Preferences, Disposition Effect and COVID-19*

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Abstract

We measure preferences and trading behavior during the emergence of the COVID-19 crisis. Firstly, we elicit and estimate present bias, patience, risk aversion and probability weighting in a large panel with high stakes and long-decision horizons. Present bias and impatience increase during the emergence of the COVID-19 crisis, and we find less risk-averse behavior. Secondly, we measure individual trading behavior and observe a strong disposition effect, which is increasing in the volatility of returns. The experimentally elicited disposition effect correlates strongly with exogenous market returns and is higher during bearish days. Finally, trust in insurers increases during the emergence of the COVID-19 crisis.

Keywords: COVID-19, risk and time preferences, trading behavior, behavioral finance, individual investors

JEL Codes: D14, G4, G11

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Risk and time preferences play a role in almost every economic decision. As a consequence, understanding individual risk and time preferences is key in the design of policy making. Over the past decades, researchers have been studying risk and time preferences. On the one hand, there is a need to measure risk and time preferences among distinct groups and across domains, and to assess the stability of preferences. On the other hand, it remains an empirical question how estimated preferences relate to actual behavior.

In the experimental economics literature, much attention has been devoted to estimating time and risk preferences. However, there remain two unresolved questions. First of all, it is unclear how simultaneously estimated risk (risk aversion and probability weighting) and time (present bias and discount rates) preferences in a high-stakes real-life context with long decision horizons compare to the previous literature. The second question is how stable preferences are over time and how they relate to personal characteristics. In the financial economics literature, much attention has been devoted to individual investment behavior, and specifically the disposition effect. So, the third question that arises: how stable are investment decisions over time and can preferences explain individual trading behavior?

In this paper, we address these three questions by eliciting risk and time preferences among individuals that additionally make investment decisions. We jointly estimate individual present bias, discount rate, risk aversion and probability weighting by extending the Convex Time Budgets method of Andreoni and Sprenger (2012a). We use a large-scale non-student sample of 1961 respondents. The individuals experimentally allocate €10,000 (11,800 USD) for long horizons up to 5 years. As such, we can expect subjects to spend more effort in thinking about their choice than in a laboratory with small stakes and short horizons.

Besides, we investigate the disposition effect, which is one of the most investigated anomalies in the financial markets since the pioneering contribution of Shefrin and Statman (1985). The term identifies an asymmetry between the fact that paper losses are realized less than paper gains. Understanding the phenomenon is crucial, since investment behavior has important implications for both portfolio management and aggregate market dynamics. We study individual investment behavior by a simple trading experiment similar to Ploner (2017). We compare the decision to take part in a risky investment of those who had experienced a loss to those who had experienced a gain.

Our cross-sectional results imply for the quasi-hyperbolic discounting model (also known as the $\beta - \delta$ model) absence of present bias, an annual discount rate of 8% and a CRRA risk aversion of 0.52. The estimated risk aversion is in line with Holt and Laury (2002), Eckel and Grossman (2008), and Balakrishnan et al. (2017) and implies risk-averse behavior, as generally observed in the literature. We find no evidence for present bias, since we estimate the present-bias factor at $\beta = 1$. Moreover, our estimated annual discount rate is lower than in most previous studies. Estimates of annual discount rates from 30%-100% are not uncommon (Frederick et al., 2002; Andreoni and Sprenger, 2012a; Cheung, 2020).

Potential reasons for our plausible discount rate and absence of present bias are the magnitude of the experimental budget, the long-term decision horizons (Thaler, 1981) and the correction for risk aversion and probability weighting.nLaboratory experiments typically have short decision horizons that run from several weeks to several months (Andersen, Harrison, M.Lauc, et al., 2010; Tanaka et al., 2010; Augenblick et al., 2015), but do not exceed more than 3 years (Harrison et al., 2002; Goda et al., 2015). Besides, the typical experimental payment equals tens of dollars (Andreoni and Sprenger, 2012a), rather than ten thousand dollars. Moreover, some previous research corrects for risk preferences in time discounting studies to avoid upward-biased time preferences (see, e.g., Andreoni and Sprenger (2012a)) but such studies do not include probability weighting. Ericson and Laibson (2019) argue that probability weighting is possibly an important mechanism in intertemporal choice, because an alternative motivation for present-bias discounting models might be that the future reward disappears.

Our time-series results show that present bias and internal discount rates increases during the emergence of the COVID-19 crisis. Furthermore, we find that risk aversion decreases as well during the emergence of the COVID-19 crisis. The results are robust to controlling for many personal characteristics.

We document the existence of a disposition effect. The disposition effect is increasing in the volatility of the underlying investment returns. In line with Ploner (2017), we find that male investor tend to have higher holding rates than female investors. In the time series, the disposition effect — experimentally elicited — has a strong significant relationship with exogenous market returns. Thus, it appears that subjects respond to (financial) news during the emergence of the COVID-19 crisis and use that information in our experiment on investment behavior. This is interesting in itself, because our experiment is framed such that it is independent of exogenous market dynamics and outside (financial) news.

The contribution to the literature is threefold. First of all, we simultaneously estimate risk and time preferences. Especially the simultaneous estimation of present bias and probability weighting is unique. Our second contribution is to assess the stability of preferences and trading behavior, by means of investigating the impact of the COVID-19 crisis. Namely, the period between March 1 and April 1 was a turbulent period on the financial market. Thirdly, we shed light on individual trading behavior by linking it to individually estimated preferences. We can for example test the realization utility model of Barberis and Xiong (2012).[1]

I. Preferences

We first explain our elicitation and estimation methodology for present bias, time preference, risk aversion and probability weighting. Secondly, we present our cross-sectional results and, finally, we show the impact of the emergence of COVID-19 on the stability of preferences.

