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Evidence From Data Science on the Relationship Between Individual Beliefs/Behaviors Survey During COVID-19 Pandemic and Risk Preferences

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Abstract

The factors that affect individual risk preference have been of central interest to behavioral economics and psychology. However, how to measure it and its stability remain a challenge. Dutch law requires financial institutions, including pension providers, to consider customers' risk preferences when offering their services. In this study, we apply data science to investigate whether individual perceptions of risk and social effects associated with COVID-19 are related to general risk preferences of individuals, while observing whether the relevant features that influence risk preferences remain consistent. A supervised machine learning task over two different target measures of risk preferences (a self reported risk preference measure from the survey and a lottery based experimental measure) using three datasets: a main study dataset with ($N = 4,282$) adult survey participants in the Netherlands and two pretest survey dataset with ($N = 314$) and ($N = 306$) respectively. The experimental measure employs a multiple price list to estimate an average number of safe choices of participants which is an integer, as such, a regression task using lasso regression over all of the datasets has been carried out to detect the relationship between behavior during the pandemic and the experimental risk preference measure. The self reported risk measure employs a likert scale to determine the risk likelihood of participants, as such, a classification task using a random forest model over the different risk tolerance classes on all of the datasets has also been studied. This assesses the stability of correlating such behavioral features to the revealed preference approach of eliciting risk preference as compared to self-reported risk preference from surveys. The hypothesis is that the individual choices selected regarding

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COVID-19 survey questions reflect the perceived risk of the pandemic, which is related to the general risk preferences of the individual. We find that adherence to social distancing and expected changes in relationships with colleagues, friends and neighbors are relevant to revealed risk preferences while stockpiling and social distancing are relevant to self-reported risk preferences. Additionally, results from correlation analysis of revealed risk preferences are more consistent and hence, more stable than self-reported risk preference.

Keywords: Machine learning, Risk preferences, Survey measure, Experimental economics.

1. INTRODUCTION

The outburst of the coronavirus pandemic has impacted all economies worldwide due to the lock-downs which led to fall in asset prices as people speculated on the short term future economic outcomes. It begs the question "What is the relationship between COVID-19 and individual risk preferences?". One aspect of dealing with the question involves studying how risk preferences affect individual risk preference and vice versa. The extent to which an individual is willing to take on risk is risk preference. It is often stated that risk is inseparable from decision-making [1–3]. Specifically, it is particularly indispensable in many economic and financial decisions. Assessing and measuring the risk preferences of individuals is critical for economic analysis and policy prescriptions. Since, an individual's willingness to take risks can predict aspects of labor market and health outcomes, addictive behaviors, investment, and migration decisions [4–8]. For example, when given a chance to win a lottery with equal 50% chances of winning either €10 or €0 and another option to win €5 for certain, a risk-neutral individual will be indifferent about both options. Individuals who prefer to with €5 for sure are considered to be risk-averse, while those willing to take a chance to win more are considered to be risk-seeking.

According to Dutch law, financial institutions need to factor in their customer risk preferences when offering products and services; as such, the measurement of risk preferences cannot be overstated [2]. Risk preference remains an important concept for investment behavior, consumer credit, insur-ance, pension plans, tax behavior, and becoming a victim of fraud [9].

Economists and psychologists have developed various experimental methodologies to elicit and assess individual risk preferences. Risk preference is one of the most important building blocks of choice theories in the behavioral sciences. In economics, it is conceptualized as preferences con-cerning the variance of monetary payoffs, whereas in psychology, risk preference is often thought to capture the propensity to engage in behavior with the potential for loss or harm [10]. Both concepts are associated with distinct measurement traditions: economics has traditionally relied on behavioral measures, while psychology has often relied on self-reports. For a more comprehensive discussion on elicitation of risk preferences, consult [11].

Stability of risk preferences is another very important aspect that is conceptually at the heart of microeconomics. However, there are many facets to the evaluation of stability of a metric. For example, (Schildberg-Hörisch, 2018) [8], posits that preference stability in economics implies that individual risk preferences are constant over time; for more extensive survey, consult [10, 12]. An-other perspective is to search for a specific function in the set of all functions such that it consistently maps individual attributes to their risk preference measure. In other words, over varying sample data, can we validate that the same attributes consistently influence the risk preference measure for external consistency. And for internal consistency, do we observe that keeping the environmental factors constant, given any two individuals that have approximately the same relevant attributes being used to estimate a risk preference measure, there is no extreme divergent result such as one being risk seeking and the other being risk averse.

The aim of our study is to investigate whether behavior attributes such as stockpiling and social distancing regarding COVID-19 are adequate predictors of risk preference. If so, do they remain consistent over various samples? Information on this relationship can be helpful to further understand the link between behavioral attitudes during an exogenous shock event such as the COVID-19 pandemic and risk preferences and simultaneously justify the use of such behavioral variables for prediction of risk preferences. The research questions of the study are as follows:

- **RQ1** Are behavior regarding Covid-19 a predictor of individual risk preference?
- **RQ2** If so, are there specific behavioral attributes that consistently influence risk preference over varying data?
- **RQ3** Does **RQ1** hold true for different measurement of risk preference?

As such, the hypothesis of our study is that behavioral attributes during the pandemic are indicative of individual risk preferences of people and thus constitutes an important feature for the prediction of risk preferences as a machine learning task. In other words, individual beliefs and behaviors exhibited during the pandemic are influence by the perceived risk of the pandemic and as such are related to the general risk preference of an individual.

2. LITERATURE REVIEW

Research on the effect of shocks on risk preferences usually starts from the underlying implicit assumption that, in the absence of the shock, preferences would have changed less. A good starting point is the study of how job market shocks cause changes in preferences. Some studies find that changes in income, unemployment, health status, and family composition do not lead to changes in risk preferences [13–15].

Specific examples of papers which find no evidence of changes in preferences after varying shocks in low income settings include (Giné et al. 2018) [16], who find no impact of household shocks such as a death in the family. (Meier and Sprenger 2015) [17], suggest that changes in measured preferences over time thus may either be noise, or may be orthogonal to socio-demographics.

Another group of papers disagrees with this assessment and does find that preferences are affected by shocks. (Fisman et al. 2014) [18], find that the Great Recession increased selfishness while (Gerrans et al. 2015) [19], and (Necker and Ziegelmeyer 2016) [20], find that it decreased risk tolerance.

