How the onset of the Covid-19 pandemic impacted pro-social behaviour and individual preferences: Experimental evidence from China*

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Abstract

We present experimental evidence on how pro-sociality, trust and attitudes towards risk and ambiguity evolved over the six weeks following the imposition of stringent Covid-19 related lockdown measures in the Hubei province of China. We compare incentivized economic decision-making in a baseline sample, collected pre-epidemic, with a series of repeated cross-sectional samples drawn from the same population between January and March, 2020. We find high rates of altruism, cooperation and aversion to risk taking under ambiguity in the immediate aftermath of the lockdown, while trust is significantly below its baseline level. Risk attitudes also differ in the post-lockdown sample, with decreased risk tolerance in the loss domain and lesser risk aversion in the gain domain. We further uncover significant transitory effects for trust and risk aversion around the date of a high-profile whistleblower's death from Covid-19. Our findings suggest that the onset of a public health crisis may have unintended consequences for economic preferences that determine population compliance with interventions designed to reduce the spread of a novel coronavirus.

Keywords: Covid-19, Social Preferences, Cooperation, Trust, Risk Preferences
JEL Codes: C93, D64, D81, D91, I18

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1 Introduction and Background

In December 2019, a novel coronavirus and associated disease (Covid-19) was first reported in the city of Wuhan, the capital of China's Hubei province. Person-to-person transmission of Covid-19 was publicly confirmed on January 20, 2020, and three days later the central government of China imposed a strict lockdown in Wuhan, quickly followed by lockdown measures in the other 15 cities of Hubei province. The Hubei lockdown lasted in its most stringent form until mid-March, by which time local virus cases had eased and restrictions gradually relaxed.

Since then, public health campaigns worldwide have sought to align private and collective interests, promoting behavioural change as the first line of defence in mitigating the virus's impact on individuals' well-being and livelihoods. Local and national lockdown measures have become essential and familiar components in the policy-maker's toolkit. The success of such measures in containing the spread of the virus relies first and foremost on the pro-social and cooperative behaviours of individuals, their trust in others and the interplay between their decision-making and perceptions of risk and uncertainty (Van Bavel et al., 2020; Nikolov et al., 2020). Recent studies conducted during the Covid-19 pandemic find that pro-sociality (Campos-Mercade et al., 2021) and risk tolerance (Müller and Rau, 2021) are important predictors of compliant behaviours.

In this paper, we use financially incentivized decision-making experiments to assess the impact of the onset of Covid-19 and associated events in China - during the stringent lockdown period from late January to early March 2020 - on pro-sociality, cooperation, trust and risk-related attitudes. Our experiment sample is drawn at random from a population of 9,000 pre-registered Wuhan University students. We administered a standard set of behavioural economics tasks to a cross-section of 396 subjects from this population at various times between late January and early March of 2020. Subjects were reached via an online platform based on the WeChat social media interface. We compare data from this sample to a pre-crisis baseline sample of 206 subjects drawn at random from the same population, recruited using the same process, and who completed the same set of decision-making tasks in May 2019. An advantage of this design is that we can track changes in incentivized behaviour using a consistent response elicitation method.

Our first empirical approach is a simple difference in means between the baseline and post-lockdown samples. To mitigate potential confounding effects of differential selection in the pre- and post-event comparison, we conduct regression analyses that control for a range of observed demographics and location-based variables that capture variable exposure to the virus. We find some evidence of greater pro-sociality and higher rates of cooperation in our post-lockdown sample; interestingly, this does not translate into higher expectations about others' cooperation in a coordination game setting. Those subjects based in Wuhan during the initial outbreak were less inclined to trust than their counterparts in other parts of China, although this observation comes with the *caveat* of a small sample size.

The impact of the Covid-19 onset on risk-related attitudes is more nuanced. Since preventative measures often involve trading off a fixed cost versus a probabilistic outcome (e.g. the cost of wearing a mask versus the risk of catching the virus), we elicit risky choices in the loss as well as gain domain. Since it is difficult to quantify the probabilities involved in an emerging crisis, we also elicit attitudes towards risk taking under ambiguity. In the baseline sample, we observe risk aversion in the gain domain and risk-seeking in the loss domain, which is consistent with the diminishing sensitivity of prospect theory (Kahneman and Tversky, 1979). Post-lockdown, subjects display less risk aversion in the gain domain and decreased risk tolerance in the loss domain. Thus, lottery choices after the shock are consistent with a linearization of the value function and a movement towards risk neutrality. These findings complement Ikeda et al. (2020), who uncover that individuals' prospect-theory risk preferences in Japan were systematically and similarly altered after the onset of Covid-19.

