Pre-Analysis Plan: Online Survey Experiment Coronavirus Pandemic Shock, Economic Preferences and Belief Updating*

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Abstract

Preferences and beliefs (such as risk preferences), for individuals who experience dramatic natural disasters (such as a major hurricane), are unstable. The diversity and breadth of the COVID-19 pandemic provide a unique, although grime, opportunity to identify the impact of catastrophic experience on economic reasoning and behaviour in both the short and long. For many this pandemic will have a particularly dramatic and gruesome effect because they live in or near one of the many epicentres. Many communities, though, have experienced comparatively minor – and in some cases essentially no – impact from this pandemic. We exploit this variation in exposure to identify the effect of personal experience on economic preferences and beliefs. Online survey experiments will be conducted in China, Italy, Chile, India, the UK and the US. We will use 1) geographical discontinuity and 2) "pre-treatment" measures of economic preferences to establish the causal influence of COVID-19 exposure on economic preferences and beliefs. We measure two groups of outcome variables: 1) economic preferences, namely risk aversion, time discounting and pro-social behaviour; 2) belief updating, in both health and economic domains. We conjecture that individuals most intensely exposed to the CORVID-19 virus will exhibit significantly different economic preferences and belief updating than those with much lower exposure. Results from the online experiments, micro-census data, and multiple regression post-stratification (MRP) methods provide detailed sub-national views of changes in economic and social behaviour for the six countries.

*Data from this project will be made available at `https://github.com/rayduch/COVID19`

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1 Overview

The diversity and breadth of the COVID-19 pandemic provide a unique, although grime, opportunity to identify the impact of catastrophic experience on economic reasoning and behaviour. First, our research identifies the causal mechanisms that link personal exposure, to intensely infected coronavirus zones, on economic preferences and beliefs. Second, the project provides policy makers with a global geographic and socio-demographic profile of pandemic "populations" and hence a foundation for evidenced-based post-pandemic economic and social policy.

Preferences and beliefs are fundamental determinants of individual decisions regarding economic behaviour. A growing body of research suggests that personal experience has a significant impact on decisions. These dramatic events will cause important long-lived changes in economic and social behaviour. We study two major groups of behavioural outcomes: One group is preferences widely studied by behavioural economist; namely, risk aversion, time discounting and pro-social behaviour. A second focus is on belief updating, in both health and economic domains. These represent important determinants of how individuals make economic decisions such as savings, purchasing insurance, investing in public goods, and personal investment portfolios.

Conventional economic theories suggest that preferences are stable and that beliefs should update only on informative signals. Nevertheless, the empirical literature demonstrates that risk preferences, for example, can change and that beliefs can be biased due to experience. Our project demonstrates the effects of catastrophic experience on preferences and beliefs. We conjecture that individuals most intensely exposed to the CORVID-19 virus, and the resulting human suffering and deaths, exhibit significantly different economic attitudes and belief updating than those with much lower exposure. Economic attitudes could shift due to the intensity of local infections and one's personal experience during the pandemic. Belief updating could be biased by personal exposure also, even though these events do not add informational value given publicly available information.

The Nuffield Centre for Experimental Social Sciences will conduct online survey experiments with approximately 1500 subjects in China, Chile, India, Italy, the U.K. and the U.S. Our online field experiments measure these economic preferences and belief updating for subjects residing in the epicentre, in proximity to the epicentre, and with virtually no exposure to the virus. First, we measure shifts in the three behavioural economic preferences by comparing our survey results to identical questions from the 2018 Global Preferences Survey. Second, we exploit proximity to epicentre, geographic discontinuities and infection/death rates to identify the varying impact of shock magnitudes on economic preferences and belief updating. Third, we include experiments in the online survey designed to identify the causes of variations in belief updating. Subjects will be re-contacted in one year in order to assess whether these treatment effects persist or are transitory. Fourth, combining our survey results with micro-census data, we employ machine learning methods and small-area estimation techniques to generate a database containing detailed profiles at the subnational level, with fine-grained demographic breakdowns, of how personal exposure to COVID-19 has reshaped global economic preferences and belief.

We have two broad conjectures: The personal exposure conjecture suggests that we will see pre- (as measured by the 2012 GPS) and post- (as measured by our 2020 Online survey) pandemic differences in economic preferences and beliefs, and their magnitude will be correlated with proximity or personal exposure to COVID-19 infections and deaths, at the individual level. At the country level, our expectation is that these pre- and post-pandemic differences will either be weak or non-existent. Alternatively, the social exposure conjecture suggests that pre- and post-pandemic shift in economic preferences and beliefs may not be correlated with personal exposure – rather they may be experienced by the national populations as a whole.

China, Chile, Italy, India, the UK and the US are the sampled countries. These countries, at the time of the online survey, April, 2020, are at distinct stages of the pandemic. While these are quite distinct countries, they all include large segments of their populations extremely proximate to the health crisis. Additionally, within all countries there is considerable geographic variation in infection rates. Therefore, in each country we include between 10 and 16 sub-national geographic administrative districts in the sample. We aimed to balance the sample on three variables: infection rates in the district (they could be relatively high, medium or low); distance from the epicentre (each country has a well-identified epicentre district); whether or not the district shares a border with the epicentre district.

To assess the overall significance of this pandemic effect we implement small-area estimation. The online sample provides a rigorous estimate of geographic and demographic heterogeneity in outcomes. Post-stratification provides an indication of outcome magnitudes for the entire population of a specific country (or for any particular region of a country or specific demographic segment). The online surveys will allow us to estimate individual-level models of the outcome variable (economic preferences and beliefs) based on 1) socio-demographic covariates and 2) geographic proximity to highly infected zones. For each country we have highly detailed stratification frames (based on micro-census data) that allow Multiple Regression Post-stratification techniques that characterize the treatment effects for the entire population including sub-national regions.

Our resulting publications will provide a unique understanding of how personal exposure to the pandemic is reshaping social and economic behaviour. Scholars with have open access to the resulting databases with detailed profiles at the subnational level, and with fine-grained demographic breakdowns, of how personal exposure to COVID-19 has reshaped global economic preferences and belief. This information is critical for coherent policies facilitating the transition from a pandemic lockdown. There will be segments of the population that become extremely risk averse, more worried about long-term, rather than immediate, outcomes and very distrustful of others. These individuals are unlikely to re-join the workforce, resume "classic" consumption and provide any social capital to the community. Policies both in the private and public sector designed to reconstruct our social and economic life will need to reflect this heterogeneity. Our project provides policy makers with a global geographic and socio-demographic profile of these pandemic "populations" and hence a foundation for evidenced-based post-pandemic economic and social policy.

This pre-analysis plan is organized as follows: we begin with a brief discussion of theory; an indication of our core conjectures evaluated with our individual-level model; our modelling strategy for generalizing these results to the country-level; how we designed the study and organized data collection; the micro-census data and small-area estimation; measurement of the outcome variables included in the online survey; estimation of the impact of exposure to coronavirus on preferences and beliefs; and finally details on the administration of the online survey. Note that the initial study is being conducted in China, Chile and Italy followed by India, the U.S. and the U.K.

2 Motivation

Preferences and beliefs are fundamental determinants of individual decision making regarding economic behaviour, such as saving, investment, consumption, technology adoption, and migration. A growing body of research suggests that personal experience has a significant impact on decisions (Malmendier and Nagel, 2011). The aim of this project is to demonstrate the effects of pandemic shocks on individuals' preferences and beliefs, and whether their impact depends on the amount of exposure to the event.