A. Experimental design

We implement the method of Convex Time Budgets (Andreoni and Sprenger, 2012a; Andreoni and Sprenger, 2012b) at a large representative group of the

[1]The third contribution is work in progress, and not yet in this version.

Dutch population. Subjects choose an amount c_t, available at time t, and an amount c_{t+k}, available after a delay of $k > 0$ periods, continuously along a convex budget set

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

where $(1+r)$ is the experimental gross interest rate and m is the experimental budget. The Convex Time Budgets (CTB) method asks subjects to maximize some utility function $U(c_t, c_{t+k})$.

In our CTB task, subjects face 20 convex budget decisions. The subjects receive 5 sets with 4 decisions each. The starting time t equals the date of the experiment or one year later. This front-end delay allows to identify present bias. The delay length k equals 1 year or 5 years. The delay length is relatively long compared to the literature, such that we can study decision making under uncertainty for long horizons. The likelihood that the later payment is actually paid out, depends on the decision set. 2 out of the 5 sets have an uncertain late payment probability of $p_{t+k} = (0.5, 0.75)$, while the other 3 sets have a certain late payment probability $p_{t+k} = 1$. Each of the five sets, contain four varying interest rates. Thus, these 20 decisions involved 20 varying annual interest rates from 0 to 800 percent. The annual risk-adjusted interest rates vary from 0 to 350.

In each CTB decision, subjects are given a budget m of €10,000. Money allocated to the early payment has a value of c_t, while money allocated to the late payment has a present value of $c_{t+k}/(1+r)$. In some decisions, the late payment is uncertain with probability p_{t+k}. For instance, when p_{t+k} is 0.7, then the late payment is paid out with a chance of 70%, and nothing is paid out with a chance of 30%. c_{t+k}/c_t defines the gross interest rate $1+r$ over k years, so $(1+r)^{1/k}-1$ gives the standardized annual interest rate r. Multiplication by the payment probability p_{t+k} defines the risk-adjusted interest rates.

Table 1 shows the front-end and back-end delays, payment probabilities and interest rates for the 20 decisions in the Convex Time Budgets method. The timing of payments with delay length k identifies time preference, while sensitivity to changing the gross interest rates $1+r$ delivers identification of risk aversion. The front-end delay identifies present bias and the uncertain late payment probabilities delivers identification of probability weighting. The advantage of the CTB method is a simultaneous measurement of present bias, time preference, risk aversion and probability weighting. For this reason, we avoid the assumption of linear utility and, consequently, we avoid upward-biased discount rate estimates if true utility is concave (Andersen, Harrison, Lau, et al., 2008; Noor, 2009).

B. Sample

We fielded our experiment via the LISS panel (Longitudinal Internet Study in the Social Sciences), gathered by CentERdata, in The Netherlands. The experiment was in the period 2 March 2020 and 31 March 2020. The panel is recruited through address based sampling (no self-selection), and households without a computer and/or internet connection receive an internet connection and computer free of charge. This household panel, representative for population in The Netherlands, receives online questionnaires each month on different topics. When respondents complete a questionnaire, they receive a monthly incentive. The data can be linked to personal characteristics, and to income and wealth data from the tax office and pension funds.

The subjects in our experiment receive a monthly incentive from the LISS panel. Our experiment is not incentivized based on the experimental answers of the subjects. Some researchers argue that answer-based incentives in economic experiments lead to more truthful reveal of preferences. However, according to the overview of Cohen et al., 2020, in the literature there seems to be little evidence for systematic differences between incentivized and unincentivized experiments. Another review by Camerer and Hogarth (1999) finds that incentives do not reliably change average performance, but tend to decrease the variance of responses. Since our sample is relatively large, compared to the prior literature, this decreases the variance of the preference estimates on an aggregate level. Furthermore, Potters et al. (2016) find no difference between incentivized and unincentivized choices. Moreover, our hypothetical choice situation avoids the need for (complex) equalization of payments, transaction costs and corresponding payment confidence.

Upon starting the experiment, subjects read through the instructions. The instructions indicated that the budget should be allocated to the early payment, or to the later payment. Moreover, the instructions stated that there is no inflation. We also avoided arbitrage opportunities by stating that the allocated budget could be consumed or saved in a deposit account *without* interest, but could not be used to invest or to payoff a mortgage.[2] The percentage of responses that are at corners equals only 38%, and the number of subjects that made zero interior allocations is only 9%. These percentages might seem high at first sight, but are low compared with the literature. Andreoni and Sprenger (2012a) find that "roughly 70 percent of responses are at corners, but only 36 of 97 subjects [37%] made zero interior allocations."

Figure 1 shows an image of a decision screen. Subjects are told to divide the amount of €10,000 between the early payment c_t and late payment c_{t+k}. The early payment in this example is to be received today at date $t = 0$ (no front-end delay), while the late payment is to be received 1 year later at $t + k = 1$ (back-end delay). The likelihood that the late payment is paid equals $p_{t+k} = 1$, i.e. 100%, in this particular decision screen. The subjects have to make four budget decisions presented in order of increasing interest rates from 1.00 to 4.50. In subsequent decision screens, the varying early and later payment dates are emphasized by underlining the dates. Probabilities of uncertain late payment, i.e. $p_{t+k} = (0.5, 0.75)$, were underlined as well. Subjects faced a total of five such decision screens, corresponding to the five decision sets. After the five decision sets, the subjects answered all 20 decisions.