Unlike many previous studies, we can go beyond a pre- and post-event comparison and identify acute preference perturbations *within* the formative period under study. This is because our post-lockdown sample is composed of five independent cross-sectional waves, collected over a period of six weeks. We observe no systematic differences in demographic characteristics among these five waves and, given the short time-frame, differential selection is likely to be mitigated. Our first post-lockdown wave was collected on January 24/26, immediately after the announcement of the Wuhan city lockdown. By this time, the daily search index on the word pneumonia using China's main search engine Baidu had risen abruptly to over 760,000 and China Central Television was devoting more than 80 percent of its news coverage to pneumonia-related stories (top panel of Figure 1).[1]

The second and third post-lockdown waves were collected on the days immediately either side of February 7. We conjecture that a formative event during the period under study was the death on this date of Dr. Li Wenliang, a high-profile Chinese whistleblower. To gain insight into the magnitude with which this event resonated in the Chinese public's consciousness, compare the two Baidu search indices in the bottom panel of Figure 1.[2] The red series tracks the index on Li Wenliang and the blue series tracks the index on Zhong Nanshan, one of China's leading medical scientists who warned about the transmissibility of Covid-19 on a visit to Wuhan in January.[3] While the Zhong Nanshan index spiked to over one million around the date of his Wuhan visit, the Li Wenliang index increased nearly five times more than this to over five million, following the announcement of his death.

The fourth and final post-lockdown waves were implemented at bi-weekly intervals after this event. By the end of the sampling period, the level of public health emergency response had been lowered by provincial governments and Wuhan had closed its mobile cabin hospitals.

Our experimental data supports the presence of transient behavioural effects during the post-lockdown period. In the first post-lockdown wave, generalized trust is low. This is perhaps unsurprising: late January was the moment of greatest uncertainty about the virus

[1]In China, Covid-19 was referred to as pneumonia early on.

[2]This event was also widely covered by media outlets in the Western world. See, for example: https://www.theguardian.com/global-development/2020/feb/07/coronavirus-chinese-rage-death-whistleblower-doctor-li-wenliang.

[3]Zhong Nanshan is often referred to as the public face of China's fight against the virus. See, for example: https://www.npr.org/2020/04/15/835308147/meet-dr-zhong-nanshan-the-public-face-of-the-Covid-19-fight-in-china?t=1596625232619.