Literature looking at how preferences are impacted by extreme events such as civil wars, pandemics and natural disasters are only just starting to become prevalent. While this literature is fascinating, authors tend to face two main difficulties. First, data on preferences is usually only available after the event and not before. Second, it is difficult to construct a control group, since these events affect different populations deferentially. Papers looking at the impact of extreme events such as the COVID-19 pandemic find amazingly divergent results. The number of these papers has been growing at a rapid rate, with no signs of converging to one consistent set of results. This lack of consistency may suggest that there are nuances involved in the experience of disaster that are not considered, or that experimental choices are filled with lots of noise.

The research on natural disasters (including earthquakes, famines, floods, hurricanes, and tsunamis) suggests that such shocks increase risk aversion [21–25], decrease risk aversion [26–30], have no effect at all on risk preferences [31], or have no consistent effect on risk preferences [32].

The most recent preceding pandemic recorded prior to COVID-19 was the H1N1 influenza outbreak in 2009. Previous research with H1N1 responses showed that people who perceived the risk of contracting H1N1 as high exhibited low risk-taking behaviors and high avoidance behaviors, like avoiding heavily populated areas [33, 34]. Some studies showed that people who exhibited more signs of worry about contracting the virus tended to engage in more preventative measures [33, 35]. Another study indicated that people who resided in areas with a high concentration of the virus reported the belief in a higher likelihood of catching the virus but showed no signs of a higher degree of engagement of preventative behaviors [36]. In terms of demographics, risk-aversive behavior was associated with older age and larger household size [34]. Additionally, previous research indicates that preventative behaviors decreased over time [34, 36], suggesting a decrease in risk perception and a subsequent increase in risky behaviors. While some research on preventative behaviors during the H1N1 pandemic exists, measures of risk-taking behaviors and delayed discounting and their relationship to H1N1 responses are far scarcer.

A study by (Angrisani et al. 2020) [37], investigates whether the COVID-19 pandemic has impacted risk preferences, comparing the results of experiments conducted before and during the outbreak. In each experiment, they elicit risk preferences from two sample groups: professional traders and undergraduate students. The finding is that, on average, risk preferences have remained constant for both pools of participants. Similar results were found by [38], from a sample of undergraduate students in Athens, Greece.

In a bid to study the heterogeneity in risk tolerance over the course of the current COVID-19 pandemic, (Guenther et al. 2021) [39], look at inter-individual differences in risk-taking during the first lockdown period in the UK (23 March 2020–26 May 2020) as a consequence of the rapid spread of the COVID-19 pandemic. Specifically, they elicit risk tolerance using four of the most widely applied risk-taking tasks in behavioral economics and psychology in two pre-registered online studies. They found that healthier participants in the study displayed significantly higher risk tolerance in self-reported risk-taking measures and no systematic nor robust patterns of association between the COVID-19-related risky behaviors and the four risk-taking tasks in the samples.

A study by (Lohmann et al. 2020) [40], 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 they use a 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.

Subsequently, another study by (Harrison et al. 2020) [41], elicited atemporal risk aversion, intertemporal risk aversion and time preferences from 598 students at Georgia State University, USA. Subjects were split over the course of the pandemic to 112, 130, 117, 99, 81 and 59 subjects in each of five waves, respectively, for the period from May to October 2020. They also have pre-pandemic data from 2019 for atemporal risk preferences for 232 subjects that were common to the COVID-19 experiment, as well as for time preferences for subjects drawn from the same population but they do not overlap with the COVID-19 experiment. Overall, they find that time preferences and intertemporal risk preferences are stable over the course of the pandemic. They also find that subjects become more atemporal risk averse during the pandemic under an Rank Dependent Utility (RDU) model but not under Expected Utility Theory (EUT). This points to the importance of having risk measures that allow one to model the structure of risk preferences which is impossible to achieve with survey measures or even with incentivized tasks that do not admit structural estimation of atemporal risk preferences.

Another study done by (Shachat et al. 2021) [42], administered incentivized lottery choice tasks in the gain and loss domain to 396 students from Wuhan University, which 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 it was declared 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 in the lottery choice tasks) during the early stages of the COVID-19 crisis.

In a more recent study, (Gassmann et al. 2022) [43], elicit preferences for risk, ambiguity as well as time preferences from students at Burgundy in France. They collected data from 596 subjects split in three waves: during lockdown (217 subjects), after the lockdown (190 subjects) and four months later (189 subjects). They also have responses from pre-pandemic data that were collected in 2016. They report decrease in patience, less risk aversion, less ambiguity aversion and less prudence during the lockdown. One should note however, that incentives in their study had a very small chance (1%) of being realized, so results should be viewed within this context. while, (Zhang and Palma, 2022) [44], explore the stability of individual risk preference during shocks like the pandemic. They found out that different risk preference measures provide differential results and this depends on what psychological traits (general or domain-specific) the measures captured and that there is a gender difference in the stability of risk-preference during shocks.

In summary, there is mostly a consensus that risk preferences remain relatively stable in lieu of the Covid-19 pandemic and in general, there is some evidence that exogenous shocks do not strongly impact risk preferences.

Our study also contributes to a rapidly growing literature assessing the impact of the Covid-19 pandemic on economic preferences and beliefs similar to the aforementioned studies from the literature with explicit focus on applied machine learning and data science. Our main contribution is the application of data science on a more substantive dataset in terms of size and representation in comparison to smaller datasets to examine the relationship between behavior during the pandemic and individual risk preferences.

3. METHODOLOGY

3.1 Dataset

This presents an overview of data collected in the study of the Netspar Theme project conducted by Maastricht University in collaboration with CBS and Flycatcher. The main study consisted of two waves. Wave 1 ran from May 12 to June 10, 2020. Wave 2 ran from June 19 to July 20, 2020. A sample of 36,000 individuals representative of the Dutch population was drawn by CBS (with an oversampling of self- employed). These individuals were invited by Flycatcher to participate in wave 1 and informed that the study consisted of two waves. Participants that completed wave 1 were invited to participate in wave 2. A total of 5228 participants completed wave 1 (14.5%). A total of 4282 participants also completed wave 2. Participants' decisions were incentivized so that their payoffs were determined by their decisions in the experiments. One out of five participants had one decision paid out. Preceding the main study are 5 pretest studies to fine tune the main study questionnaire. Particularly pretest 4 and pretest 5 have similar mediums of eliciting risk preferences. 314 and 306 participants completed the survey for pretest 4 and pretest 5 respectively. We hypothesize that the specific decision-making constructs regarding COVID-19 reflect the perceived risk of the pandemic, which influence the general risk preferences of the individual.