We invite individuals between the ages of 40 and 70 years, which is by construction representative for The Netherlands for those ages. We have observations from 1961 respondents. Table 2 presents the mean, median and standard deviation for some characteristics of our sample. The male to female ratio is nearly 50%, and the average age 56.36 years corresponds with the av-

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

erage of the invited ages between 40 and 70 years. The average and median education level corresponds with vocational education and training (in Dutch 'MBO'). The individual monthly after-tax income equals on average €1,885, which is slightly lower than the modal income of the Dutch population. The median duration was 15 minutes to answer our experiment, and the subjects evaluated our experiment reasonably well (in terms of five assessment criteria on a 5-points Likert scale: *Difficult, Clear, Think, Interesting* and *Fun*).

The variable *Pastresponses* measures when individuals tend to answer the LISS questionnaires in the years 2019 and 2020. The variable is defined as the ratio between the date of answering the survey and the total period that the questionnaire is open. The total period that the questionnaire is open is measured as the difference in days between the start date and the final date of the questionnaire. On average, subjects answer the LISS questionnaires within 23% of the total open survey time. The dummies *Week 2, Week 3* and *Week 4* show how much of the respondents in our experiment answered during the second week (11 - 17 March), third week (18 - 24 March) and fourth week (25 - 31 March) of March 2020.

C. Results

In this section, we firstly describe the aggregate behavior in the CTB method Then, we discuss the parameter estimation of individual preferences. We end with (cross-sectional) preference estimates. To the extent of our knowledge, the simultaneous individual estimation of time preferences, present bias and discounting, together with risk preferences, risk aversion and probability weighting, is a new contribution to the literature.

Aggregate analysis - Figure 2 summarizes aggregate choice behavior in the CTB. We plot the mean and median allocated Euros chosen at the early payment c_t against the gross interest rate $(1+r)$ for each of the five decision sets. The amount of Euros allocated to the early payment declines monotonically with the interest rate, indicating that people wait for the late payment when interest rates are higher. Additionally, as expected, the amount of earlier Euros increases when the late payment probability is lower. So, Figure **??** reveals that choices respond to changing interest rates and payment probabilities in a predicted way.

Evidence for present bias, or hyperbolic discounting, would be observed in Figure 2 as the earlier allocated Euros are substantially higher when $t = 0, k = 5, p_{t+k} = 1$ compared to $t = 1, k = 5, p_{t+k} = 1$. Instead, we observe that the mean and median early allocated budget at each interest rate is roughly constant across those front-end delays. Although masked by these aggregate results, individual heterogeneity is important, as shown by the individual analysis.

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

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

$$\max_{c_t, c_{t+k}} \delta^t \left[\pi(p_t)U(c_t + w_1) + (1 - \pi(p_t))U(w_1)\right] + \beta\delta^{t+k} \left[\pi(p_{t+k})U(c_{t+k} + w_2) + (1 - \pi(p_{t+k}))U(w_2)\right], \tag{2}$$

where δ is the one period discount factor and β is the present-bias factor. The quasi-hyperbolic form captures the notion of time-inconsistent behavior, since $\beta < 1$ indicates present bias. Moreover, it nests exponential discounting (i.e. standard time-consistent behavior, Samuelson, 1937) when $\beta = 1$. The values c_t and c_{t+k} (including interest) are the experimentally allocated payments, and $\pi(p_t)$ and $\pi(p_{t+k})$ are the corresponding subjective probabilities of payment. We use a simple Prelec probability weighting function $\pi(p) = p^\eta$ where p is the objective probability and $\pi(p)$ the subjective (distorted) prbability. The terms w_1 and w_2 are additional utility parameters which could be interpreted as background consumption or income (see, e.g., Andersen, Harrison, Lau, et al., 2008). Background consumption is frequently assumed to be zero or estimated in many experimental studies Andreoni and Sprenger (2012a), but we use individual monthly after-tax income in line with Andersen, Harrison, Lau, et al. (2014).

We posit the agent has a time separable Constant Relative Risk Aversion

(CRRA) utility function of the form

$$U(x) = \frac{1}{1-\gamma} x^{1-\gamma}, \text{ for } \gamma \neq 1 \tag{3}$$

where γ is the coefficient of relative risk aversion parameter of the individual. With this functional form, $\gamma = 0$ denotes risk neutral behavior, $\gamma > 0$ denotes risk aversion and $\gamma < 0$ denotes risk seeking behavior.[3]

Solving the subject's standard intertemporal maximization problem (2) subject to the budget constraint (1) yields the first-order condition:

$$\frac{c_t + w_1}{c_{t+k} + w_2} = \begin{cases} \left(\beta\delta^k(1+r)\frac{\pi(p_{t+k})}{\pi(p_t)}\right)^{\frac{1}{-\gamma}} & \text{if } t = 0 \\ \left(\delta^k(1+r)\frac{\pi(p_{t+k})}{\pi(p_t)}\right)^{\frac{1}{-\gamma}} & \text{if } t > 0 \end{cases} \tag{4}$$

Notice that in our experimental design the early payment is certain, such that $p_t = 1$. The experimental answers depend (non linearly) on the parameters of interest (present bias, discounting, risk aversion and probability weighting), as well as the experimentally varied parameters (interest rate, delay length and payment probability).