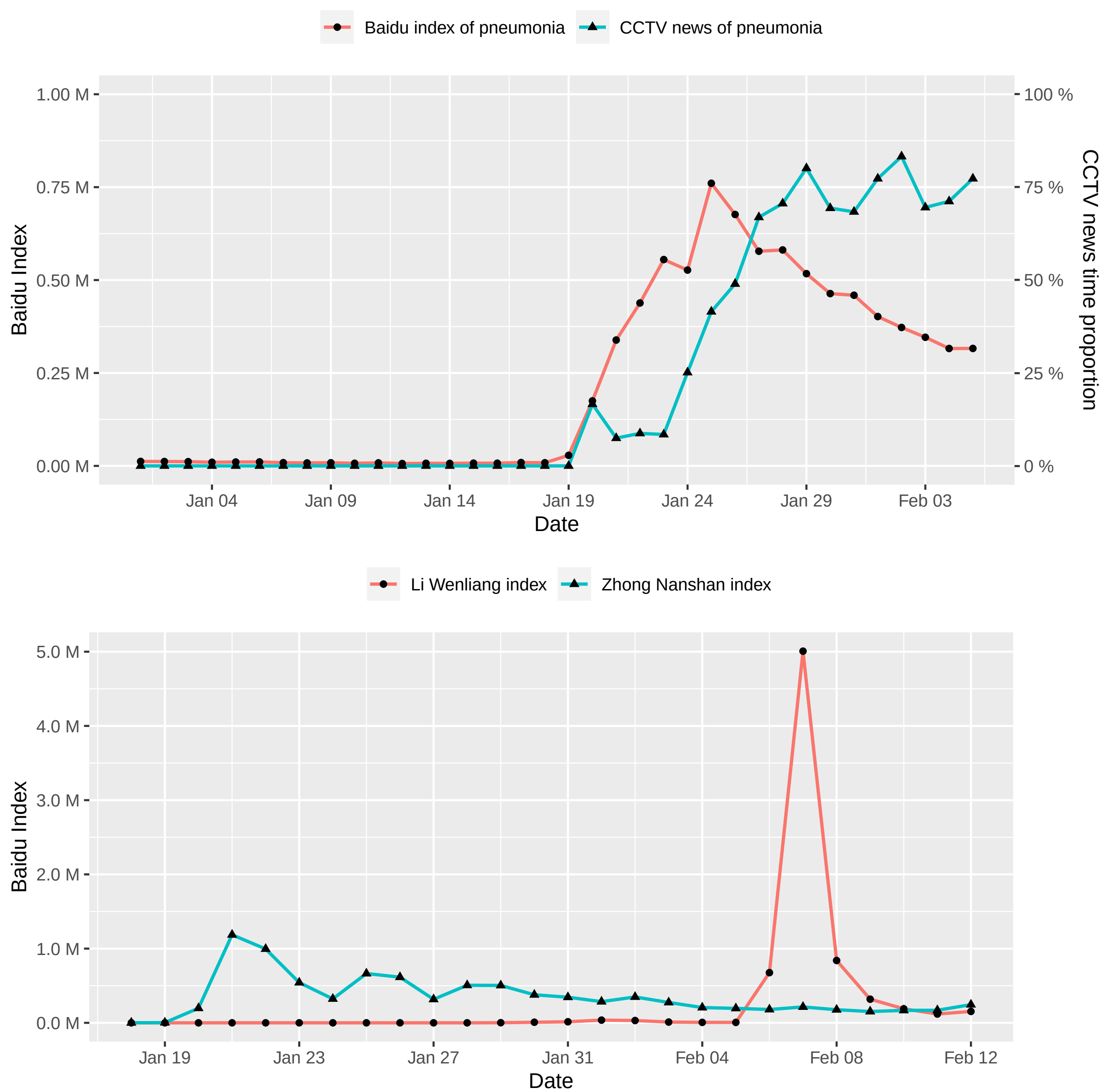

Figure 1: Public awareness of Covid-19 and related events in the early stages of the crisis

Notes. *Top panel*: The red series is the Baidu search index on the word pneumonia (in Chinese language). Max value is 760,460; The blue series is the time proportion spent covering pneumonia-related stories (later called Covid-19) on China Central Television (CCTV) news. Max value is 83%. *Bottom panel*: The red series is the Baidu search index on Li Wenliang. Max value is 5,007,063; The blue series is the Baidu search index on Zhong Nanshan, the chief scientist in China who first revealed human to human transmission of Covid-19. Max value is 1,186,091.

in Wuhan. By the second post-lockdown wave, trust recovers while the remaining behavioural measures remain largely stable. Immediately after the death of Dr. Li Wenliang, trust moves significantly lower and we also observe a short-lived increase in risk aversion and a dip in cooperation. Both these measures recover towards their late January levels by the time of the final sampling wave.

The paper continues in Section 2 with a discussion of our contribution in the context of related literature and summarizes why we believe the uniqueness of our research setting to be a strength. In Section 3, we outline the experimental design, including details of sampling, the decision-making tasks and protocol. In Section 4, we present the experimental results. In Section 5, we conclude with a comparison of our results to the literature, a discussion of their implications for lockdown policies during an emerging public health crisis, and outline several important limitations of our study.

2 Contribution in context

This paper contributes to an established economics literature on the stability of economic preferences.[4] Canonical models of economic decision-making assume that individuals' preferences are stable over time. This assumption is at odds with psychological channels and the importance of personal experiences for economic behaviours (Hertwig et al., 2004; Filipski et al., 2019; Banks et al., 2020). Preference stability has been challenged by a series of empirical works in economics and finance (e.g. Choi et al., 2009; Malmendier and Nagel, 2011; Guiso et al., 2018; Andersen et al., 2019).

Prior experimental research suggests that traumatic life events can have a significant effect on risk-related behaviours. Several studies report that individuals become more risk averse for various time horizons after experiencing a natural disaster (Kim and Lee, 2014; Cameron and Shah, 2015; Beine et al., 2020). Still others uncover an increased preference for risk-seeking (Eckel et al., 2009; Page et al., 2014; Hanaoka et al., 2018; Kuroishi and

[4] For a survey of some important results in this literature, see Chuang and Schechter (2015)

Sawada, 2020) or suggest that the direction of the effect may be mediated by personal losses during a crisis (Said et al., 2015). Further research has been undertaken to the long-term impact of natural disasters (Andrabi and Das, 2017; Fleming et al., 2014; Cassar et al., 2017), economic recessions (Fisman et al., 2015), and wars (Bauer et al., 2016) on trust, reciprocity and cooperative behaviours. If there is a consensus, it is that the impact of formative events on economic preferences is context-specific.