Three risk measures were also collected in the survey. In the first measure, self-assessed risk preference, participants reported their general risk preferences on an 11-point (0 - 10) Likert scale of increasing risk aversion with the endpoints labeled as 'avoid all risk' and 'like to take risk' and the midpoint indicating risk neutrality. The remaining two measures elicited risk preferences and were contextualized under the revealed preference approach.One of these two measures uses the multiple price list (MPL), participants in the survey receive a list of pairs of lotteries. In each pair, the participant must choose between the two options; say, option A and option B. The list is designed such that the expected value of both or one of the options changes down the list. Assuming expected utility theory, the point where the participant switches from choosing one option to the other allows the researcher to infer information about the participant's risk preference. As an alternative measure of risk preference the convex time budget was employed, where participants receive a monetary budget that they are free to allocate to either of two accounts. The first account pays out some amount of money at an early date with certainty. The second account pays out a larger amount of money at a later date but only with some probability as depicted in (Bokern et. al, 2021) [2]. For this work, we focused on the self reported risk preference and the MPL elicited risk preferences. The self reported risk preferences prediction task is can considered a classification task since the likert scale consist of 11 options that can be predicted; while the average number of safe choices selected in the MPL questions as a prediction task is considered a regression task since the average number of safe choices derived from the MPL results to be predicted is of the integers domain.

3.2 Data Preprocessing

All 18 survey questionnaire results relating to COVID-19 in the considered datasets [1] were collected as explanatory variables for regression of the MPL average number of safe choices selected by

[1] See Appendix 2 for the full list of Covid-19 related survey questions

participants and the self reported risk measure. All the variables related to COVID-19 were on a likert scale and thus observed as categorical variables encoded with one hot encoding. All datasets were processed by the removal of people that did not complete the survey. The missing data have been imputed using an iterative imputation method [45] based on the XGBoost model. This is as a result of survey of the state of the art on data imputation and selection is based off implementing the various methods on our validation dataset which is a subset of the training data in this study.

3.3 LASSO Regression Model

Least Absolute Shrinkage and Selection Operator (LASSO) presented by Tibshirani [46] is a linear algorithm that minimizes the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant, and it is a well-known sparse regression method which regularizes the coefficient parameter under sparse assumption. It is an extension of ordinary least squares. It tends to generate some coefficients that are exactly zero. The basic framework is summarized as follows: Considering a sample consisting of N cases, each of which consists of p covariates and a single outcome. Supposing y_i is the response variable and $x_i = (x_i1, x_i2, ..., x_ip)^T$ is the covariate vector for the i^th case, $\beta = (\beta_1, \beta_2, ..., \beta_p)^T$, so the objective of LASSO is to solve the optimization problem:

$$argmin_{\beta_0,\beta\epsilon\mathbb{R}^p} \frac{1}{N}\sum_{i=1}^{N}(y_i - \beta_0 - x_i^T)^2 \tag{1}$$

$$s.t. \sum_{j=1}^{p} |\beta_j| \leq t$$

where $t \geq 0$ is a pre-specified free parameter that determines the amount of regularization. If t is large, all the coefficients are almost zero. For smaller values of t, the LASSO shrinks some of the estimated coefficients equal to zero. Suppose X represents the $N \times p$ covariates matrix, N is the number of samples, p is the number of the covariates, y represents a response vector as expected output. Formula 1 can be wrote more compactly as

$$argmin_{\beta\epsilon\mathbb{R}^p} \left\{\frac{1}{N}\left\|y - X\beta^T\right\|_2^2\right\} \tag{2}$$

$$s.t. \left\|\beta_j\right\| \leq t$$

The LASSO estimator is expressed by the following Lagrangian form:

$$L(\beta,\lambda) = min_{\beta\epsilon\mathbb{R}^p} \left\{\frac{1}{N}\left\|y - X\beta^T\right\|_2^2 + \lambda\left\|\beta\right\|_1\right\} \tag{3}$$

3.4 Random Forest Classification Model

Random forest (RF) is an ensemble classifier that aggregates the results of multiple decision trees via majority voting (Kulkarni et al., 2016). In other words, the final class of a sample is determined by the most popular class of multiple decision trees. These multiple decision trees are built based on bootstrap sampling of the training dataset, and the variables in each tree are randomly selected as a subset of the whole predictor variable set. Each decision tree in the RF model follows the top-down splitting principle. Starting from the root node, the division is performed according to the principle of minimum impurity, and the growth is stopped when the number of records in a node is below a pre-set threshold value. A commonly used impurity measurement is the Gini index. The mathematical formula for calculating the Gini index is as follows:

$$Gini(p) = \sum_{k=1}^{K} p_k(1 - p_k) \tag{4}$$

where p_k is the frequency of samples belonging to class k on the node, and K is the total number of classes. Based on this type of strategy, as an ensemble classifier, RF often has a higher prediction accuracy rate than a single classifier, such as a single decision tree [47].

3.5 Experimental Design

Two response variables have been selected over three datasets to investigate whether individual beliefs and behavior associated with COVID-19 are indicative of the survey participants risk preferences (both revealed and self reported). Over varying dataset, the stability of the risk preference measure with regards the consistency of the important features according to a representative model have also been studied.

In other to select the most effective, various machine learning models such as linear regression, lasso, ridge regression, elastic net, bayesian ridge regression and gradient boosting regression techniques have been employed to model the average number of safe choices as a response for the explanatory variables, and the most optimal model in terms of prediction metrics and interpretability for the average number of safe choices is the lasso regression model. Subsequently, logistic regression, linear discriminant analysis, ridge classifier, K-nearest neighbour classifier, decision tree, catboost and random forests have been employed to model the self reported risk preference as a response for the explanatory variables, and the corresponding optimal model in this case is the random forest.

The Hypothesis of this study is that individual beliefs and behaviors associated with the COVID-19 pandemic are influenced by the perceived risk of the pandemic, and as such are related to the general risk preferences of an individual. As such we formulate the following research questions:

- RQ1: Are behaviors regarding COVID-19 a predictor of risk preference?
- RQ2: Are there specific behavioral attributes that consistently influence risk preference over varying data?

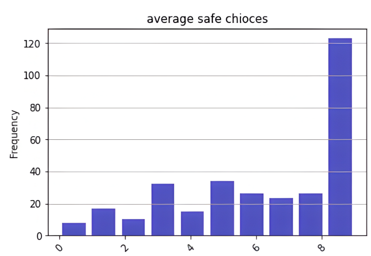
- RQ3: Does RQ1 hold true for the different measurements of risk preference?