Standard economic models assume that individual preferences are stable across time. More recently, a growing number of studies have suggested that risk preferences and thus, risk-taking behaviour, can be altered by various negative shocks such as financial crises, trauma from conflict or violence, and natural disasters (e.g., earthquakes, hurricanes, floods, and tsunamis). However, there is little consensus about the direction in which such negative shocks affect risk preferences. Past studies find conflicting patterns even within the same domain. For example, regarding the impact of natural disasters, some find increased risk aversion (e.g. Cassar, Healy and von Kessler, 2017; Cameron, Gelbach and Miller, 2008), while others find decreased risk aversion (e.g. Eckel, El-Gamal and Wilson, 2009; Page, Savage and Torgler, 2014). Furthermore, even if such effects exist, little is known about whether they are transitory or persistent.

Secondly, regarding beliefs, standard economic models assume that personal payoffs should not influence beliefs when they do not carry informational value. For example, the amount of personal losses from an earthquake should not change the objective probability of subsequent earthquake, but it seems that people do update beliefs based on uninformative payoff experiences (e.g. Gallagher, 2014). Jiao (Forthcoming) proposes a theory and experimental tests of payoff-based belief distortion, in which personally experienced gains and losses influence belief updating, in the sense that gains lead an agent to underweight/misperceive negative signals about future outcomes, whereas losses do the opposite. Under the shock of a pandemic event, individuals with different amount of exposure to the event could update belief in the health domain differently. It is also important to understand, whether exposure to negative events generates pessimism that is general or domain-specific.

The central concern of our project is the impact of pandemic events on economic reasoning, given that 1) with increasing frequency individuals nowadays are confronted by serious catastrophic shocks, environmental, medical, terrorist, etc., and 2) with increasing frequency these events are having significant effects on economic activity. Our research question: do these events have a causal impact on the beliefs and preferences of economic agents? What is the causal effect? A better understanding of these issues will have implications for economic behaviour, such as investment, insurance, health care, etc., as well as for economic policies designed to address these shocks to the economy.

As an aside, we are careful not to treat the variations in infections and deaths across districts necessarily as an exogenous shock. It might be the case, but even here one could be sceptical, that the initial occurrence of an outbreak (or patient zero) is exogenous. But clearly what happens after this initial outbreak is shaped by a variety of social, economic, and political factors. And in fact we exploit this to some extent – there will be neighbouring districts exposed to the identical initial shock but that respond quite differently and experience very different infection and/or death rates – Lombardy and Veneto in Northern Italy are a case in point.

3 Core Conjectures

The experimental design aims to test a number of core propositions about how economic attitudes and beliefs respond to a global health disaster:

- Economic preferences are correlated with the severity of personal experience with COVID-19
  - Risk aversion is positively correlated with an individual's exposure to coronavirus infection rates
  - Risk aversion is positively correlated with an individual's proximity to the coronavirus epicentre
  - Time discounting is positively correlated with an individual's exposure to coronavirus infection rates
  - Time discounting is positively correlated with an individual's proximity to the coronavirus epicentre
  - Other-regarding preferences are positively correlated with an individual's exposure to coronavirus infection rates
  - Other-regarding preferences are positively correlated with an individual's proximity to the coronavirus epicentre
- Belief updating is correlated with the severity of personal experience with COVID-19

4 Modelling Global Pandemic Populations

The online surveys are designed to identify in particular how personal exposure to COVID-19 affects economic preferences and beliefs. Our contention is that these changes in preferences and beliefs will have dramatic implications for social and economic life throughout the world. The claim is based on our assumption that there are large segments of the global population that have had intense personal exposure to highly infected areas. Alternatively, either the "treatment" effect, i.e., changes in economic preferences and beliefs, is quite small or the global footprint of what we are calling pandemic "populations" is relatively small. Some combination of these two empirics would support the null.

Hence, an important element of the project is simply understanding the global breadth of this highly exposed pandemic population. The online experiments provide a measure of how (whether!) treatment effects are a function of proximity to highly infected coronavirus zones. The small-area estimation component of the project provides an indication of the treatment effects for the entire population of a specific country (or for any particular region of a country). In each country we will estimate an individual-level model of the outcome variable (economic preferences and beliefs) based on 1) socio-demographic covariates and 2) geographic proximity to highly infected zones. In addition, for each country we have a highly detailed stratification frame that will allow us to use versions of Multiple Regression Post-stratification techniques to characterize the treatment effects for the entire population including sub-national regions. While it is true that these post-stratifications will be based on online convenience samples that are not representative of their national populations, our experience is that they can provide quite robust sub-national estimations Cerina and Duch (2020).

5 Design Strategy

For our design we exploit the fact that this is a naturally occurring disaster that is global but personal exposure varies quite dramatically both within and across countries. And it is this variation in the extent to which populations had personal experience with the virus that will help us assess the impact of negative personal shocks on economic preferences and belief updating.

Country sample. First, the study initially includes countries from three continents: Asia, Europe, and South America: Italy, China, Chile and India. These are countries that at the time of the online survey, April, 2020, were at distinct stages of the coronavirus pandemic. While these are quite distinct countries in terms of economic development and cultural traditions, they all include large segments of their populations who were extremely proximate to the health crisis.

Sample of districts. Within all four countries there is considerable geographic variation in infection rates. In each country we included between 10 and 16 sub-national geographic administrative districts in the sample. These are summarized in Table 1. We aimed to balance the sample on three variables: infection rates in the district (they could be relatively high, medium or low); distance from the epicentre (each country has a well-identified epicentre district); whether or not the district shares a border with the epicentre district). And in some countries, there is an additional dimension. For instance, in China, we also use the color code for the number of infections as a variable.

Sample size. We used the software program G*Power to conduct a power analysis. Our goal was to obtain .95 power at the standard .05 alpha error probability. With a target sample size of 150 participants within each district, we can detect an effect size of 0.42. This means, in terms of the Global Preference Survey time and risk preference measures we use, moving up or down by two deciles on these measures within a country.[1] We also attempt to over-recruit to guarantee 150 valid responses in each district. Our expectation is that we would have a minimum of 1,500 subjects in each of the sampled countries.

[1]These are calculated based on the individual-level data from Falk et al. (2018).