We also add to a rapidly growing literature assessing the impact of the Covid-19 pandemic on economic preferences and beliefs (Angrisani et al., 2020; Binder, 2020; Brück et al., 2020; Coibion et al., 2020; Fetzer et al., 2020; Li et al., 2020; Lohmann et al., 2021). Given the importance of context and cultural factors in determining the evolution of preferences in response to an exogenous shock, we restrict attention to related evidence from China.[5].

Li (2020) conducted an online experiment in China in early March 2020, eliciting incentivized measures of attitudes towards risk and ambiguity. He finds that ambiguity averse subjects are more pessimistic about the impact of the pandemic on economic growth and are more likely to reduce consumption and increase savings as a result. Unlike in the present study, there is no pre-epidemic sample available to examine how these attitudes may have been affected by the onset of Covid-19.

Closely related is Bu et al. (2020), who administered a survey to a panel of graduate students at the Wuhan University of Science and Technology before and after initial reports of the virus emerged.[6] They observe a significant decrease in levels of financial risk taking and planned risk taking between waves and exploit geolocation data to show that those subjects quarantined in Wuhan allocate 45 percent less to a hypothetical gamble relative to those based in other provinces of China. The authors conduct a repeat survey in April 2020, in which they observe that financial risk taking rebounds after the quarantine in Wuhan ends, suggesting that Covid-related effects on economic preferences are likely to be short-

[5]Several perturbations in pro-social and risk-related preferences have been documented for Europe since the onset of the Covid-19 pandemic (Brañas-Garza et al., 2020; David and Sade, 2020; Huber et al., 2020; Graeber et al., 2020)

[6]Wuhan University of Science and Technology is a separate research institution to Wuhan University.

lived. A drawback of their study is that they rely on non-incentivized and so possibly less reliable preference measures. We will also provide evidence to suggest that the timing of their initial post-event survey may have captured acute fluctuations in risk aversion during the post-lockdown period.

Lohmann et al. (2021) employ a comprehensive battery of behavioural economics tasks to examine the impact of exposure to the Covid-19 crisis on risk, time and trust preferences, cooperative, pro-social and norm enforcement behaviours, in a representative sample of 183 cities across China. Their longitudinal design affords strong internal validity using a difference-in-difference estimator to exploit within-subject variation between October and December 2019 versus mid-March 2020. They find a significant rise in anti-social behaviour among individuals most exposed to the virus, which is also associated with an increase in virus-related concern (as measured using the Baidu search index) and negative sentiment (based on text analysis from a popular Chinese micro-blogging site). They provide evidence that these changes are driven by psychological channels. They find no robust effect of exposure to the virus on risk aversion or trust.

Guo et al. (2020) deploy the same set of decision-making tasks as implemented in this study but using a quite different design, intended to measure behavioural and emotional responses of Wuhan University subjects to the transmission of viral social media videos connected to the Covid-19 crisis. Unlike the current paper, theirs is not an event study: they only elicit responses at a single point in time, during late January 2020.

3 Experimental Design

3.1 Sampling information

A timeline of our experimental sessions and events related to the Covid-19 pandemic is presented in Figure 2. All subjects in our experiments were Wuhan University students, randomly selected from a population of 9,000 subjects who had previously registered to participate in decision-making experiments. Subjects were not informed about the tasks that they would be asked to complete before registering for an experimental session.