4. RESULTS AND DISCUSSION

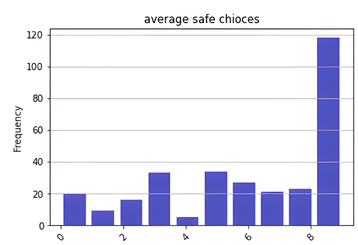
The assumption of this work is that the COVID-19 variables alone are insufficient to effectively predict or estimate any risk preference measure of an individual. As such, accuracy of prediction is not the goal of the modeling task but rather feature selection and importance are paramount to this study.

4.1 Elicited Risk Preference

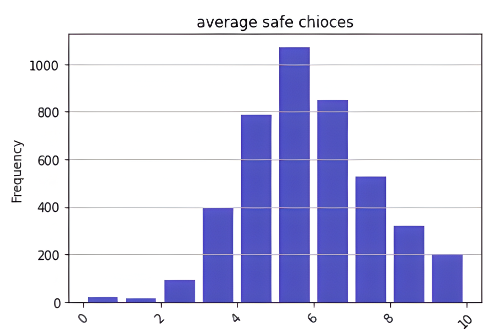
This depicts the average number of safe choices from the survey lottery using multiple price list selected by participants. FIGURE 1a,b shows the distribution of the selected choices of participants in the survey in the pretest 4 and pretest 5 dataset correspondingly, with the majority selecting above eight average number of safe choices.



(a) Pretest 4



(b) Pretest 5



(c) Main Study

Figure 1: Revealed risk preference distribution of survey participants

However, from the main study with substantially more participants the observed distribution tends towards a Gaussian distribution and the most frequent average number of safe choices is about six as illustrated in FIGURE 1c.

Lasso regression on the COVID-19 variables eliminates all explanatory variables from the pretest 4 dataset apart from the six variables in FIGURE 1c. Which are COVID social distancing, two different levels of the expected changes over six months of the participant's relationship with friends, participant perceived reliability of sources, expected changes in colleague relationship and the perceived infection rate of other people. FIGURE 2. shows the plot of the lasso coefficients as a measure of feature importance in the pretest 4 dataset.

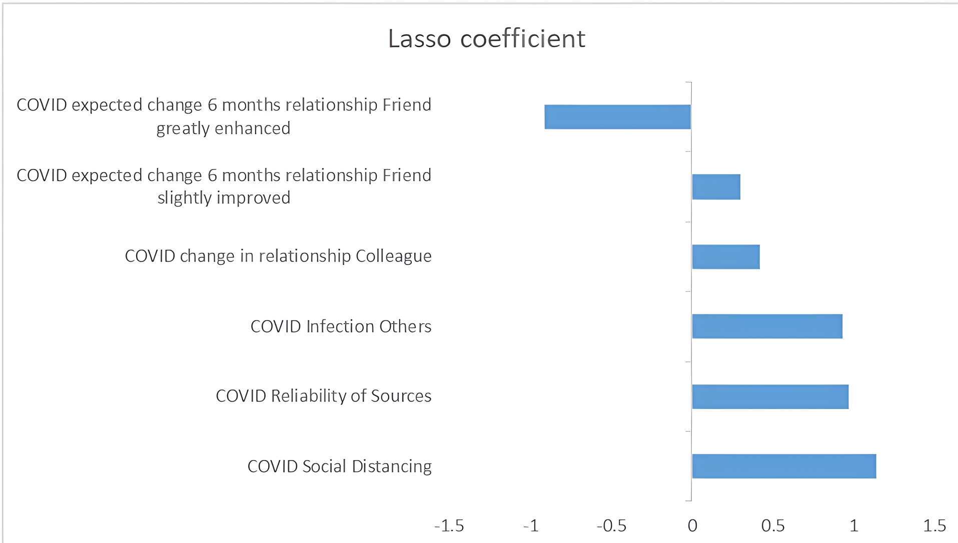


Figure 2: Lasso regression coefficients of COVID-19 variables for pretest 4 dataset.

From the FIGURE 2, COVID social distancing always with a positive coefficient of 1.14 has the highest magnitude of the positively correlated variables, it implies that people that observe social distancing all the time have the strongest positive coefficients with the average number of safe choices selected from the survey and hence are the most risk averse. Other positive influences include individual perception of reliability of information sources and how much others are infected with COVID-19. However, the perception of expected change in relationship with friends has the strongest negative coefficient (-0.91); especially individuals that believe the change in relation has a substantial impact on their financial situation, and hence are the more likely to be risk seeking. TABLE 1 shows the p-values of the regression without considering the influence of other explanatory variables and they are all less than 0.05 and thus statistically significant, except the general perception of change in colleague relation as a result of COVID-19 with p-value of 0.022.

Similarly for pretest 5 dataset, Lasso regression selects mostly the same variables with the inclusion of Handwashing and perceived use of face masks by other people. FIGURE 3. shows the plot of the lasso coefficients as a measure of feature importance in the pretest 5 dataset.

The perceived use of facemask by other people with a positive coefficient of 0.49 has the highest magnitude of the positively correlated variables. Other positive influences include how much participants observe hand washing and social distancing. On the other hand, the perceived notion of slightly affected change in the relationship with colleagues due to the pandemic has the strongest negative coefficient (-0.40).

The coefficient associated to COVID expected change in relationship with colleagues stated as greatly enhanced is negative possibly because the expected change in relationship stated as slightly

Table 1: Lasso regression coefficients and p-values for pretest 4 dataset. The p-values are univariate and cover dependencies between individual features and the risk preference variable while all other features remain constant.

Variable description	Lasso coefficient	P-values
COVID Infection Others	0.93	0.009
COVID change in relationship Colleague	0.42	0.022
COVID expected change 6 months relationship Friend slightly improved	0.30	0.002
COVID expected change 6 months relationship Friend greatly enhanced	-0.91	0.000
COVID Reliability of Sources	0.97	0.013
COVID Social Distancing	1.14	0.000