Table 1: Targeted Districts

		Infections	Border	Proximity	Other
Italy					
Pair A	Piacenza	Medium	Yes	Outside, near	
	Lodi	Medium	N/A	Inside	
Pair B	Piacenza	Medium	Yes	Outside, near	
	Parma	Medium	Yes	Outside, near	
Pair C	Bergamo	High	N/A	Inside, Central	
	Brescia	High	N/A	Inside	
Pair D	Cremona	Medium	N/A	Inside	
	Mantova	Low	N/A	Inside	
Pair E	Vicenza	Low	Yes	Outside, near	
	Treviso	Low	No	Outside, near	
Pair F	Treviso	Low	No	Outside, near	
	Venezia	Low	No	Outside, far	
Pair G	Milano	High	N/A	Epicentre	
	Monza e della Brianza	Medium	N/A	Adjacent to Epicentre	
China					Color Code
Pair A	Wuhan, Hubei	Very High	N/A	Epicentre	Same
	Huanggang, Hubei	Medium	N/A	Adjacent to Epicentre	Same
Pair B	Xiangyang, Hubei	High	N/A	Epicentre	Different
	Yichang, Hubei	Low	N/A	Near, same province	Different
Pair C	Huangshi, Hubei	High	N/A	A bit far	Same
	Huanggang, Hubei	High	N/A	Adjacent to Epicentre	Same
Pair D	Nanyang, Henan	Low	Yes	Outside, near	Same
	Zhumadian, Henan	Low	No	Outside, far	Same
Pair E	Nanyang, Henan	Low	No	Outside, far	Same
	Xinyang, Henan	Low	No	Outside, farther	Same
Pair F	Shenzhen, Guangdong	Medium	No	Outside, far	Same
	Dongguan, Guangdong	Low	No	Outside, far	Same
Chile					
Pair A	Las Condes	High	N/A	centre	
	Providencia	Medium	N/A	centre	
Pair B	Providencia	High inf rate	N/A	centre	
	Nunoa	Low inf rate	N/A	centre	
Pair C	La Florida	Medium	N/A	Inside centre	
	Puente Alto	High	N/A	Outside centre	
Pair D	Temuco	High	no	Similar	
	Valdivia	Low	no	Similar	
Pair E	Los andes	low	yes	near	
	San Felipe	low	no	near	
Pair F	osorno	similar	no	far	
	chillan	similar	no	near	
Pair G	Chillan	high	no	far	
	Los Angeles	low	no	far	

Regression Discontinuity. We will adopt regression discontinuity (RD) in the design. The RD design was first introduced by Thistlethwaite and Campbell (1960) in their study of the impact of merit awards on the future academic outcomes (career aspirations, enrolment in post-graduate programs, etc.) of students. Similar to our study, Black (1999) exploited the presence of discontinuities at the geographical level (school district boundaries) to estimate the willingness to pay for good schools.

In our investigation of the effect of epicentre or proximity to epicentre on economic preferences and beliefs, we use the preferences and beliefs measured from surveys as the outcome variable, Y. The hit of Coronavirus can be considered "random" ex ante on both sides of the boundary, because the two geographically adjacent areas are similar enough prior to the crisis. So, it would be simply luck determining which area between each pair is hit more. Our main estimating equation relates the preference or belief measures Y_i of individual i to a vector of individual characteristics X_i and a set of boundary fixed effects Z_{bi}, which is equal to one if individual i is within a specific distance of the boundary b, and zero otherwise.

$$Y_{ij} = \alpha + X_i'\beta + Z_{bi}'\delta + \gamma \text{infection}_j + \epsilon_i \tag{1}$$

The individual characteristics are measured from the demographic questions in our survey, including age, gender, employment status, educational background, occupation, and income. The boundary fixed effects are measured from the information of the respondent's postal codes. Based on each respondent's postal code, we can estimate the shortest distance from the respondent's area to the geographical border between two districts. Infection is the number of infection cases within district j.

We can test the boundary discontinuity by explicitly checking the balance of covariates on either side of the boundary, test the sensitivity of results to controlling for these covariates, and the sensitivity to different definitions of being 'close' to the boundary. The covariates we will consider include population, GDP, social capital, well-being, etc.

Pre-treatment Measures. For all of the countries in the sample we have pre-treatment measures from national probability samples that were part of the 2012 Global Preferences Survey. For the three categories of economic preferences (risk preferences, time discounting and social preferences) we include the same battery of identical questions that were include in the 2012 GPS.

The GPS data will provide estimates at the national level of pre-treatment means for all of the economic preference measures that are described below. We will also use MRP methods to generate sub-national, or small-area, estimates for these variables – most importantly, we will generate estimates of these GPS economic preference values for all of the districts that are included in our online sample in each country.

The 2012 GPS demographic variables included in the MRP analysis will be: age (the actual age is recorded in GPS), gender (dichotomous), income (the GPS records Annual Household Income in International Dollars), employment status (see the categories in Table 3), and education level (see the categories in Table 2). Note that the Online experiments in China, Italy and Chile will have the same demographic variables and they will be coded or re-coded into these GPS categories. We currently do not have a region variable from the GPS study although we could request this variable.

GPS Categories	China	Italy	Chile
Completed elementary education or less	Never Schooled (including informal education such as literacy courses)	No formal education and can neither read nor write	PreKinder
	Elementary school	No formal education but can both read and write	Kindergarten
		Elementary school qualification (or equivalent)	Basic education
			Primary or Preparatory (Old System)
			Never attended
Secondary - 3 year Tertiary Secondary ed	Junior middle school	Middle school (or vocational school) qualification	Scientist-Humanist
	Senior middle school	Completion of lower/middle level of the Music Conservatory or National Academy of Dance (2-3 years)	Professional Technique
	Vocational senior secondary school/technical school	Vocational school diploma	Humanities (Old System)
	Specialized secondary school	Teacher training school diploma	
	Polytechnic college	Art school diploma	
		Technical institute diploma	
		Teacher training institute diploma	
		High school diploma (classical, scientific, etc.)	
		Diploma from the Academy of Fine Arts, Dramatic Arts, ISIA, etc., Conservatory (former system)	
Completed four years of education beyond	Undergraduate (Bachelor's degree)	University degree (2-3 years) under the former system (including schools dedicated to specialised programmes and vocationally-oriented community colleges)	Senior Technician (careers 1-3 years)
	Graduate (Master's degree or above)	Academic diploma of Higher Artistic, Music and Dance Training (A.F.A.M.), level I	Professional (careers 1-4 years)
		Three-year degree (level I) under the new system	Master's
		Academic degree of Higher Artistic, Music or Dance Training (A.F.A.M.), level II	Doctorate
		Degree (4-6 years) under the former system, single-cycle specialised level II degrees or specialistica/magistrale under the new system, two-year specialised degree (level II) under the new system	

Table 2: Educational Background

GPS	China	Italy	Chile
Employed full time for an employer	Employed (including reemployed retiree)	COND PROF = 1 and POS PROF != 1,3 and TEMPO PIENO = 1	I had a paid job (including internships or paid internships)
Employed full time for self		COND PROF = 1 and POS PROF = 1,3 and TEMPO PIENO = 1	I was an independent worker (self-employment) I worked in my own business
Employed part time do not want full time		COND PROF = 1 and TEMPO PIENO = 2	
Unemployed	Unemployed/Waiting for job assignment	COND PROF = 2 - 3	I didn't work, but I was willing to do it I didn't work, nor I was willing to work
Employed part time want full time		COND PROF = 1 and TEMPO PIENO = 2	
Out of workforce	Retired from government agencies or institutions Retired from enterprises or other work units Student enrolled at school Full-time homemaker Long-term sick leave	COND PROF = 4 - 7	I was a student (full or part time) I took care of my home (homeowner) I didn't work because I couldn't (for example, disabled) I was retired
No correspondence	Other neither work nor at school Pregnant/maternity leave		I had paid work but was absent due to leave, strike, illness, vacation or other reason I worked as an apprentice or doing an unpaid internship I worked without pay (pay in kind / volunteer work / help to family members) I had not job but did "pololos"

Table 3: Employment Status

Pre-treatment Census Micro Data. The data collection also includes recent, census micro-data, or large-N survey data, for the sampled countries. These large micro-data sets will serve as the stratification frames for the small area estimation of outcomes and treatment effects. The small area estimation will require that we match the socio-demographic categories in the CESS Online survey with those in the GPS and also, most importantly, with socio-demographic cells in the micro-data stratification frames. The CESS Online surveys employ the mirco-data census categories for demographics. Tables 2 and 3 summarizes the concordance between the micro-data/CESS Online and the GPS definitions.