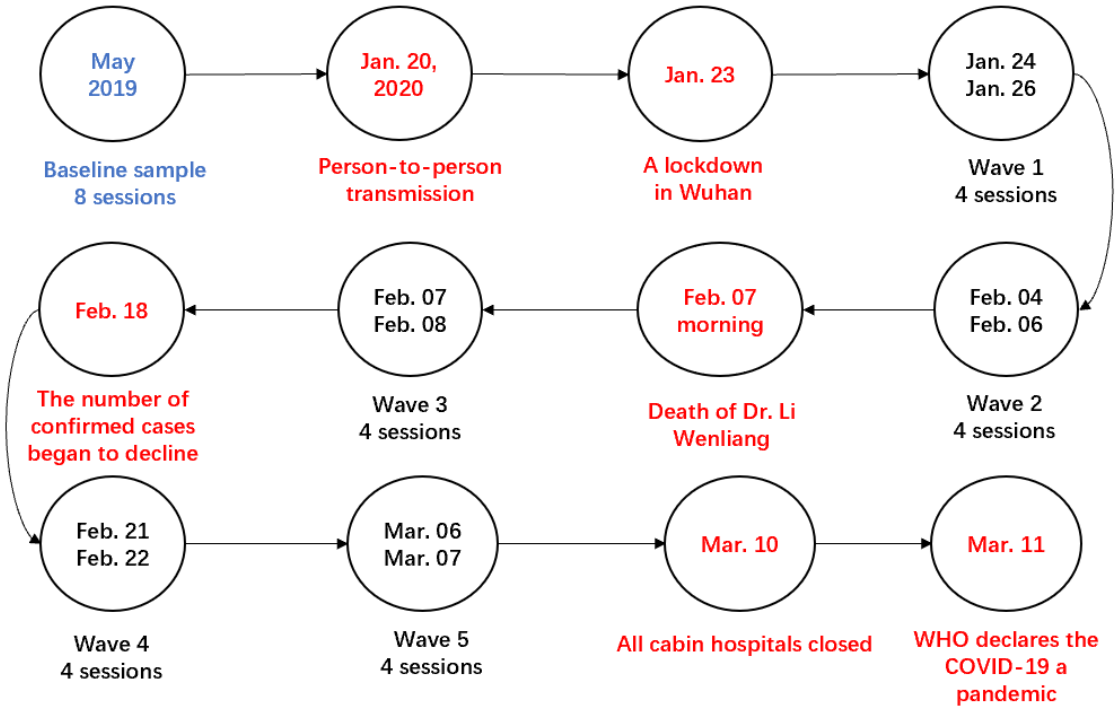

Figure 2: Timeline of events and experimental sessions

Our baseline sample consists of 206 subjects recruited from this population, in May 2019, for an unrelated research project investigating the impact of the experimental interface on economic decision-making. Following the lockdown of Wuhan city on January 23, 2020, we collected comparable data from a further 396 (different) subjects from the same population, spread evenly across five sampling waves.[7] The first wave of 80 subjects was collected on January 24/26, in the immediate aftermath of the Hubei lockdown. The second and third waves of 78 and 80 subjects, respectively, were collected on February 4/6 and 7/8, immediately before and after the death of Dr. Li Wenliang (see earlier discussion). The

[7]In separate work in progress, we find that subjects' interface affects certain risk-related behaviours. Accordingly we maintain a consistent experimental interface between the pre-crisis baseline sample and the subsequent experimental waves. We also exclude from our analysis data a further four subjects in our 2020 waves and eighteen subjects in our baseline sample who completed the tasks using a computer after we asked them to complete tasks using a mobile phone.

fourth wave of 78 subjects was collected on February 21/22, by which point there were over 63,000 confirmed cases and 2,250 deaths in Hubei province. The final wave of 80 subjects was collected on March 6/7. By this stage, the number of local confirmed cases in Wuhan had dropped to less than one hundred per day, with almost no local confirmed cases in China outside of Wuhan.[8] Wuhan closed its final mobile cabin hospital on March 10, just one day before the WHO declared a global pandemic.

In total, we recruited 602 subjects across the baseline and post-lockdown samples. An important factor in determining the generalizability of our results is the extent to which these two samples are comparable. It is possible that those subjects from the population who elected to participate in the experiments during the post-lockdown period differed in unobserved ways to those in the baseline sample. We acknowledge this concern and make two responses.

First, we control in our analysis for a range of observed demographic, location-based and interface variables (Table 1). The only systematic differences we identify between samples are in the proportions of female subjects and economics majors, which are higher in the baseline sample. All results derived below are robust to controlling for these variables. We also use geo-location data to identify those subjects based in Wuhan or elsewhere in Hubei province during the crisis. Since most students from areas outside of Wuhan had already left the city in early January to celebrate the Lunar New Year holiday, we can exploit quasi-random variation in exposure to the virus.

Second, we followed up with 92 subjects from our baseline sample over February 15 and 16, 2020 and elicited repeat measures for the full set of decision-making tasks. We will discuss the comparability of behaviours between this repeat sample and the temporally closest post-lockdown waves after presenting the main results.