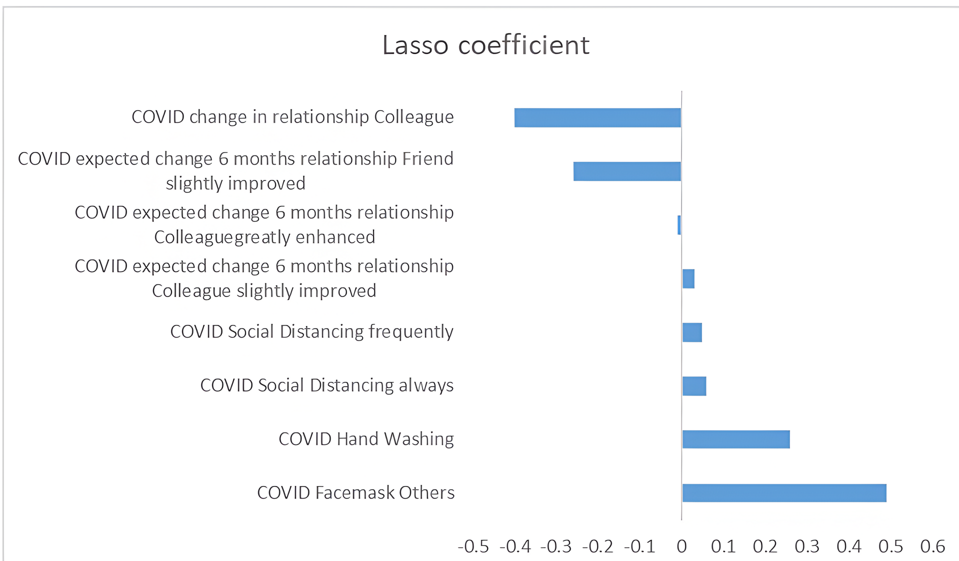


Figure 3: Lasso regression coefficients of COVID-19 variables for pretest 5 dataset.

improved is correlated with the expected change in relationship being greatly enhanced. What we are seeing here is that for those who claim COVID expected change in relationship with colleagues being greatly enhanced on average, given those who claim a change in relationship is slightly improved, the average number of safe choices selected is comparatively less. We observe a direct positive correlation analysis with social distancing. The point to highlight remains that COVID change in relationship and social distancing remains constant as important features for predicting MPL risk preference.

However, from TABLE 2, the observed p-values have four that are greater than 0.05 and thus implies that the data is more noisy and less statistically significant in those cases. This is also reflected in the smaller coefficients of the lasso regression.

In the main study dataset, Lasso regression retained even more explanatory variables including social distancing, infection worries, source of information, how often participants seek health in-

Table 2: Lasso regression coefficients and p-values for pretest 5 dataset. The p-values are univariate and cover dependencies between individual features and the risk preference variable while all other features remain constant.

Variable description	Lasso coefficient	P-values
COVID Social Distancing frequently	0.05	0.007
COVID Social Distancing always	0.06	0.014
COVID change in relationship Colleague	-0.40	0.000
COVID Hand Washing	0.26	0.060
COVID Facemask Others	0.49	0.015
COVID expected change 6 months relationship Friend slightly improved	-0.26	0.001
COVID expected change 6 months relationship Colleague slightly improved	0.03	0.000
COVID expected change 6 months relationship Colleague greatly enhanced	-0.01	0.000

formation, changes to working condition, perceived changes in relationship with family members and expected changes over six months to participants' financial situation and career perspectives. FIGURE 4. Illustrates the plot of the lasso coefficients as a measure of feature importance in the main study dataset.

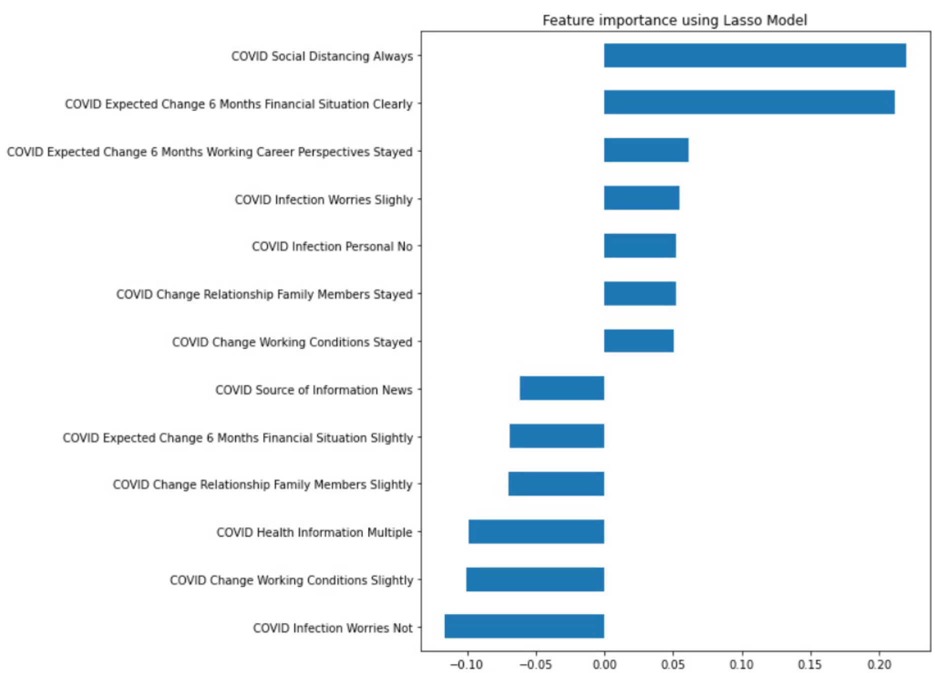


Figure 4: Lasso regression coefficients of COVID-19 variables for main study dataset.

The COVID-19 social distancing variable with a positive coefficient of 0.49 has the highest magnitude of the positively correlated variables. Other positive influences include clear expected changes to participant financial situation and working career perspectives over six months, slight infection worries, no changes in working condition and relationship with family . On the other hand, participants with no worries on getting the infection have the strongest negative coefficient (-0.40).

The main study is the fine-tuned survey question with the most representative sample and from here we also observe that individuals that always keep to social distancing are most risk averse with regards to the average number of safe choices as illustrated in TABLE 3. Other positive influences include the clear expectation of the financial situation changes due to COVID and infection worries. These are intuitively justified as uncertainty in finances and worrying about getting the infection likely encourages more caution. On the other hand, individuals that do not have COVID infection worries, individuals with the belief that COVID have only a slight impact on their working conditions and individuals that get health information from multiple sources have a negative coefficient with regards to the average number of safe choices and are willing to take more risk.

Table 3: Lasso regression coefficients and p-values of the regression on the main study data without considering the influence of other explanatory variables and they are all less than 0.05 and thus statistically significant. Most likely, with more representative data, the p-values have improved as compared to the pretest datasets.