6 Micro-data and Small Area Estimation

An important research goal here is simply to estimate the magnitude of changes in economic preferences and beliefs. By observing these preferences and beliefs prior to the pandemic and also varying the sample by proximity to coronavirus infections we can generate quite precise "treatment" effects. Our design explicitly anticipates considerable heterogeneity in treatment effects – preferences and updating of beliefs in response to exposure to the pandemic will be conditioned on priors, geography and socio-demographics, for example.

Given this heterogeneity estimating an average treatment effect for a convenience sample, regardless of how large, is only the first step in assessing the overall effect of such an information policy. An ultimate goal of this study is to estimate the effects of the coronavirus pandemic for the entire populations for each of the countries in which we conduct the studies.

We propose mapping the estimated treatment effects to the overall populations using classic Multi-level Regression with Post-stratification (MRP). We will explicitly design out prediction and post-stratification strategies with the aim of improving the consistency and precision of estimated outcomes for subsets of populations. There are in fact quite diverse applications for MRP techniques ranging from political preferences and outcomes to epidemiology forecasts (Cerina and Duch, 2020; Downes et al., 2018; Park, Gelman and Bafumi, 2004; Leemann and Wasserfallen, 2017).

The method has four fundamental components: 1) a post stratification dataset that defines the individual-level categories that predict the outcome of interest; 2) an individual-level model that includes these categorical variables and, possibly, aggregate-level variables that predict the outcome of interest; 3) a sampling frame that indicates how the individual-level observations will be collected; and 4) a post-stratification algorithm. The goal is to map the estimated treatment to each of the cells in the population frame (highly educated women in the province of Hubei, for example). The average treatment for a province, Hubei for example, is simply the cell population weighted average across all cells in the municipality. In order to estimate an overall information treatment for the entire country we incorporate post-stratification estimation into the design.

6.1 Post-stratification

Post-Stratification I We have a post stratification dataset that includes the individual-level categories that predict our outcomes and treatment effects (change in risk aversion, for example). This post-stratification frame includes the following:

- aggregate measures at the district or province level: most importantly coronavirus infection and death rates; quarantine measures; but also measures of socio-economic development.
- The joint distribution, within each province or district, of the following individual-level variables: age, education, gender, employment status and income. We have the following data sources:
  - China (National Bureau of Statistics of China, 2018)
  - Italy (Inztituto Nationale di Statistica, 2016, 2014)
  - Chile (Instituto National de Estadisticas Chile, 2018)

Post-Stratification II. We will conduct surveys with approximately 1,500 subjects in each country. These subjects will be distributed in the districts and provinces described in Table 1. The survey will include variables measuring the identical individual-level variables included in the post-stratification frames for each country. A critical requirement is that survey response categories match those in the post-stratification frame. This correspondence was described earlier and summarized for education and employment in Tables 2 and 3.

Post-Stratification III. The data generated in the surveys will allow us to estimate individual-level models of preferences and beliefs. These models will include the individual-level co-variates (identical to those in the stratification frame) along with aggregate-level measures including the malfeasance profile of the municipality. These are the basis for estimating what are equivalent to multi-level regression models. Missing values in the co-variates are imputed with a random-forest multiple-imputation strategy implemented via the packages `ranger` (Wright and Ziegler, 2015) and `missForest` (Stekhoven and Bühlmann, 2011). These provide a flexible non-parametric framework for imputing mixed-type data. Imputation error is estimated via calculating the Out of Bag (OOB) error for each imputed covariate, at each iteration.

Post-Stratification IV. A fourth step estimates the distribution of changes in preferences and beliefs for the individual cells within each of the province or district stratification frames. Context matters. So,for example, we expect the distribution of beliefs to be quite different in districts that were highly exposed to the coronavirus infections versus those that were less affected. Estimation using random forest techniques will follow (Cerina and Duch, 2020). We will train a probability machine to estimate the corruption priors of subjects, contacted in the baseline survey, conditional on their socio-demographic characteristics and aggregate-municipal level variables (including the coronavirus infection and death rate measures). We expect to be sufficiently powered to generate these estimates for all provincial and district units in our sample of countries.

Our next step in generating the area forecast is to assign an estimate of the economic preferences and beliefs for each of the cells in the country population frames. The trained forest is used to provide category-level predictions.

Post-Stratification V. The cells of the stratification are populated with counts obtained from the census micro-data we have collected for each country. A fifth step simply weights these estimated preferences and beliefs in each cell with the cell population and sums over all cells. This will give us a province or district and national profile of economic preferences and beliefs.

7 Outcome Measures in Online Survey.

There are two broadly defined outcomes of interest in this study: classic economic preferences that shape economic behaviour and beliefs.

Economic Preferences. There are three economic preferences that we argue are shaped by shocks such as this pandemic:

Risk Preferences. We include a battery of risk preference questions that are modelled on those frequently employed by economists. The two risk preference questions included are identical to those implemented in the Global Preference Survey (GPS). These are presented in the Risk Preference section of Table 4.

- The risk staircase measure is adopted from Falk et al. (2018).
- The self-assessed risk attitude measure from Falk et al. (2018).
- A domain-specific risk-attitude survey scale is adapted from Weber, Blais and Betz (2002).

Time Discounting. Similarly, we include questions measuring patience – these are presented in the Time Preference section of Table 4.

- The time discounting staircase is adapted from Falk et al. (2018).
- The self-assessed time preference measure from Falk et al. (2018).

Other Regarding Preferences. A battery of questions measuring social preferences are also included. We included the GPS questions concerning negative reciprocity, positive reciprocity, trust and altruism. These are presented in the Social Preferences section of Table 4.

- Trust from Falk et al. (2018).
- Reciprocity (positive and negative) from Falk et al. (2018).
- Altruism from Falk et al. (2018).

Table 4: Global Preferences Survey Economic Preference Questions

Risk Preference	
Q240	Self assessment of risk attitude
Q131-162	Staircase risk attitude elicitation
Time Preference	
Q254.1	Self assessment of time preference
Q255.5	Postpone tasks
Q178-Q338	Staircase time preference elicitation
Negative Reciprocity	
Q254.2	Punish someone who treats you unfairly
Q254.3	Punish someone who treats others unfairly
Q255.2	Revenge
Positive Reciprocity	
Q255.1	Willingness to return a favor
Q257	Scenario: give a present
Trust	
Q255.3	People have only the best intentions
Altruism	
Q254.4	Willingness to give to good causes without expecting anything in return
Q258	Scenario: win lottery
Control	
Q255.4	I'm good at math.

7.1 Beliefs

One focus of this project is on belief updating. Coronavirus is a pandemic shock – all subjects will have consumed information about the shock and its effects in a variety of domains. Theory suggests how these beliefs should update in response to this information. And, critically, we expect this updating to vary by proximity to the pandemic shocks, even though country- or world-level information is broadly available. We include a range of related beliefs in our data collection – a small number of them are incentivized:

Coronavirus Perceptions. Perceptions of the magnitude of the coronavirus shock. We measure subjects' perceptions about the magnitude of the pandemic both in their immediate local area and more broadly. Of particular concern is the extent to which the personalized and local shocks affect their belief about the likelihood of a future pandemic event like the COVID-19 in their local area and more broadly. In our analyses, it is important to measure the personal exposure to the pandemic, in addition to the measuring community exposure by using the number of infections in the person's local area. Perceptions of the Coronavirus questions were adapted from the Lau et al. (2005) study regarding SARS. These questions about Coronavirus perceptions can be divided into personal and non-personal.