[8] Virus case data is obtained from WHO situation reports, which can be found at: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/.

Table 1: Sample characteristics (control variables).

	Full sample	Baseline	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Number of subjects	602	206	80	78	80	78	80
Age	20.41	20.17	20.11	20.58	20.70	21.05	20.23
	[1.84]	[1.67]	[1.51]	[1.90]	[1.78]	[2.68]	[1.27]
Female	0.59	0.69	0.56	0.45	0.56	0.56	0.55
	[0.49]	[0.46]	[0.50]	[0.50]	[0.50]	[0.50]	[0.50]
Econ major	0.22	0.32	0.20	0.19	0.20	0.12	0.11
	[0.41]	[0.47]	[0.40]	[0.40]	[0.40]	[0.32]	[0.32]
Monthly Expenditure	2.58	2.57	2.54	2.51	2.62	2.59	2.65
	[0.68]	[0.71]	[0.62]	[0.68]	[0.68]	[0.71]	[0.66]
Annual Income	2.60	2.62	2.50	2.68	2.66	2.55	2.59
	[0.94]	[0.93]	[0.87]	[1.05]	[1.01]	[0.91]	[0.90]
Wuhan	0.10		0.11	0.10	0.12	0.06	0.08
	[0.29]		[0.32]	[0.31]	[0.33]	[0.25]	[0.27]
Other Hubei	0.21		0.18	0.19	0.25	0.14	0.31
	[0.41]		[0.38]	[0.40]	[0.44]	[0.35]	[0.47]
Phone Size (in)	5.89	5.74	6.04	5.93	5.93	5.99	5.93
	[0.54]	[0.58]	[0.47]	[0.48]	[0.59]	[0.49]	[0.52]
iOS	0.21	0.25	0.19	0.13	0.25	0.10	0.26
	[0.41]	[0.44]	[0.39]	[0.34]	[0.44]	[0.31]	[0.44]

Note: Mean values with standard deviation in square brackets.
Monthly Expenditure (Annual Income): 1 = less than 800 (30,000) RMB ; 2 = 800 (30,000) $\sim$ 1500 (100,000) RMB; 3 = 1500 (100,000) $\sim$ 2500 (200,000) RMB; 4 = 2500 (200,000) $\sim$ 4000 (400,000) RMB; 5 = greater than 4000 (400,000) RMB.

3.2 Economic games

The following two sub-sections describe the decision-making tasks that were implemented in our experiment.[9] We employed a standard set of incentivized two-person games used in the experimental economics literature to measure strategic behaviours. In each game, subjects were randomly matched into pairs within the session and assigned to the role of either player 1 or player 2. Details of the games and what they measure are summarized below:

- Dictator game. Player 1 is allotted 5 RMB and decides how to allocate this sum of money between the two players in the pair. Player 1's allocation is final. Player 2 has no decision to make. Amounts allocated by player 1 provide a measure of subjects' altruism.

- Ultimatum game. Player 1 is allotted 8 RMB and proposes an allocation of this sum between the two players in the pair. Player 2 can choose to accept or reject the allocation. In case of rejection, both players receive zero payoff for the task. Acceptance rates capture subjects' perceptions of fairness; offers capture expectations about reciprocity.

- Trust game. Player 1 is allotted 8 RMB and decides how much of this sum of money to send to player 2. Any money sent is multiplied by a factor of three before reaching player 2. Any money not sent is kept by player 1. Player 2 observes the multiplied transfer and decides how much of it to return to player 1. Any money not returned is kept by player 2. Amounts sent capture subjects' trust; amounts returned capture subjects' trustworthiness.

- Prisoner's Dilemma game. Each player makes a simultaneous decision to Cooperate or Defect. The choices are framed neutrally as options C or D. If both players choose

[9] We collected data from a further four tasks designed to inform on subjects' levels of cognitive reasoning, lying propensity and time preferences, which are not reported on here. Details of these tasks are included in the experimental instructions.

Cooperate, both players earn 6 RMB. If both players choose Defect, both players earn 3 RMB. If one player chooses Cooperate and the other player chooses Defect, the cooperating player earns 0 RMB and the defecting player earns 9 RMB. Choices in this game provide a measure of subjects' cooperative tendencies.