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

[3] It is important to precisely distinguish with the CRRA utility function that at times is formulated as $U(x) = \frac{1}{\alpha}x^{\alpha}$, where α is the curvature of the CRRA utility function. This is equivalent to our formulation with $\alpha = 1 - \gamma$.

find

$$\ln\left(\frac{c_t+w_1}{c_{t+k}+w_2}\right)=\left(\frac{\ln\beta}{-\gamma}\right)\cdot\mathbb{1}_{t=0,\ p_{t+k}=1}+\left(\frac{\ln\delta}{-\gamma}\right)\cdot k$$
$$+\left(\frac{1}{-\gamma}\right)\cdot\ln(1+r)+\left(\frac{\eta}{-\gamma}\right)\cdot\ln(p_{t+k}). \tag{5}$$

$\mathbb{1}_{p_{t+k}=1}$ is an indicator function for a certain probability of late payment. As Ericson and Laibson (2019) argue, present-biased models are fundamentally a theory of time preference, while intertemporal choices also reflects factors such as risk. An alternative motivation for present bias in discounting the receipt of a future reward is that the reward may disappear. Risk that a future reward may disappear, can lead to present bias apart from pure time preferences. Thus, to avoid interference between the estimation of present bias and probability weighting, we consistently estimate present bias only in the CTB scenarios where late payment is certain.

Given an additive error structure and fixed non-estimated values for background consumption, such an equation is easily estimated with parameter estimates for $\beta, \delta, \gamma, \eta$ obtained via nonlinear combinations of coefficient estimates. Equation (5) shows clearly that present bias β is identified through the front-end delay, discounting δ through the back-end delay, risk aversion γ follows from changes in the interest rate and probability weighting η follows from changes in the payment probability.

Individual analysis - Table 3 presents the estimated time and risk preferences at the individual level. For each subject, we estimate the preference parameters by equation (5) and, then, we compute summary statistics. To limit the number of estimated parameters, we restrict $w_1 = w_2$ and use monthly after-tax individual income as proxy for background consumption.[4] We estimate the parameters $\hat{\beta}, \hat{\delta}, \hat{\gamma}, \hat{\eta}$ by two-limit Tobit.

Firstly, echoing the results in Figure 2, we find no evidence of present bias. We estimate the median present-bias factor $\hat{\beta}$ at 1.000 with a tight standard error, which is in line with Andreoni and Sprenger (2012a). Secondly, the estimated annual discount factor $\hat{\delta}$ has a median value of 0.924 with a standard error of 0.006. The annual discount rate, $(1/\hat{\delta}) - 1$, equals 8.2%. This value is in line with (long-term) market interest rates and lower than most previous studies. Estimates of annual discount rates over hundred percent are not uncommon, as illustrated by the overview article of Frederick et al. (2002). Cheung (2020) estimates an annual discount rate of 62.6%, when controlling for CRRA curvature. The CTB design of Andreoni and Sprenger (2012a) corrects for CRRA curvature and present bias, but they still estimate an annual discount rate of 27.5%. A close estimate is that of Andersen, Harrison, Lau, et al. (2014), who report an annual discount rate of 7.3% in the quasi-hyperbolic model, while controlling for (classical) risk aversion.

Potential reasons for absence of present bias and our highly plausible annual discount rate are the magnitude of the experimental budget and the long-term decision horizon. Thaler (1981) shows that discount rates drop sharply as the size of wealth increases, which is known as the magnitude effect, and he reports that discount rates drop sharply as the length of time increase. We confirm both findings in our large non-student sample. The experimental

[4]The idea is that subjects essentially integrate experimental payments with regular (background) income.

budget of €10,000, combined with the decision horizon of 5 years, are both (much) larger than many of the previous studies. Horizons are frequently used up to several weeks (Augenblick et al., 2015), 3 months (Tanaka et al., 2010), 6 months (Andersen, Harrison, M.Lauc, et al., 2010), 1 year (Dohmen et al., 2010; Andersen, Harrison, Lau, et al., 2014), 2 years (Goda et al., 2015) and 3 years (Harrison et al., 2002).

A paper that comes close to ours in terms of large stakes and long decision horizons is Potters et al. (2016), who use a (lower, but still relatively high) experimental budget of €1,000 with a decision horizon up to retirement age. They report an annual discount rate of 1%. Another reason might be that not all previous studies correct for risk aversion and probability weighting when estimating time preferences, such that discount rates might be upward biased (Andreoni and Sprenger, 2012a).

The third finding is that the median CRRA risk aversion $\hat{\gamma}$ is 0.525. Since the risk aversion estimate is > 0, with a tight standard error of 0.014, we can conclude that subjects behave risk averse. Our finding is in line with previous research on CRRA risk aversion, such as Holt and Laury (2002), Eckel and Grossman (2008), and Balakrishnan et al. (2017). Finally, we estimate a probability weighting parameter $\hat{\eta}$ strictly larger than 1, which implies that respondents underweight probabilities. For example, an objective probability p of 50% is approximately interpreted as $\pi(p) = 0.42$ by the subject.

C. COVID-19

We implemented our experiment during the emergence of the COVID-19 crisis in The Netherlands, between the turbulent period of March 1 and April 1, the peak period of global stock market crashes and severe lockdown measures in The Netherlands. On March 1 The Netherlands had 10 confirmed cases, 0 deaths and no measures, while April 1 The Netherlands had 13.614 contaminations, 1.173 deaths and a so-called intelligent lockdown. In this section, we show that present bias, discounting and risk aversion start to be affected by the COVID-19 crisis from the second half of the month March onward. We believe our results are new and unique to the literature, because we measure preferences (simultaneously) during the *emergence* of a pandemic.

We divide the month March in four periods, identical to the aforementioned dummies: (i) Week 1, March 2 - March 10, (ii) Week 2, March 11 - March 17, (iii) Week 3, March 18 - March 24, (iv) Week 4, March 25 - March 31. The observations we have per week are respectively 866, 340, 339 and 416. Based on a Dutch news website (`NU.nl`), we sketch the following timeline of events concerning COVID-19 in The Netherlands:

- March 6: first corona patient dies, special measures for province North-Brabant.
- March 9: forbidden to shake hands.
- March 12: measures extended to the national level until March 31, events $>$ 100 persons canceled and, if possible, you must work from home.
- March 15: schools, universities and catering industry close.
- March 16: concerns about Intensive Care capacity, and prime-minister

Rutte gives a speech on herd immunity.