- Perception of current coronavirus situation. See Perceptions of Corona section in Table 5.
  - Personal
  - Non-personal: own area, country, other countries

Health Beliefs. Given the nature of this shock, we are particularly interested in measuring a range of beliefs in the health domain. We expect that due to the pandemic event, individuals updated beliefs in the health domain according to the amount of exposure to the pandemic. Specifically, they are more pessimistic about health-related issues if they are exposed to a larger extent. We measure beliefs in the health domain with varying relatedness to Coronavirus. The idea is that, the Coronavirus shock should most immediately change beliefs about this particular disease, and less about beliefs in more remotely related health domains.

Within each belief category, we ask respondents' beliefs at both the personal and non-personal domains. This will enable us to test self-serving beliefs. The idea behind this is that people who have self-serving beliefs typically think that good things are more likely to happen to themselves but bad things are more likely to happen to others. However, depending on the magnitude of the negative shock experienced by the individual, the self-serving belief may reverse due to pessimism.

Our health belief questions can be divided into:

- Coronavirus-related: Prediction of future Coronavirus-like events. See Corona Beliefs section in Table 5.
  - Personal
  - Non-personal: own area, country, other countries
- Coronavirus-unrelated:
  - Life expectancy. See Health beliefs section in Table 5.
    * Personal
    * Non-personal: own area, country, other countries
  - Unrelated disease. See Corona-Unrelated Belief section in Table 5.
    * Bird flu

Our health belief questions that ask about percent chances are based on Health and Retirement Study, used in e.g. Hurd (2009). For instance:

- Next we would like to ask your opinion about how likely you think various events might be. When I ask a question I'd like for you to give me a number from 0 to 100, where "0" means that you think there is absolutely no chance, and "100" means that you think the event is absolutely sure to happen.

  For example, no one can ever be sure about tomorrow's weather, but if you think that rain is very unlikely tomorrow, you might say that there is a 10 percent chance of rain. If you think there is a very good chance that it will rain tomorrow, you might say that there is an 80 percent chance of rain.

  What is the percent chance that you will live to be 75 or more?

The phrasing of our health beliefs questions about Coronavirus are adapted from on Lau et al. (2005).

Economic related beliefs. Economic beliefs concern the probability of various economic outcomes in the respondent's own household, local area and country. Due to the magnitude of the Coronavirus shock, the quarantine and lock-down strength across countries, its impact on the economy has also been felt. Therefore, it is reasonable to believe that agents also update their beliefs about the economy depending on their exposure to the pandemic. Individuals who are most exposed to the shock should update economic beliefs more pessimistically. We also ask the economic beliefs at both the personal and non-personal levels.

Beliefs about economic outcomes. We ask these questions to assess how the pandemic event shifts beliefs about economic outcomes.

Our economic-related questions can be divided into:

- Perception of current situation
  - Personal: Income. See Household Finance section in Table 5.
  - Non-personal: country's stock market, GDP, prices, business condition. See Economic Perception section in Table 5.
- Prediction of future situation
  - Personal: Income, unemployment. See Household Finance section in Table 5.
  - Non-personal: own area and country's inflation, income, unemployment, business condition. See Economic Beliefs section in Table 5.

The economic belief questions were adapted from the Health and Retirement Survey of Hurd (2009) and the Survey of Consumers Business-Conditions in Curtin (1982).

Coronavirus-unrelated beliefs. Apart from Coronavirus-unrelated beliefs in the health domain mentioned before (life expectancy and bird flue), we also measure Coronavirus-unrelated beliefs of rare events in two other domains, adapted to different country's situations. But in general, these domains are natural disaster and sports event. The idea behind this is to test the spill-over effect of potential Coronavirus-induced pessimism in other domains. These questions are in the Corona Unrelated section of Table 5.

- The Natural Disaster domain asks belief about a future natural disaster in the respondent's country, e.g. earthquake or flood. This is less related to the current crisis, but still is about a disaster.

- The Sports Event domain asks belief about the outcome of a future sports event of the respondent's national team. This is least related to the current crisis out of the three Corona unrelated beliefs.

Physical and mental health. We ask questions about the subject's physical and mental health and current emotional state in order to measure the impact of the Coronavirus pandemic on each individual's physical and mental health. These are important control variables when assessing the impact of Coronavirus on economic beliefs and preferences. Our conjecture is that even for people who live in the same area, there is considerable variation in terms of the impact felt. This will lead to heterogeneity of the treatment effect, both in terms of the impact of Coronavirus treatment in our geographical discontinuity design, and in terms of their belief updating responses to our information treatment. These questions are presented in the Health and Mental State section of Table 5.

Health and Mental State. These questions are adapted from the following studies.

- Life satisfaction (World Value Survey).
  - All things considered, how satisfied are you with your life as a whole these days? Using this card on which 1 means you are "completely dissatisfied" and 10 means you are "completely satisfied" where would you put your satisfaction with your life as a whole?
  - Taking all things together, would you say you are: very happy, rather happy, not very happy, not happy at all.
  - All in all, how would you describe your state of health these days? Would you say it is: very good, good, fair, poor.
- Health and mental health (Health and Retirement Study).
  - Compared with 1 year ago, would you say that your health is much better now, somewhat better now, about the same, somewhat worse, or much worse than it was then?
  - What about your emotional health: how do you feel emotionally at the moment? Is it excellent, very good, good, fair, or poor?
- Discrete Emotions Questionnaire is from Harmon-Jones, Bastian and Harmon-Jones (2016).

- Mental health during pandemic event is from Lau et al. (2005)
  - Do you agree with the following statements? 1=strongly disagree; 10=strongly agree: I feel apprehensive/horrified/helpless because of COVID-19.

Table 5: Perception and Belief Questions

	Personal	Non-Personal				Timeframe		
	Self	Area	Country	Global	General	Past	Present	Future
Perceptions of Corona								
Q119.1 Corona perception your area		x					x	
Q119.2 Corona perception your country			x				x	
Q119.3 Corona perception other countries your continent				x			x	
Q124 Lockdown perception		x					x	
Q125 Corona risk perception					x		x	
Q126.1 Wear mask	x							x
Q126.2 Avoid crowd	x							x
Q126.3 Not to school	x							x
Q126.4 Avoid hospital	x							x
Q129 People around you positive	x						x	
Q129 People around you symptoms	x						x	
Q129 People around you died	x						x	
Household Finance								
Q264 Better than a year ago?	x						x	
Q266 Better in a year?	x							x
Q267 Better in 5 years?	x							x
Q268.1 Job loss in 5 years?	x							x
Q268.2 Income higher than last year?	x							x
Health Beliefs								
Q104.1 Self live to 75	x							x
Q106.1 Others live to 75			x					x
Corona Beliefs								
Q104.2 Corona resurgence your area		x						x
Q104.3 Corona resurgence your country			x					x
Q104.4 Corona resurgence other countries your continent				x				x
Q104.5 You develop Corona	x							x
Q106.2 Others develop Corona			x					x
Economic Beliefs								
Q106.3 Stock market rise			x					x
Q106.4 Prices rise your country			x					x
Q106.5 Prices rise your area		x						x
Q106.6 Unemployment rise your country			x					x
Q106.7 Unemployment rise your area		x						x
Q106.8 Income rise your country			x					x
Q106.9 Income rise your area		x						x
Q237.1 Business conditions next year your area		x						x
Q237.2 Business conditions next year your country			x					x
Q238.1 Business conditions next 5 years your area		x						x
Q238.2 Business conditions next 5 years your country			x					x
Economic Perception								
Q109 Stock market change			x			x		
Q249 GDP change			x			x		
Q250 Stock market change during Corona			x			x		
Q233 Prices change during Corona			x			x		
Q234 Prices rise			x			x		
Q235 Prices fall			x			x		
Corona-Unrelated Belief								
Q260 Bird flu (health domain)					x			x
Q211 Earthquake (disaster domain)					x			x
Q213 Olympic gold medal (sports)			x					x