- Stag Hunt game. Each player makes a simultaneous decision to choose a Safe or Risky option. The choices are framed neutrally as options A or B. If both players choose Safe, both players earn 3 RMB. If both players choose Risky, both players earn 8 RMB. If one player chooses Safe and the other player chooses Risky, the safe player earns 3 RMB and the risky player earns 0 RMB. As suggested by Skyrms (2004), we interpret a Risky choice as the propensity to coordinate. We measure the level of coordination in the Stag Hunt game as the percentage of players choosing the Risky action.

3.3 Individual decision-making tasks

In addition to the economic games described in the previous sub-section, we elicited information about subjects' attitudes towards risk and ambiguity by implementing the following incentivized decision-making tasks:[10]

- Risk attitude elicitation (gain domain). Subjects are presented with a series of nine pairwise choices between a lottery (option A) and a sure amount of money (option B). The lottery remains fixed across all choices: a 50 percent chance of receiving 9 RMB, and a 50 percent chance of receiving 3 RMB. The sure amount increases uniformly with each choice from 3 RMB to 9 RMB in increments of 0.75 RMB.[11] After all choices have been made, the system randomly selects one of the nine pairs of options and, depending on the option chosen for this pair, determines the payoff for the task. A later switching point (higher certainty equivalent) indicates greater willingness to take

[10] We exclude data from 29 (13) [21] subjects who switch more than once in the risk attitude gain domain (loss domain) [ambiguity] elicitation task.

[11] This task is an adaptation of the well-established Holt and Laury (2002) multiple price list format.

risks.

- Risk attitude elicitation (loss domain). Identical to the risk attitude elicitation in the gain domain except that now the lotteries and sure amounts are framed as losses and the sure amount decreases uniformly with each choice from 9 RMB to 3 RMB. A later switching point (higher certainty equivalent) indicates greater willingness to take risks. The payoff-relevant amount was subtracted from the subject's earnings at the end of the experiment.

- Ambiguity attitude elicitation. Identical to the risk attitude elicitation except that now, if subjects choose the lottery, a ball is randomly drawn from an opaque urn. The urn contains both red and blue balls, but the number of each colour is unknown. If the draw is red, they earn 9 RMB. If the draw is blue, they earn 3 RMB.[12] A later switching point (higher certainty equivalent) indicates greater willingness to seek out unknown situations.

3.4 Procedural details

Invitations to participate in an experimental session were sent using the cloud-based Ancademy platform (https://www.ancademy.org/). Ancademy is based on the open interface of WeChat. Upon joining a session, subjects were redirected to a welcome screen describing the general experiment guidelines. The economic games and individual decision-making tasks were then completed sequentially, with instructions provided on arrival at each task.[13] Feedback was provided only after completion of all tasks. We excluded from a session either the Ultimatum or Trust game task.[14] At the end of a session, subjects answered a short questionnaire eliciting standard demographic information, before viewing a screen containing

[12]This task is based on the original thought experiment of Ellsberg (1961).

[13]An English translation of the original experiment instructions for each task is available in the Supplementary Materials.

[14]We did this to preclude the possibility that second movers condition their actions on the first mover's prior decision (due to the sequential nature of the tasks).

his or her decision outcomes and payment information.

Subjects were paid based upon the outcomes of all tasks. We made payments via the WeChat pay facility on the same day. The experimental tasks were computerized using oTree (Chen et al., 2016). Subjects were instructed to complete the tasks using their mobile phone and we were able to check compliance with this instruction in the data. Subjects were able to contact the experimenter via WeChat during the course of a session in case of any questions. No subject could participate in more than one session. Sessions lasted approximately forty-five minutes and payments averaged 65.68 RMB (about 9.5 US dollars), including a participation fee of 10 RMB.

4 Results

4.1 Pre- versus Post-lockdown analysis

We first conduct statistical comparison tests of the null hypotheses that our preference measures are equal between baseline and post-lockdown samples. Table 2 summarizes the non-parametric test results. We observe some evidence of an increase in pro-sociality between samples as measured by first-mover amounts sent in the Dictator and Ultimatum games, although the evidence for this is weak (respectively, p-value = 0.083 and p-value = 0.076). The propensity to cooperate in a Prisoner's Dilemma game increases by nearly one-third in the post-lockdown sample (p-value = 0.017). This does not, however, coincide with an improvement in coordination: the percentage of players choosing the Risky action in the Stag Hunt game is 11 percentage points lower in the post-lockdown sample versus the baseline (p-value < 0.01). There is no significant difference in amounts sent by first-movers in the Trust game (p-value = 0.50); later we will provide evidence to suggest that this null trust result masks systematic variation within the post-lockdown waves.[15]

[15] It is difficult to draw valid inferences from unconditional statistics on second-mover decisions and so we postpone discussion of these measures for the Trust and Ultimatum games until the regression analysis.