- March 17: emergency financial support for companies and the self-employed.
- March 19: minister of Health steps down due to fatigue.
- March 20: new testing rules, only people that are severely ill can be tested because test capacity is too low.
- March 22: national NL-alert (via smartphones) to keep 1.5m distance and to stay at home in case of symptoms as coughing and having a cold, because it was too crowded at some places.
- March 23: new additional measures such as prohibiting all meetings, gatherings and events till June 1. Townships can close busy places or shops, and penalties are being given if rules are broken.
- March 26: group formation on the streets is forbidden by means of an emergency order. This measure was announced on March 23 already.
- March 31: all lockdown measures are extended.

Note that the severity of the COVID-19 crisis, as well as the extremity of lockdown measures, becomes apparent and pronounced during the third and fourth weeks of March. Figure 3 shows the number of COVID-19 cases in The Netherlands, and corroborates the timeline of lockdown measures: during the second part of March the number of total cases increases rapidly and the amount of new cases starts to stabilize at roughly 1000.

We analyze the development of preferences during COVID-19 by regressing the individually estimated preferences (present-bias factor, discount factor and risk aversion) on week dummies. A potential concern might be that subjects who answer the questionnaire towards the deadline of the survey (i.e., end of the month) are impatient, or dynamically inconsistent. For this reason, we include as personal characteristics on socio-demographic and financial variables. Moreover, to alleviate the concerns further, we use as control variable *Past responses* that measures when individuals typically answered past LISS questionnaires.[5] Finally, we include additional controls that measure how respondents perceived the questionnaire. We use OLS estimation with robust standard errors to control for unobserved heterogeneity.

Table 4 shows the results of our estimations. Regarding time preferences, the present-bias and discount factors decrease statistically significant during the third week and fourth week. Additionally, the economic effects are also large. The present-bias factor decreases by -0.3 and the discount-factor decreases by -0.03. Risk aversion decreases significantly during week 3 as well, implying that subjects become less risk averse.[6]

Trust in insurers - Rather than only analyzing preferences, our survey also included a question on trust in insurers. Based on a 7-points Likert scale (i.e., from strongly disagree to strongly agree), the subject answers the question:

I have trust in insurers.

Figure 4 shows the cross-sectional distribution of trust insurers among our sample. The mean of the distribution lies at 4, indicating a neutral value of trust in insurers. Most of the subjects, however, have a low(er) degree of trust

[5]We also included the standard deviation of *Past responses* in the estimation to alleviate further concerns, but results remain unchanged (not shown).

[6]We estimated the same regression model for only the group of respondents that participated in the disposition effect experiment ($N = 287$). Results remain similar to those in Table 4.

in insurers since most of the mass of the distribution lies towards the left of the mean.

Table 5 present a time-series analysis of trust in insurers during the emergence of the COVID-19 crisis. Using an ordered probit regression, we regress the dependent variable *Trust in insurers* on week dummies, socio-demographic and financial variables, and controls. Throughout the month, trust in insurers increases as we see rising coefficients for the week dummies. During week 4, the effect is statistically significant and shows that individuals develop a higher degree of trust in insurers during the emergence of the COVID-19 crisis. Our result is in line with Miltenburg and Schaper (2020) from The Netherlands Institute for Social Research, who also report (Figure 1) that trust in seven institutions increases rapidly during the emergence of COVID-19.[7] The seven institutions include administration of justice, government, parliament, newspapers, television, labor unions and large corporations.

Disposition effect

This section studies individual trading behavior for a large subsample ($N = 287$) of our respondents. Specifically, we investigate the well-known anomaly that paper losses are realized less than paper gains, which is known as the disposition effect. The main contribution is that we measure the disposition effect during the emergence of a pandemic and, secondly, that we can link

[7]The Netherlands Institute for Social Research, SCP, is a government agency which conducts research into the social aspects of all areas of government policy. The main fields studied are health, welfare, social security, the labour market and education, with a particular focus on the interfaces between these fields. The reports published by SCP are widely used by government, civil servants, local authorities and academics.

trading behavior with preferences and personal characteristics.[8]

A. Experimental design

To assess the existence of a disposition effect, we use a methodology similar to that of Ploner (2017). Subjects in the experiment face four choices over simple risky prospects. We compare the decision to take part in a risky investment of those who had experienced a loss and those who had experienced a gain.

All prospects are simple win/loss gambles with the same probability assigned to the win and the loss outcome. The win and loss outcomes differ across the 4 prospects, see Table **??** for an overview of our experimental conditions. Prospect 1 has a negative expected value, and prospect 4 has a positive expected value. Prospects 4a and 4b differ in expected return and standard deviation.

Subjects are given an endowment of €10,000 and must choose to invest it in one product. In prospect 1 the subject chooses between asset A or B, in prospect 2 the subject chooses between asset C or D, and in prospect 3 the subject chooses between asset E or F. The subjects are aware that A, C and E warrants a win if the outcome of a coin toss is heads, and a loss otherwise. The opposite holds for products B, D and F. The two assets are ex-ante identical and perfectly anti-correlated. In prospect 4 the subject chooses to invest in asset X (4a) or asset Y (4b). Asset X has a lower expected return and higher standard deviation than asset Y. X and Y warrant a win if the outcome of a coin toss is heads, and a loss otherwise.

[8]We are currently busy with the latter analyses, so this is work in progress.

After becoming aware of the outcome of the first coin toss, each subject chooses whether she wants to hold on to the investment for 1 year or to sell it immediately. When holding on, a second coin toss is performed next year and earnings are computed as in the first coin toss. When selling, the earnings of the first toss are immediately paid to the subject. The delay of one year is chosen consistently with the preferences' part of the survey, such that we can compare trading behavior with individually estimated preferences.