7.2 Information Treatments in Survey.

In our survey, we include an information treatment to test how people update belief given new information. We conduct this test in two domains of beliefs, health and economic respectively. In each domain, we provide two types of information, either neutral or positive. After reading the information, subjects are asked a belief question and an action intention question. Each subject gets one type of information in each domain. Each domain treatment is independent and within each domain subjects are randomly assigned to an information treatment.

In the health domain, subjects are randomly assigned to one of the following information vignettes:

- Neutral: Some experienced medical scientists have started working on the vaccination for COVID-19.
- Positive: Some experienced medical scientists have started working on the vaccination for COVID-19, and they have had a breakthrough finding.

Subjects are then asked about:

- Their belief that there could be a COVID outbreak in the following year;
- Their intention to get more private health insurance.

In the economic domain, subjects are randomly assigned to one of the following information vignettes:

- Neutral: Some economists have studied the economic impact of COVID-19.
- Positive: Some economists have studied the economic impact of COVID-19, and predicted that the economy will bounce back in the second half of 2020.

Subjects are then asked about:

- Belief about stock market and unemployment in the following year
- Intention to invest in financial markets

8 Estimating Impact of Exposure to Coronavirus on Preferences and Beliefs

The severity of the subject's personal experience with the pandemic is measured by their proximity to COVID-19 infections and deaths. We effectively have two measures of proximity. First, proximity can simply be measured by the number of COVID-19 infections and related deaths in the subject's immediate geographic vicinity – what we are calling their district (and obviously this precise definition will vary by country). Second, proximity can be measured in terms of the subject's proximity to the COVID-19 epicentre – in all of the countries in our sample there is a well-defined epicentre. In many district cases, although not all (which we exploit), the two measures give identical information. A third measure indicates whether a subject resides in a district that shares a border with the epicentre district.

8.1 Economic Preferences: Proximity

Our conjecture is that we will observe a significant change in standard measures of economic preferences for those individuals who had high personal exposure to COVID-19. In order to assess this conjecture, we will implement a simple pre- and post-treatment comparison of means for districts and for the country as a whole. As we described earlier, we have approximately 12 districts in our sample from each country. The responses to the Online Experiment conducted in April 2020 represent our post-treatment measures. And, for each of these districts we have a pre-treatment measure on economic preferences (the district measures are derived from the 2012 GPS survey and an MRP estimation strategy described earlier). And, of course, we have the overall pre-treatment measure of economic preferences for the whole country from the 2012 GPS. Post-treatment measures of economic preferences are estimated from the MRP imputed averages, based on the limited sample of districts, for each of the countries (see the earlier discussion). We entertain a number of possible outcomes:

- the null is essentially that at the country level, economic preferences are identical in pre- and post-treatment; AND that we see exactly the same pattern regardless of personal exposure to COVID-19
- our personal exposure conjecture is that we will see pre- and post-treatment differences in economic preferences and their magnitude will be correlated with proximity or personal

exposure to COVID-19 infections and deaths, at the individual level; AND at the country level these pre- and post-treatment differences will either be weak or non-existent. This is our Hypothesis 1 (H1).

- A third possible outcome is what we the call the social exposure effect. There may in fact be a pre- and post-treatment shift in economic preferences, but they may not be correlated with personal exposure – rather they may be experienced by the national populations as a whole. In this case we would expect to see similar shifts regardless of proximity to COVID-19 infections and deaths and the shift would be registered significantly at the national level also. This is our Hypothesis 2 (H2).

We evaluate these different plausible outcomes with respect to each of the three categories of economic preferences.

Risk Preferences. Previous studies have documented both increases or decreases of risk aversion after experiencing negative shocks, such as natural disaster and financial crisis. The majority of the evidence points to an increased risk aversion after lifetime experience of loss events (e.g. Malmendier and Nagel, 2011). Therefore, we hypothesize that higher exposure to the pandemic makes people more risk averse.

Proximity	**Risk Aversion (Staircase)**			**Self-Assessed Risk Aversion**	
	Pre-treat	**Post-treat**	**Insurance Buy**	**Pre-Treat**	**Post-Treat**
High H1	Medium	Very High	High	Medium	Very High
Medium H1	Medium	High	Medium	Medium	High
Low H1	Medium	Medium	Low	Medium	Medium
Country H1	Medium	Medium	N/A	Medium	Medium
High H2	Medium	Very High	High	Medium	Very High
Medium H2	Medium	Very High	High	Medium	Very High
Low H2	Medium	Very High	High	Medium	Very High
Country H2	Medium	Very High	N/A	Medium	Very High

Table 6: Risk Preferences: Proximity Hypotheses

Time Discounting. Previous studies have documented that experience of near fatal events, such as earthquake, increase present-focused expenditures, i.e. making individuals less patient in their consumption-saving decisions (e.g. Lien, Peng and Zheng, 2015). However, it is also plausible that experience of pandemic events makes people more willing to save for emergency purposes. Therefore, which effect dominates may depend on the personal exposure to the event.

Proximity	Patience (Staircase)		Self-Assessed Patience	
	Pre-treat	Post-treat	Pre-Treat	Post-Treat
High H1	Medium	Very Low	Medium	Very Low
Medium H1	Medium	Low	Medium	Low
Low H1	Medium	Medium	Medium	Medium
Country H1	Medium	Medium	Medium	Medium
High H2	Medium	Very Low	Medium	Very Low
Medium H2	Medium	Very Low	Medium	Very Low
Low H2	Medium	Very Low	Medium	Very Low
Country H2	Medium	Very Low	Medium	Very Low

Table 7: Time Preferences: Proximity Hypotheses

Social Preferences. A pandemic event is a crisis that requires collaborations all across the society to tackle. Charitable donations and international aids are increasing during the time of the pandemic. Therefore, we hypothesize that there should also be a positive influence of the pandemic on social preferences.

Table 8: Social Preferences: Proximity Hypotheses

Proximity	Trust		Altruism		Reciprocity	
	Pre-treat	Post-treat	Pre-Treat	Post-Treat	Pre-Treat	Post-Treat
High H1	Medium	Very High	Medium	Very High	Medium	Very High
Medium H1	Medium	High	Medium	High	Medium	High
Low H1	Medium	Medium	Medium	Medium	Medium	Medium
Country H1	Medium	Medium	Medium	Medium	Medium	Medium
High H2	Medium	Very High	Medium	Very High	Medium	Very High
Medium H2	Medium	Very High	Medium	Very High	Medium	Very High
Low H2	Medium	Very High	Medium	Very High	Medium	Very High
Country H2	Medium	Very High	Medium	Very High	Medium	Very High

8.2 Economic Preferences: Discontinuity.

It is remotely possible that proximity could be confounded with other factors, such as district-specific characteristics (population, GDP, social capital, etc.) – we cannot entirely discount this possibility. In our design though we attempt to match districts so that we could exploit discontinuities that would at least provide further assurances that the effects were not being generated by confounds that we did not identify.