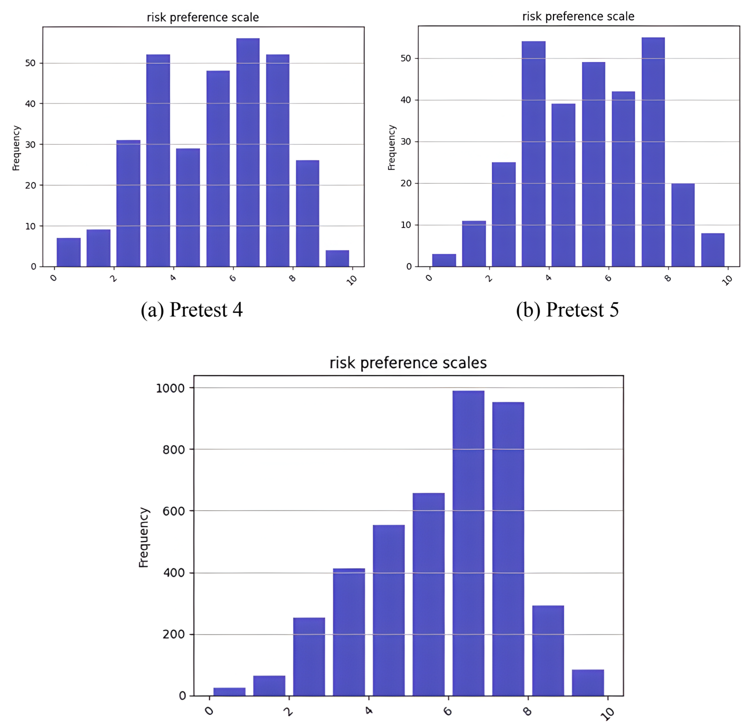
Variable description	**Lasso coefficient**	**P-values**
COVID Social Distancing always	0.22	0.011
COVID expected change 6 months Financial Situation clearly	0.21	0.005
COVID expected change 6 months Working career perspectives	0.06	0.031
COVID infection worries slightly	0.05	0.000
COVID infection worries not	-0.12	0.024
No COVID infection personally	0.05	0.009
COVID change in relationship Family slightly	-0.04	0.000
COVID change in relationship Family stayed same	0.05	0.006
COVID change in Working Condition stayed same	0.03	0.018
COVID change in Working Condition slightly	-0.10	0.000
COVID Health information multiple	-0.06	0.000
COVID Source of information news	-0.01	0.010
COVID expected change 6 months Financial Situation slightly	-0.03	0.002

4.2 Self-reported Risk Preference

This is self reported from the survey and the preference lies on the spectrum of the likert scale of 0 – 10, with 0 indicating very risk averse and 10 indicating very risk seeking. This covers the full spectrum of the risk preference measure that provides a strong case for the application of multi-class classification supervised learning task. FIGURE 5a,b,c shows the distribution of the selected choices of participants in the survey in the pretest 4, pretest 5 and main study dataset respectively. It is observed that they all tend towards a Gaussian distribution.

The feature importance computed as the mean and standard deviation of accumulation of the impurity decrease within each tree of the trained random forest is illustrated in FIGURE 6.

It is observed that Covid Stockpiling of about 3 times has the most positive correlation with the self-reported risk preference with regards to the pretest 4 dataset from FIGURE 6. Other positive



(a) Pretest 4 (b) Pretest 5

(c) Main Study

Figure 5: Self reported risk preference distribution for all the datasets (a) pretest 4 (b) pretest 5 (c) main study participants

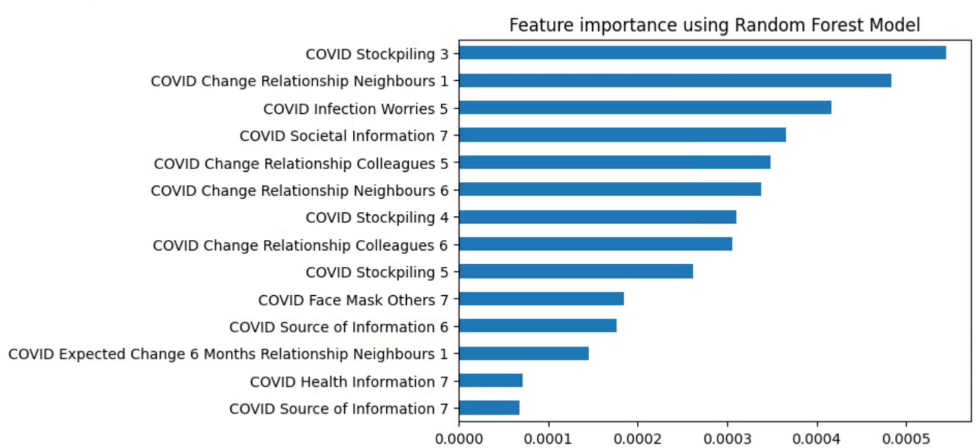


Figure 6: Feature importance plot of the Random forest model for Self reported risk preference on pretest 4 dataset.

influences include the perception of expected change in relationship with neighbors and colleagues, perceived use of facemask by others, how often health information is consulted by participants, source of information and infection worries.

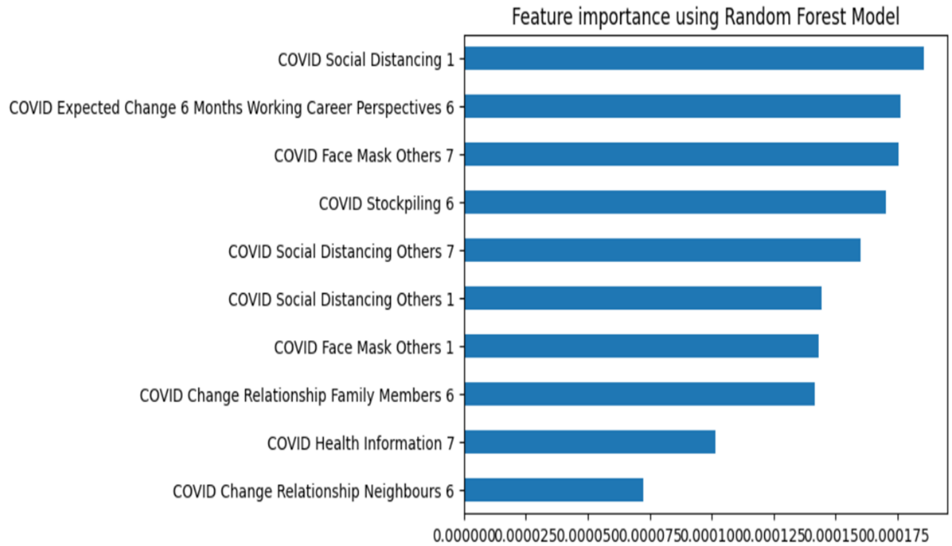


Figure 7: Feature importance plot of the Random forest model for Self reported risk preference on pretest 5 dataset.

In the case of the pretest 5 dataset, rarely social distancing variable have the most positive correlation with the self reported risk preference measure and are thus more risk seeking as illustrated in FIGURE 7. This implies that participants that rarely adhere to social distancing have higher likert scale value for the risk preference measure. Other positive influences include the stockpiling, perception of expected change in working career perspective, relationship with neighbors and family, perceived use of facemask by others, and how often health information is consulted by participants.