Given this setting, a straightforward measure of the disposition effect is obtained by comparing the fraction of hold choices (*hold rate*) among those losing and those winning after the first coin toss. Under the standard assumptions of utility maximization, the same tendency to hold on to the investment should be observed among those who registered a loss and those who registered a win in the first coin toss.

B. Results

Cross-sectional analysis - Table 6 shows the hold rates among the investments that registered a loss and a win in the first coin toss, as well as the difference between both. Clearly, the difference is positive and large for all prospects, which shows that the hold rate among losing stocks is higher than among winning stocks. The difference in hold rates is statistically significant according to a non-parametric Wilcoxon signed rank test, p-value ¡ 0.00.[9] This is evidence of a disposition effect for all prospects. The disposition effect becomes stronger (i.e., larger difference in hold rates) if the stakes become bigger (i.e., larger

[9] Because of repeated choices by a subject, the test uses the individual averages across prospects.

standard deviation), such as for prospects 2, 3 and 4a. Interestingly, the hold rate among winners remains roughly constant throughout all prospects, while the hold rate among losers increases if standard deviations increase.

Time-series analysis - We analyze how the disposition effect correlates with personal characteristics, and how it reacts to news on the stock market. The financial market during March 2020 was globally volatile, with record-breaking losses but also gains. We estimate a generalized linear fixed-effects model with a Logit link to study how hold rates (dependent variable) correlate with losses, asset characteristics, personal characteristics and week dummies.

Table 7, Model 1, reports our regression analysis about the determinants to hold on to the investment. The variable *Loss* is highly significant and positive. This confirms that those experiencing a loss are more likely to hold on to the investment than those experiencing a gain, which is precisely the disposition effect. The finding is robust to many control variables. In line with Ploner (2017), we find that males are more likely to hold on to investments than females. Based on the week dummies, we do not find evidence that hold rates change during the month March.[10]

However, rather than using week dummies, we use actual returns on the Amsterdam Exchange (AEX) Index during the period that our experiment took place.[11] Model 2 shows that the *Return* on the AEX is significantly negative related to holding rates in our experiment. If returns on the AEX increase, then hold rates in our experiment decrease. Stated differently, if AEX

[10]We have also interacted the week dummies with *Loss*, but do not find changes in trading behavior.

[11]During non-trading days, such as weekends, we interpolated returns such that we can use as many experimental observations as possible.

returns increase, then sell rates increase. Identical to *Loss*, *Return* provides evidence for a disposition effect and, moreover, subjects appear to incorporate financial news into their experimental decision making. This is interesting in itself, because our experiment is framed such that it is completely independent of exogenous market returns and (financial) news.

Boom and bust - We study how the disposition effect develops during boom and bust periods on the financial market, during the COVID-19 crisis.

Figure 5 shows the difference in daily sample-average hold rates among losing and winning stocks (the disposition effect) together with daily returns on the AEX index. In general, we observe that if returns on the AEX decrease at day t, then the disposition effect rises in the days after t. Vice versa, if the AEX returns increase at day t, then the disposition effect decreases (i.e., the difference in hold rates declines towards zero) in the days after day t. It appears that (financial) news takes time to be incorporated in our experiment, but subjects react quite strongly on stock market events. The Spearman's rank correlation between the AEX returns at $t-1$ (based on the closing price) and the disposition effect at date t equals -0.33 and is statistically significant with a p-value of 0.08. Stated differently, we find that the disposition effect increases during bust period and decreases during boom periods, which is in line with Bernard et al. (2018).

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Tables

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

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

Table 2: **Summary statistics sample.** *Partner* equals 1 if the household head has a partner. *Education* is given in classes, 1 is the lowest (primary education) and 5 is the highest (university). *Duration* is the time taken to complete the survey in minutes. *Difficult, Clear, Think, Interesting* and *Fun* measure with a 5-points Likert scale whether the survey was difficult, whether the survey was clear, whether the survey made the subject think about the material, whether the survey was interesting and whether the survey was fun. *Past responses* is the average response date during all past core LISS questionnaires in 2019 - 2020, which is given as a fraction between the beginning and closing date of the questionnaire. *Week 2, Week 3* and *Week 4* are dummies that indicate during which week the subject answered the questionnaire.

	Mean	Median	Standard Deviation	N
Male	0.49	0.00	0.50	1,961
Age (years)	56.36	57.00	8.55	1,961
Partner (household head)	0.73	1.00	0.44	1,961
Education (classes)	3.86	4.00	1.41	1,954
Income (€)	1,885	1,800	1,168	1,961
Duration (min.)	951	15	4050	1,946
Difficult	3.17	3.00	1.47	1,947
Clear	3.42	4.00	1.29	1,947
Think	3.08	3.00	1.32	1,947
Interesting	3.17	3.00	1.35	1,947
Fun	3.26	3.00	1.33	1,947
Past responses	0.23			1,948
Week 2	0.17			1,961
Week 3	0.17			1,961
Week 4	0.21			1,961

Table 3: **Individual present bias, discounting, risk aversion and probability weighting estimates.** Two-limit Tobit maximum likelihood estimates for CRRA utility $\frac{x^{1-\gamma}}{1-\gamma}$ and Prelec-weighting function $\pi(p) = p^{\eta}$. Background consumption w_i equals monthly after-tax income, which varies across subjects. Standard errors are calculated as $\sigma/\sqrt{N}$, where σ is the standard deviation. The top 5 percent of parameter estimates are winsorized.

