfo Nayga (University of Arkansas) - rnayga@uark.edu

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 Additional Tables

Table A1: Structural estimates (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)	0.497***	(0.038)	0.537***	(0.030)	0.496***	(0.038)
2020A wave	0.031	(0.043)	0.016	(0.054)				
2020B wave	-0.022	(0.042)	-0.027	(0.055)				
2020 events:								
Before first case					0.048	(0.050)	0.038	(0.063)
Before first death					0.034	(0.058)	0.016	(0.073)
Before curfew					-0.089	(0.104)	-0.132	(0.139)
Curfew starts					0.018	(0.050)	0.001	(0.065)
Curfew announced relaxation					-0.070	(0.052)	-0.064	(0.070)
α_r								
Constant			0.891***	(0.062)			0.889***	(0.062)
2020A wave			-0.042	(0.087)				
2020B wave			-0.014	(0.089)				
2020 events:								
Before first case							-0.026	(0.103)
Before first death							-0.048	(0.113)
Before curfew							-0.120	(0.199)
Curfew starts							-0.048	(0.102)
Curfew announced relaxation							0.015	(0.116)
K								
Constant	0.210***	(0.017)	0.229***	(0.020)	0.210***	(0.017)	0.229***	(0.020)
2020A wave	-0.013	(0.023)	-0.004	(0.029)				
2020B wave	0.028	(0.024)	0.033	(0.030)				
2020 events:								
Before first case					-0.020	(0.027)	-0.015	(0.033)
Before first death					-0.013	(0.031)	-0.003	(0.038)
Before curfew					0.037	(0.061)	0.059	(0.083)
Curfew starts					0.012	(0.030)	0.024	(0.038)
Curfew announced relaxation					0.049	(0.031)	0.047	(0.038)
μ	0.129***	(0.003)	0.126***	(0.003)	0.129***	(0.003)	0.126***	(0.003)
ν	0.065***	(0.002)	0.063***	(0.002)	0.065***	(0.002)	0.063***	(0.002)
N	40700		40700		40700		40700	
Log-likelihood	-23924.699		-23915.255		-23909.657		-23899.064	
AIC	47865.398		47852.510		47847.314		47838.128	
BIC	47934.310		47947.264		47967.910		48010.408	

Notes: Standard errors in parentheses. * 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.

Table A2: Structural estimates (sample restricted to those that participated to all three waves)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.589***	(0.038)	0.560***	(0.050)	0.589***	(0.038)	0.557***	(0.050)
2020A wave	-0.075	(0.061)	-0.052	(0.075)				
2020B wave	-0.042	(0.064)	-0.041	(0.084)				
2020 events:								
Before first case					-0.013	(0.076)	-0.007	(0.090)
Before first death					-0.150*	(0.086)	-0.121	(0.108)
Before curfew					-0.118	(0.130)	-0.033	(0.172)
Curfew starts					0.026	(0.078)	0.030	(0.100)
Curfew announced relaxation					-0.142	(0.088)	-0.167	(0.114)
α_r								
Constant			0.919***	(0.089)			0.913***	(0.089)
2020A wave			0.067	(0.133)				
2020B wave			0.001	(0.148)				
2020 events:								
Before first case							0.018	(0.157)
Before first death							0.083	(0.185)
Before curfew							0.253	(0.345)
Curfew starts							0.011	(0.173)
Curfew announced relaxation							-0.076	(0.186)
K								
Constant	0.184***	(0.021)	0.198***	(0.025)	0.184***	(0.021)	0.199***	(0.025)
2020A wave	0.026	(0.032)	0.015	(0.037)				
2020B wave	0.028	(0.035)	0.028	(0.043)				
2020 events:								
Before first case					0.000	(0.041)	-0.003	(0.047)
Before first death					0.055	(0.043)	0.040	(0.051)
Before curfew					0.052	(0.073)	0.010	(0.087)
Curfew starts					0.009	(0.046)	0.009	(0.057)
Curfew announced relaxation					0.053	(0.045)	0.065	(0.053)
μ	0.127***	(0.005)	0.126***	(0.005)	0.126***	(0.005)	0.124***	(0.005)
ν	0.061***	(0.003)	0.060***	(0.003)	0.060***	(0.003)	0.060***	(0.003)
N	16850		16850		16850		16850	
Log-likelihood	-9865.632		-9864.626		-9830.785		-9828.598	
AIC	19747.265		19751.253		19689.570		19697.195	
BIC	19809.121		19836.306		19797.820		19851.837	

Notes: Standard errors in parentheses. * 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.

Table A3: Structural estimates (sample constrained to only those that accepted electronic bank transfer)

	EUT (1)		RDU (2)		EUT (3)		RDU (4)	
r								
Constant	0.546***	(0.029)	0.508***	(0.036)	0.546***	(0.029)	0.507***	(0.036)
2020A wave	0.027	(0.042)	0.013	(0.053)				
2020B wave	-0.026	(0.042)	-0.028	(0.055)				
2020 events:								
Before first case					0.034	(0.050)	0.034	(0.063)
Before first death					0.047	(0.059)	0.018	(0.074)
Before curfew					-0.088	(0.097)	-0.122	(0.129)
Curfew starts					0.007	(0.052)	-0.017	(0.066)
Curfew announced relaxation					-0.067	(0.053)	-0.047	(0.072)
α_r								
Constant			0.895***	(0.060)			0.893***	(0.060)
2020A wave			-0.037	(0.085)				
2020B wave			-0.005	(0.090)				
2020 events:								
Before first case							0.002	(0.100)
Before first death							-0.077	(0.111)
Before curfew							-0.099	(0.187)
Curfew starts							-0.068	(0.100)
Curfew announced relaxation							0.057	(0.123)
K								
Constant	0.204***	(0.016)	0.222***	(0.019)	0.204***	(0.016)	0.222***	(0.019)
2020A wave	-0.012	(0.022)	-0.005	(0.028)				
2020B wave	0.033	(0.024)	0.036	(0.030)				
2020 events:								
Before first case					-0.017	(0.026)	-0.017	(0.032)
Before first death					-0.017	(0.030)	-0.002	(0.038)
Before curfew					0.031	(0.054)	0.047	(0.074)
Curfew starts					0.020	(0.031)	0.038	(0.039)
Curfew announced relaxation					0.049	(0.030)	0.039	(0.038)
μ	0.133***	(0.003)	0.130***	(0.003)	0.132***	(0.003)	0.130***	(0.003)
ν	0.067***	(0.003)	0.065***	(0.003)	0.066***	(0.003)	0.065***	(0.003)
N	41850		41850		41850		41850	
Log-likelihood	-24922.902		-24914.645		-24908.082		-24897.777	
AIC	49861.805		49851.291		49844.165		49835.555	
BIC	49930.940		49946.351		49965.151		50008.392	

Notes: Standard errors in parentheses. * 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.

Table A4: 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	949	