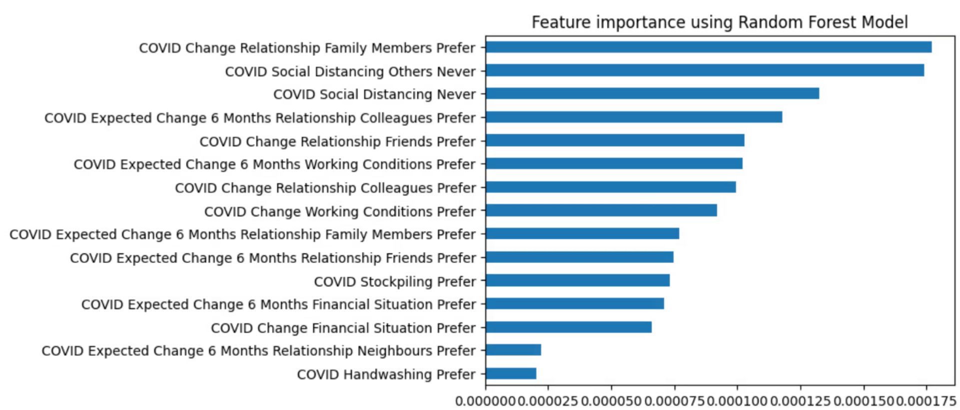


Figure 8: Feature importance plot of the Random forest model for Self reported risk preference on the main study dataset.

Observing FIGURE 8, social distancing, stockpiling and expected changes to relationships due to COVID-19 are still the relevant features. However, Only participants that claim to prefer not to answer about most of their COVID behaviors are prevalent in the list of relevant features. There is not much information to be inferred from this option. Also, the p-values derived from the self reported risk preference model are all less than 0.05 and as such are not statistically significant.

This calls into question the relationships observed between the self reported risk measure and the explanatory variables.

As such, **RQ1** and **RQ3** is validated with the statement that the lasso regression and random forest models for the different risk preference measures on the datsets yielded statistically significant coefficient values with p-values less that 0.05. Upon the consideration that 3 different datasets with the pretest 4 & 5, as well as the main study data provide relatively consistent results of behaviors like hand washing, social distancing and infection worries as important features for estimating risk preference implies that **RQ2** hold for such features. Finally, exogenous shock such as the Covid-19 pandemic do not strongly influence the intrinsic individual risk preference but rather provide valuable features like social distancing behaviors that can be used for estimating individual risk preferences.

5. LIMITATIONS

Sample Size: The pretest datasets have about 300 observations each and thus machine learning models based on them are prone to underfitting. However, the main study data is more representative and mitigates to some extent, the effect of sample size.

Regression vs Classification: There is an argument for regressing over the Likert scale of self report risk preference which ensures more consistency of the overall models of both risk preference measures. This study opted for both regression and classification to optimize for the feature selection importance regardless of the task.

Univariate p-values: The p-values were calculated fitting each individual variable to the target which does not account for correlated features. However, lasso regression makes up for this in a way since it sets its coefficient for redundant variables to zero.

6. CONCLUSION

This study investigated whether behavior attributes such as stockpiling and social distancing regarding COVID-19 are adequate predictors of risk preference over varying dataset and risk preference measures. The idea is that information on this relationship can provide insight on the link between behavioral attitudes during an exogenous shock event such as the COVID-19 pandemic and risk preferences and simultaneously justify the use of such behavioral variables for prediction of risk preferences.

The results presented above suggest that Individual beliefs and behaviors associated with the COVID-19 are Indicative of the general risk preferences of the individual. This is evident from mostly statistically significant p-values obtained from the models of the revealed risk preference measure from the MPL lottery experiment. However, The self reported risk preference measure does not generate statistically significant results. As such, the revealed risk preference measure appears to be more stable than the self reported risk preference measure with regards to feature selection and importance.

Social distancing and changes in relationship as a result of COVID are consistently important features influencing experimental risk preference over all the datasets considered and weakly over even the different measures of risk preference considered in this study. This can be built upon as features to estimate risk preference behavioral measure of individuals in a machine learning model. The broader implication of this work is the potential to generalize estimation of risk preference without the need to conduct expensive surveys, especially if the precision for risk preference measurement is not of uttermost importance and just a general risk preference of a group or population is required for policy making decision. Additionally, setting up behavioral measures policy during pandemic could make use of the estimated general risk preferences of the population as a factor in decision making and implementation which impact the economics of such policies. Potential future research direction is the study of similar relationships with other preferences measure such as time preference, loss aversion and higher order preferences like ambiguity. Also, given that there is some evidence to lack of correlation between different risk preferences measures, do they each consistently tend to have similar relationship to the behaviors exhibited during the pandemic would make an interesting study in the context of different biases of different risk measures.

7. AVAILABILITY OF DATA AND MATERIALS

The administrative input dataset from Statistics Netherlands analysed during the current study are not publicly available due privacy concerns of the official statistics management organization policy for the Netherlands but are available from the corresponding author in collaboration with Statistics Netherlands on reasonable request and agreement.

8. COMPETING INTERESTS

The authors declare that they have no competing interests.

9. FUNDING

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10. AUTHOR’S CONTRIBUTIONS

O.A. carried out all the analysis and wrote the first draft of the paper. A.R. edited and revised the draft and supervised the work. L.I. and M.D. participated in the revision and supervision of the work.

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Appendix

A1. Multiple Price List

MPL1

Table 4: Multiple price list variation 1.

Lottery	OPTION A					OPTION B				
	Probablity	Amount	Probablity	Amount	Expected value	Probablity	Amount	Probablity	Amount	Expected value
#1	0.1	€80	0.9	€64	€66	0.1	€154	0.9	€4	€19
#2	0.2	€80	0.8	€64	€67	0.2	€154	0.8	€4	€34
#3	0.3	€80	0.7	€64	€69	0.3	€154	0.7	€4	€49
#4	0.4	€80	0.6	€64	€70	0.4	€154	0.6	€4	€64
#5	0.5	€80	0.5	€64	€72	0.5	€154	0.5	€4	€79
#6	0.6	€80	0.4	€64	€74	0.6	€154	0.4	€4	€94
#7	0.7	€80	0.3	€64	€75	0.7	€154	0.3	€4	€109
#8	0.8	€80	0.2	€64	€77	0.8	€154	0.2	€4	€124
#9	0.9	€80	0.1	€64	€78	0.9	€154	0.1	€4	€139
#10	1	€80	0	€64	€80	1	€154	0	€4	€154

MPL2

Table 5: Multiple price list variation 2.