	Median	Standard Error	25th Percentile	75th Percentile	Min	Max	N
Present bias $\hat{\beta}$	1.000	0.048	0.819	1.471	0.199	9.664	1961
Discount factor $\hat{\delta}$	0.924	0.006	0.829	1.044	0.571	1.690	1961
Annual discount rate	0.082	0.006	-0.043	0.207	-0.408	0.752	1961
Risk aversion $\hat{\gamma}$	0.525	0.014	0.387	0.862	-0.371	2.497	1961
Probability weighting $\hat{\eta}$	1.238	0.115	-0.326	2.446	-4.999	18.198	1961

Table 4: **Preferences during COVID-19.** OLS regressions of individual-level parameter estimates. Controls include *Past responses, Duration, Difficult, Clear, Think, Interesting* and *Fun*. Robust standard errors are reported below the estimated coefficients, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent variable =	Present-bias factor $\hat{\beta}$	Discount factor $\hat{\delta}$	Risk aversion $\hat{\gamma}$
Week 2	-0.025	-0.017	-0.023
	-0.148	-0.017	-0.040
Week 3	-0.300**	-0.031*	-0.099**
	-0.137	-0.017	-0.040
Week 4	-0.265*	-0.036**	-0.019
	-0.155	-0.018	-0.046
Male	-0.014	0.006	-0.022
	-0.111	-0.013	-0.032
Age	0.022***	0.002**	0.010***
	-0.006	-0.001	-0.002
Partner	0.013	-0.029**	-0.074**
	-0.106	-0.013	-0.031
Education 4	-0.203	-0.065***	-0.112**
	-0.166	-0.019	-0.047
Education 5	-0.015	0.001	-0.004
	-0.131	-0.016	-0.038
Education 6	-0.201*	-0.042***	-0.105***
	-0.119	-0.015	-0.034
Income (/1000)	-0.135***	-0.002	0.044***
	-0.042	-0.005	-0.012
Constant	1.107***	0.956***	0.253**
	-0.427	-0.054	-0.124
Controls	YES	YES	YES
Observations	1,927	1,927	1,927
R-squared	0.033	0.024	0.039

Table 5: **Trust in insurers during COVID-19.** Ordered probit regression with $Trust$ as dependent variable, which indicates the trust in insurers on a 7-points Likert scale. Controls include *Past responses, Duration, Difficult, Clear, Think, Interesting, Fun* and the constants for the cutoff levels. Robust standard errors are reported below the estimated coefficients, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Dependent variable =	Trust
Week 2	0.015
	-0.069
Week 3	0.11
	-0.073
Week 4	0.166**
	-0.076
Male	-0.046
	-0.055
Age	-0.003
	-0.003
Partner	0.089*
	-0.054
Education 4	-0.069
	-0.085
Education 5	-0.078
	-0.062
Education 6	-0.018
	-0.061
Income (/1000)	0.089***
	-0.026
Controls	YES
Observations	1,870

Table 6: **Prospects and hold rates of winners/losers.** This table shows the number of subjects (N) in each prospect together with the win and loss outcomes in Euros, and the expected value and standard deviation. Losers and winners are the hold rates among losing and winning products, and the table reports the difference in hold rates between losers and winners.

		Experimental Conditions				Disposition Effect		
Prospect	N	Win (€)	Lose (€)	Expected Value	Standard Deviation	Losers	Winners	Diff
1. Product A or B	287	+3,000	-4,000	-500	4,950	0.393	0.210	+0.183
2. Product C or D	287	+4,000	-4,000	0	5,657	0.507	0.221	+0.286
3. Product E or F	287	+5,000	-4,000	+500	6,364	0.589	0.225	+0.363
4a. Product X	90	+6,000	-5,000	+500	7,778	0.569	0.231	+0.338
4b. Product Y	193	+4,000	-2,000	+1,000	4,243	0.449	0.221	+0.228

Table 7: **Disposition effect during COVID-19.** The dependent variable *Hold* captures the decision to hold ($Hold = 1$) or sell ($Hold = 0$) the investment. This table shows the results of fitting a generalized linear fixed-effects model with a Logit link. The *Loss* variable is equal to 1 when the subject suffered a loss after the first coin toss, and equal to 0 otherwise. Controls include *Past responses, Duration, Difficult, Clear, Think, Interesting* and *Fun*. t-statistics are reported below the estimated coefficients.

	Model 1	Model 2
Loss	1.292	1.091
	9.441	7.473
Return		−7.42
		−3.222
Expected Value	0.1898	0.2166
	1.468	1.562
Standard Deviation	0.1511	0.1425
	2.228	1.955
Male	0.4115	0.3266
	2.651	1.969
Age	−0.01539	−0.01667
	−1.822	−1.834
Partner	0.04737	−0.05618
	0.343	−0.370
Education 4	−0.2743	−0.3593
	−1.070	−1.227
Education 5	−0.366	−0.4468
	−2.091	−2.350
Education 6	−0.34	−0.4065
	−1.955	−2.182
Income (/1000)	−0.007217	0.0003345
	−0.108	0.005
Week 2	−0.07984	−0.08868
	−0.403	−0.421
Week 3	−0.2338	0.02914
	−1.041	0.118
Week 4	0.105	0.325
	0.506	1.424
Constant	−2.304	−2.247
	−3.152	−2.892
Controls	YES	YES
Observations	1120	972
AIC	5048.078	4382.087
BIC	5153.520	4489.433
LogLikelihood	-2503.039	-2169.043

Figures

Figure 1: **Decision screen (translated from Dutch).** Every decision the subject allocates $m =$ €10.000 between the early payment today and the late payment date with delay $k = 1$ year. In this decision screen, the late payment is with a probability p_{t+k} of 100%. The gross interest rate $1 + r$ over k years in the 4 scenarios varies from 1.00 to 4.50.