The most powerful test of the causal effect of infections is to use bordering districts – one high and one low on infections and/or deaths – e.g., Cremona and Mantova provinces in Italy:

- personal exposure/risk of death in Cremona is much higher than personal exposure/risk of death in Mantova, although they are adjacent provinces both in Lombardy region.

- expectation is that economic preferences change more for the former than for the latter

There are mainly three variables, for which we can explore causality due to our discontinuity design

- Infections (adjacent counties, huge difference in cases)
- Distance to the epicentre (adjacent counties with similar cases but different distances to epicentre)
- Bordering with epicentre (adjacent counties with similar cases, but one sharing border with epicentre)

Risk Preferences. The direction of the effect is similar to that in Table 6. But here we explore three types of paired districts. Within each pair, the main variation between the two districts come from either infections, distance to epicentre or bordering with epicentre. Our hypotheses is that higher infections, or being closer to the epicentre, make people more risk averse.

			Covariates		**Outcomes**	
	Areas	**Infections**	**Proximity**	**Bordering**	**Risk Aversion (Staircase)**	**Self-Assess**
Pair 1	A	High			High	High
	B	Low			Low	Low
Pair 2	C		Near		High	High
	D		Far		Low	Low
Pair 3	E			Yes	High	High
	F			No	Low	Low

Table 9: Risk Preferences: Discontinuity Hypotheses

Time Discounting. The direction of the effect is similar to that in Table 7. Our hypotheses is that higher infections, or being closer to the epicentre, make people less patient.

	Areas	Infections	Covariates Proximity	Bordering	Outcomes Patience (Staircase)	Self-Assess
Pair 1	A	High			Low	Low
	B	Low			High	High
Pair 2	C		Near		Low	Low
	D		Far		High	High
Pair 3	E			Yes	Low	Low
	F			No	High	High

Table 10: Time Preferences: Discontinuity Hypotheses

Social Preferences. The direction of the effect is similar to that in Table 8. Our hypotheses is that higher infections, or being closer to the epicentre, make people more other-regarding.

Table 11: Social Preferences: Discontinuity Hypotheses

	Areas	Infections	Covariates Proximity	Bordering	Trust	Outcomes Altruism	Reciprocity
Pair 1	A	High			High	High	High
	B	Low			Low	Low	Low
Pair 2	C		Near		High	High	High
	D		Far		Low	Low	Low
Pair 3	E			Yes	High	High	High
	F			No	Low	Low	Low

8.3 Belief Updating: Proximity

We conjecture that there is a significant change in beliefs in two dimensions, health and the economy for individuals who had high exposure to COVID-19. In order to assess this conjecture, we will implement a pre- and post-treatment comparison of means for districts and for the country as a whole. But the pre- and post-treatment comparison can only be done for economic beliefs. In economic beliefs, we have both the personal level about household finance, and the country level. For the belief pre-treatment measure, we have various versions the survey of consumer sentiments. The responses to the Online Experiment conducted in April 2020 represent our post-treatment measures. We entertain a number of possible outcomes:

- the null is essentially that at the country level, economic beliefs are identical in pre- and post-treatment; AND that we see exactly the same pattern regardless of personal exposure to COVID-19.

- our personal exposure conjecture is that we will see pre- and post-treatment differences in economic beliefs and their magnitude will be correlated with proximity or personal exposure to COVID-19 infections and deaths, at the individual level; AND at the country level these pre- and post-treatment differences will either be weak or non-existent. This is our Hypothesis (H1).

- A third possible outcome is what we the call the social exposure effect. There may in fact be a pre- and post-treatment shift in economic beliefs, but they may not be correlated with personal exposure – rather they may be experienced by the national populations as a whole. In this case we would expect to see similar shifts regardless of proximity to COVID-19 infections and deaths and the shift would be registered significantly at the national level also. This is our Hypothesis 2 (H2).

We expect in high impact zones (areas with higher infection cases, shorter distance to epicentre and sharing border with epicentre):

- Coronavirus is perceived to be more severe for the country and global level, even though country and global level data are the same for high and low impact zones.

- Beliefs could be more pessimistic about household financial conditions.

- Beliefs could be more pessimistic about national economic conditions.

Additionally, beliefs are going to exhibit less self-serving bias when comparing self and others, and when comparing own area and the country.

Household Finance. The pandemic has influenced the life of hundreds of millions of people around the world. Their lives change due to the quarantine and lock-downs. Sales and revenues have decreased for small and large companies, and lots of people are laid off. This will have a negative impact on people's forecasts of their own financial situation. Therefore, we expect that people closer to the epicentre are more impacted, and thus are more pessimistic about their own household financial situations.

Table 12: Household Finance: Proximity Hypotheses

Proximity	1-year Pessimism		5-year Pessimism		Employment Pessimism	
	Pre-treat	Post-treat	Pre-Treat	Post-Treat	Pre-Treat	Post-Treat
High H1	Medium	Very High	Medium	Very High	Medium	Very High
Medium H1	Medium	High	Medium	High	Medium	High
Low H1	Medium	Medium	Medium	Medium	Medium	Medium
Country H1	Medium	Medium	Medium	Medium	Medium	Medium
High H2	Medium	Very High	Medium	Very High	Medium	Very High
Medium H2	Medium	Very High	Medium	Very High	Medium	Very High
Low H2	Medium	Very High	Medium	Very High	Medium	Very High
Country H2	Medium	Very High	Medium	Very High	Medium	Very High

National Economy. It is not hard for people to observe and make inference about national economic outlook based on the information they read in the news everyday. A lot of the economic activities around the world are paused. And the first quarter economic growth of many countries have been predicted to drop tremendously. Thus we expect people to hold pessimistic beliefs about their own national economies, and more importantly, to extrapolate the situation around them for the national economies, which they shouldn't do. Information about a nation's economy is widely available, so the higher exposure of the pandemic one experiences around him/her should not add informational value to predicting the national economy.

Table 13: National Economy: Proximity Hypotheses

Proximity	1-year Pessimism		5-year Pessimism		Employment Pessimism		Stock Market Pessimism	
	Pre-treat	Post-treat	Pre-Treat	Post-Treat	Pre-Treat	Post-Treat	Pre-Treat	Post-Treat
High H1	Medium	Very High	Medium	Very High	Medium	Very High	Medium	Very High
Medium H1	Medium	High	Medium	High	Medium	High	Medium	High
Low H1	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Country H1	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
High H2	Medium	Very High	Medium	Very High	Medium	Very High	Medium	Very High
Medium H2	Medium	Very High	Medium	Very High	Medium	Very High	Medium	Very High
Low H2	Medium	Very High	Medium	Very High	Medium	Very High	Medium	Very High
Country H2	Medium	Very High	Medium	Very High	Medium	Very High	Medium	Very High

8.4 Belief Updating: Discontinuity

With the discontinuity design, we can compare beliefs in both health and economic domains between the two adjacent districts we choose in each pair.