Lottery	OPTION A					OPTION B				
	Probablity	Amount	Probablity	Amount	Expected value	Probablity	Amount	Probablity	Amount	Expected value
#1	0.1	€99	0.9	€41	€47	0.1	€134	0.9	€19	€31
#2	0.2	€99	0.8	€41	€53	0.2	€134	0.8	€19	€42
#3	0.3	€99	0.7	€41	€58	0.3	€134	0.7	€19	€54
#4	0.4	€99	0.6	€41	€64	0.4	€134	0.6	€19	€65
#5	0.5	€99	0.5	€41	€70	0.5	€134	0.5	€19	€77
#6	0.6	€99	0.4	€41	€76	0.6	€134	0.4	€19	€88
#7	0.7	€99	0.3	€41	€82	0.7	€134	0.3	€19	€100
#8	0.8	€99	0.2	€41	€87	0.8	€134	0.2	€19	€111
#9	0.9	€99	0.1	€41	€93	0.9	€134	0.1	€19	€123
#10	1	€99	0	€41	€99	1	€134	0	€19	€134

MPL3

Table 6: Multiple price list variation 3.

Lottery	OPTION A					OPTION B				
	Probablity	Amount	Probablity	Amount	Expected value	Probablity	Amount	Probablity	Amount	Expected value
#1	1	€52			€52	0.5	€30	0.5	€130	€80
#2	1	€57			€57	0.5	€30	0.5	€130	€80
#3	1	€63			€63	0.5	€30	0.5	€130	€80
#4	1	€68			€68	0.5	€30	0.5	€130	€80
#5	1	€73			€73	0.5	€30	0.5	€130	€80
#6	1	€78			€78	0.5	€30	0.5	€130	€80
#7	1	€82			€82	0.5	€30	0.5	€130	€80
#8	1	€88			€88	0.5	€30	0.5	€130	€80
#9	1	€94			€94	0.5	€30	0.5	€130	€80
#10	1	€101			€101	0.5	€30	0.5	€130	€80

MPL4

Table 7: Multiple price list variation 4.

Lottery	OPTION A					OPTION B				
	Probablity	Amount	Probablity	Amount	Expected value	Probablity	Amount	Probablity	Amount	Expected value
#1	1	€39			€39	0.33	€20	0.67	€110	€80
#2	1	€46			€46	0.33	€20	0.67	€110	€80
#3	1	€56			€56	0.33	€20	0.67	€110	€80
#4	1	€64			€64	0.33	€20	0,67	€110	€80
#5	1	€70			€70	0.33	€20	0,67	€110	€80
#6	1	€75			€75	0.33	€20	0,67	€110	€80
#7	1	€79			€79	0.33	€20	0,67	€110	€80
#8	1	€84			€84	0.33	€20	0,67	€110	€80
#9	1	€88			€88	0.33	€20	0,67	€110	€80
#10	1	€93			€93	0.33	€20	0,67	€110	€80

MPL5

Table 8: Multiple price list variation 5.

Lottery	OPTION A					OPTION B				
	Probablity	Amount	Probablity	Amount	Expected value	Probablity	Amount	Probablity	Amount	Expected value
#1	0.5	€90	0.5	€70	€80	0.5	€103	0.5	€35	€69
#2	0.5	€90	0.5	€70	€80	0.5	€109	0.5	€35	€72
#3	0.5	€90	0.5	€70	€80	0.5	€115	0.5	€35	€75
#4	0.5	€90	0.5	€70	€80	0.5	€122	0.5	€35	€79
#5	0.5	€90	0.5	€70	€80	0.5	€128	0.5	€35	€82
#6	0.5	€90	0.5	€70	€80	0.5	€131	0.5	€35	€83
#7	0.5	€90	0.5	€70	€80	0.5	€138	0.5	€35	€87
#8	0.5	€90	0.5	€70	€80	0.5	€153	0.5	€35	€94
#9	0.5	€90	0.5	€70	€80	0.5	€170	0.5	€35	€103
#10	0.5	€90	0.5	€70	€80	0.5	€186	0.5	€35	€111

A2. COVID-19 Related questions

- Are you or were you infected by COVID-19?
- How much do you worry about getting infected by COVID-19?
- Is or was one of your family members or close friends infected with COVID-19?
- How many people do you know personally of whom you are sure that they are or were infected with COVID-19?
- ”In your opinion, to what extent did the following matters change as a consequence of COVID-19?”
  - Relationship Family
  - Relationship Friends
  - Relationship Neighbors
  - Relationship Colleagues
  - Financial Situation
  - Labor Circumstances
  - Career Perspectives
- ”In your opinion, to what extent do you expect the following matters to change in the upcoming 6 months as a consequence of COVID-19?”
  - Relationship Family
  - Relationship Friends
  - Relationship Neighbors
  - Relationship Colleagues

  - Financial Situation
  - Labor Circumstances
  - Career Perspectives
- Since the beginning of March, on average how often did you watch the news or social media to inform yourself about COVID-19 and its consequences for public health?
- Since the beginning of March, on average how often did you watch the news or social media to inform yourself about COVID-19 and its societal consequences?
- In general, how reliable do you perceive the information that you have received on COVID-19?
- What was your most important source for information about COVID-19?
  - Television
  - Radio
  - Newspaper
  - Social media
  - News websites
  - Official websites
  - Family and friends
  - Others (name)
- Since the beginning of March, how often did you stockpile in the supermarket?
- Since the beginning of March, how often did you help others that are or were negatively affected by COVID-19?
- Because of COVID-19, it is recommended to keep distance from others (so-called social distancing) when you go outside. According to your own estimate, to what extent do/did you adhere to this regulation?
- Because of COVID-19, it is recommended to take extra care with regards to hygiene, for instance to regularly wash your hands with water and soap. According to your own estimate, to what extent do/did you adhere to this regulation?
- When do you expect that all regulations with regards to COVID-19 will be lifted such that the situation in the Netherlands will be the same as before the crisis?

A3. Survey General risk question

Table 9: Sample of general risk question from survey

Risk	Scale: 0 ”not at all willing to take risks” – 10 ”very willing to take risks”
General	Can you tell me to what extent you are, in general, willing or unwilling are to take risks?
Domain-Specific	People can behave differently in different situations. How do you assess your willingness to take risks in the following matters:
Occupation	… in your career choice?
Health	… in your health? [with option “not applicable”]
Personal Finances	… in your personal financial affairs?
Job finances	… in your work-related financial matters?