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

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

Figure 2: **Choice behavior.** Mean and median allocated Euros at early payment c_t against the gross interest rate $1 + r$ per payout probability p in the Convex Time Budgets.

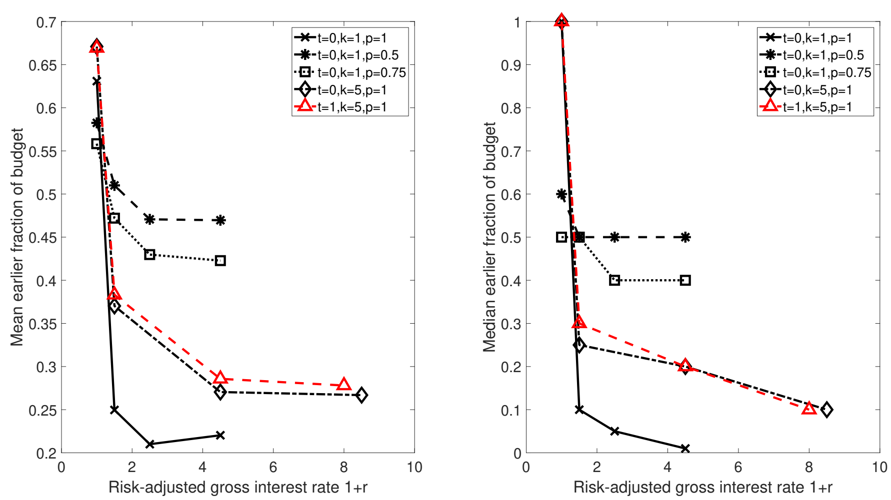

Figure 3: **COVID-19 in The Netherlands.** New (blue) and total (orange) cases in The Netherlands during the days in March (horizontal axis).

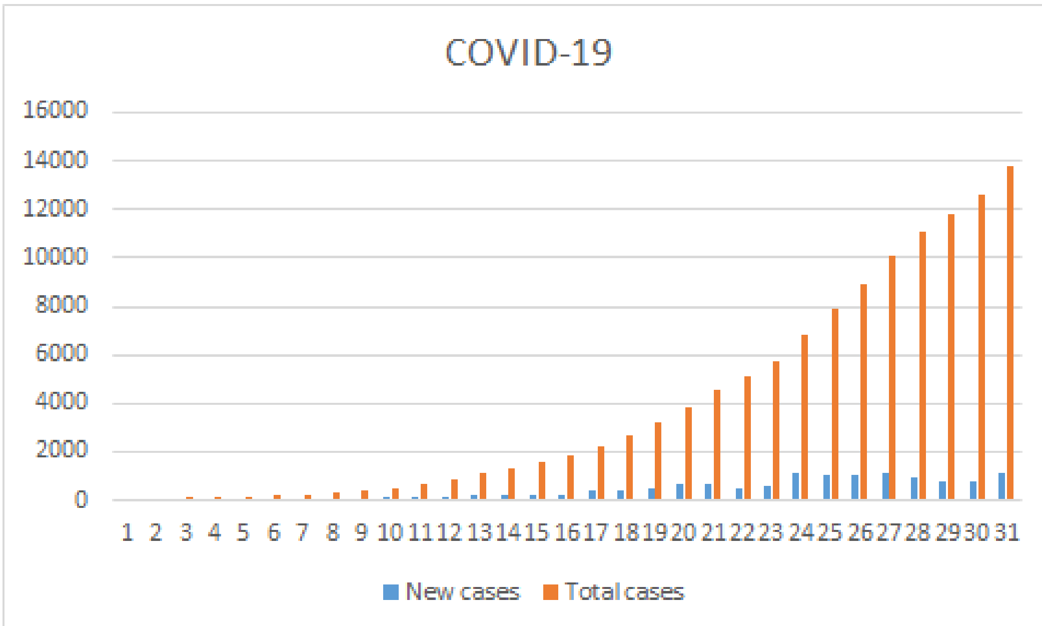

Figure 4: **Distribution of trust in insurers.**

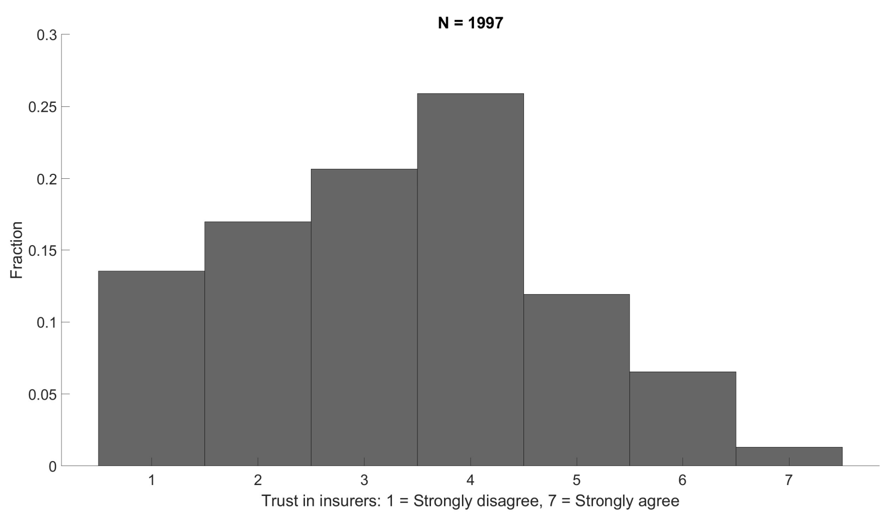

Figure 5: **Disposition effect during boom and bust periods.**