We expect in high impact zones (areas with higher infection cases, shorter distance to epicentre and sharing border with epicentre):

- Coronavirus is perceived to be more severe for the country and global level, even though country and global level data are the same for high and low impact zones.
- Beliefs are more pessimistic in corona-related domains.
- Beliefs could be more pessimistic in other health domains.
- Beliefs could be more pessimistic about household financial conditions.
- Beliefs could be more pessimistic about national economic conditions.
- Beliefs could be in general more pessimistic in things that are not related to coronavirus at all.
- Beliefs are going to exhibit less self-serving bias when comparing self and others, and when comparing own area and the country.

Health Beliefs. The Coronavirus is a global negative shock in the public health domain. Therefore, the most influenced beliefs should be those connected to health-related issues. We expect people to extrapolate their experience of the Coronavirus around them to future health-related issues, such as the future occurrence of an epidemic of an infectious disease like the Coronavirus, as well as in the general health domain, such as life expectancy. We expect the experience of more infections around people and being closer to the epicentre to make them more pessimistic in the health domain.

Table 14: Coronavirus Beliefs: Discontinuity Hypotheses

			Covariates		**Outcomes: Pessimism**	
	Areas	**Infections**	**Proximity**	**Bordering**	**Corona**	**General Health**
Pair 1	A	High			High	High
	B	Low			Low	Low
Pair 2	C		Near		High	High
	D		Far		Low	Low
Pair 3	E			Yes	High	High
	F			No	Low	Low

Household Finance Our hypotheses here are in the same direction as those in Table 12. We expect the experience of more infections around people and being closer to the epicentre to make people more pessimistic about their personal and household financial situations.

Table 15: Household Finance: Discontinuity Hypotheses

			Covariates		**Outcomes: Pessimism**		
	Areas	**Infections**	**Proximity**	**Bordering**	**1 Year**	**5 Years**	**Unemployment**
Pair 1	A	High			High	High	High
	B	Low			Low	Low	Low
Pair 2	C		Near		High	High	High
	D		Far		Low	Low	Low
Pair 3	E			Yes	High	High	High
	F			No	Low	Low	Low

National Economy Our hypotheses here are in the same direction as those in Table 13. We expect the experience of more infections around people and being closer to the epicentre to make people more pessimistic about their countries' economic outlook, even though their personal exposure to the pandemic should not add useful information to this prediction task.

Table 16: National Economy: Discontinuity Hypotheses

			Covariates		**Outcomes: Pessimism**			
	Areas	**Infections**	**Proximity**	**Bordering**	**1 Year**	**5 Years**	**Unemployment**	**Stock Market**
Pair 1	A	High			High	High	High	High
	B	Low			Low	Low	Low	Low
Pair 2	C		Near		High	High	High	High
	D		Far		Low	Low	Low	Low
Pair 3	E			Yes	High	High	High	High
	F			No	Low	Low	Low	Low

Coronavirus-Unrelated Beliefs. Our hypotheses here are in the same direction as those in Table 12. We expect the experience of more infections around people and being closer to the epicentre to make people more pessimistic in other domains even if it is unrelated with Coronavirus.

Table 17: Coronavirus-Unrelated Beliefs: Discontinuity Hypotheses

			Covariates		**Outcomes: Pessimism**		
	Areas	**Infections**	**Proximity**	**Bordering**	**Bird Flu**	**Sports**	**Natural Disaster**
Pair 1	A	High			High	High	High
	B	Low			Low	Low	Low
Pair 2	C		Near		High	High	High
	D		Far		Low	Low	Low
Pair 3	E			Yes	High	High	High
	F			No	Low	Low	Low

Self-serving beliefs. Self-serving bias predicts that people are more optimistic about self than about others. If we compare high impact zone and low impact zone, we may see the reverse. What's more interesting is to observe the reverse for areas with the same number of cases but just different distance to the epicentre.

Other Discontinuity Considerations. When doing the above discontinuity analysis, we will also consider the following:

- Are people within two neighbouring counties different before the Coronavirus crisis? We know for sure that people's belief about Coronavirus can't be different, because Coronavirus did not exist at all. In terms of economic beliefs and preferences, they shouldn't be very different if they are in the same region.
- What if the hit of Coronavirus is not random between counties in different regions? This could be because more people in a county would be infected if the county has a larger population, or higher mobility during spring festival or ski season. To deal with this, we collect data of the population and GDP of the selected districts. We first try to choose comparable counties. We also control for these in our analyses.

Control variables. In performing the above analyses, we will control for several variables.

- We collect information about the personal experience of individuals during crisis: the number of people around you who are confirmed positive of/had symptoms of/died from

COVID-19. People living in the same district may have different personal experience during the crisis.

- We ask about each individual's perceived severity of the disease and perceived strength of the quarantine.
- We collect information on objective measures of the strength of quarantine.
- Demographic Questions.

9 Heterogeneous Treatment Effects

We expect the treatment effects due to several covariates we measure. These treatment effects refer to our proximity analysis, discontinuity analysis, as well as responses to our information treatment. And by heterogeneous treatment effect, we mean even for people who live in the same area and thus share exposure to the coronavirus crisis, including number of infections in the area, proximity to the epicentre, they may still have different economic preferences and beliefs due to some covariates at the individual level. Here we list these covariates we measure and the potential reason for them to cause heterogeneous treatment effects.

- *Age*: People of different age cohorts may be heterogeneously impacted. This is because of the limited knowledge the public has about COVID-19, one important narrative is that the disease asymmetrically infects more old people. We thus expect to observe a larger treatment effect on older people in our aforementioned hypotheses.
- *Income and Employment*: People with different levels of income/employment status may be heterogeneously impacted. This is because to tackle with the crisis, in terms of health care/quarantine/lockdown, one needs sufficient liquidity. We thus expect to observe a larger treatment effect on relatively poor or unemployed people who do not have sufficient resources to deal with the crisis.
- *Personal Experience*: People who witnessed different number of people around them infected/hospitalized/deceased due to COVID-19 may be heterogeneously impacted. This is because personal experience creates an additional layer of variation than the district-level exposure measurement. We thus expect to observe a larger treatment effect on people who have more personal experience.

- *Physical and Mental Health*: People who have different subjective evaluation of their own physical and mental health may be heterogeneously impacted. This is because subjective evaluation of health is another measure of personal experience.

10 Subject Recruitment and Administration of Online Survey

The participating subjects in all countries with the exception of China have been recruited into the Nuffield CESS Online subject pool. Most of the recruitment is conducted via Facebook Ad Manager. In order to participate in the CESS Online subject pool, subjects are required to review the ethics rules concerning CESS experiments and the strict data privacy and protection procedure to which CESS adheres. Subjects are required to agree to a consent form prior to participating in any experiments.

The English version of the online survey experiment questionnaire is available in the Appendix. There is no deception or misleading information or directions in the questions and tasks we ask of the subjects. The experiment lasts approximately 15-20 minutes. With the exception of the Chinese version, all versions of the questionnaire are programmed in Qualtrics.

With the exception of China, subjects are compensated for their participation (show-up fee) and they are compensated for a handful of the decisions that they make. The Nuffield CESS compensation policy is to pay subjects no less than the national minimum wage. The earnings for participating in a 15-20 minute experiment are as follows:

- Chile: the average earnings are 3,000 CLP – the show-up payment is 2,000 CLP – subjects are paid via bank accounts.

- Italy: the average earnings are 5 Euros – the show-up payment is 1 Euros – subjects are paid via PayPal

- China: subjects are paid 10 RMB for participation. Payments are done by a Chinese survey company WenJuanXing (WJX) via WeChat and Weibo online platforms in China.

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