Table 2: Descriptive statistics pre-/post-lockdown.

Sample	2019 Baseline mean	sd.	2020 Post-lockdown mean	sd.	
Dictator game $[0, 5]$	1.45	1.08	1.65	1.08	*
Stag Hunt game {0,1}	0.88	0.33	0.77	0.42	***
Prisoner's Dilemma game {0,1}	0.31	0.46	0.41	0.49	**
Trust game sent $[0, 8]$	3.39	2.59	3.68	2.62	
Ultimatum game offer $[0, 8]$	3.08	1.04	3.30	1.21	*
Risk attitude, gain {1,2,...,10}	4.45	1.13	4.71	1.34	**
Risk attitude, loss {1,2,...,10}	6.42	1.14	6.27	1.18	**
Ambiguity attitude {1,2,...,10}	4.49	0.33	4.23	1.55	***
Observations	206		396		

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, based on two-tailed Wilcoxon rank-sum tests except for Stag Hunt and Prisoner's Dilemma games, which are based on two-tailed Fisher's Exact tests.

We also uncover significant differences in risk-related attitudes between the two samples. Recall that risk neutrality would require a switching point between 5 and 6 in our risk elicitation tasks. The aggregate measures in both samples imply risk aversion in the gain domain and risk-seeking in the loss domain, which would be consistent with the diminishing sensitivity predictions of prospect theory.[16] In our post-lockdown sample, the average switching point moves significantly higher in the gain domain elicitation task (p-value $= 0.011$) and significantly lower in the loss domain elicitation task (p-value $= 0.039$). In other words, subjects' preferences move towards risk neutrality after the Covid-19 shock. There is also heightened ambiguity aversion among subjects in the post-lockdown sample, who reveal a significantly lower valuation of uncertain lotteries (p-value < 0.01).

These diverging patterns in risk-related attitudes can be seen in Appendix Figure A1, in which we present cumulative probability distributions of the underlying switching points

[16] We are unable to say more than this because our design does not permit identification of the underlying value or probability weighting functions.

across the risk and ambiguity attitude elicitation tasks.[17] Approximately 80% of subjects in both the baseline and post-lockdown samples display risk aversion in gains and risk-seeking in losses. The post-lockdown distribution of switching points in the gain domain lies weakly to the right of the baseline distribution; the reverse is observed in the loss domain among all but the most risk-seeking subjects. There is also a shift left in the distribution of switching points in the ambiguity elicitation task post-lockdown.

Since differential selection between baseline and post-lockdown samples is a potential confound, we cannot rely on perfect randomization from the population to establish a causal effect. Thus, we conduct regression analyses to check whether the aggregate differences reported above remain after controlling for the set of observable sample characteristics documented in Table 1. In particular, this enables us to account for the imbalances observed in gender and academic major. The regression results are reported in Table 3. In the main text, we report specifications based on OLS and Logistic regressions only. The impact of the exogenous Covid-19 shock is captured by a dummy variable for the post-lockdown sample. The results are robust to the use of alternative estimation methods that mitigate statistical issues involved in the use of censored and count data for the dependent variable (see Appendix Table A2 and A3).

The regressions support all but one of the aggregate results reported in Table 2. There is support at the 5% level of statistical significance for the observed reductions of risk aversion in gains and risk tolerance in losses, and for the increase in ambiguity aversion, post-lockdown. We observe a strong positive effect of the post-lockdown dummy on cooperation in the Prisoner's Dilemma and the negative effect on coordination in the Stag Hunt game (both p-values < 0.01). There is also some evidence of higher altruism and trust in the post-lockdown sample (p-value $= 0.054$ and p-value < 0.060, respectively).[18] Offers in the Ultimatum Game, however, are no longer significantly above those in the baseline sample (p-values $= 0.46$). This

[17] Similar inferences can be made from the kernel density estimates; the cumulative probabilities are preferred here because they do not rely on any distributional assumptions.

[18] The impact on trust is significant at the 5% level if we account for censoring in the dependent variable (see Table A2).

effect appears to be subsumed by a strong positive coefficient estimate on the indicator for being in Hubei (outside Wuhan) during the lockdown period. Other notable heterogeneous effects include a significant fall in trust among those subjects located in Wuhan during the lockdown (p-value < 0.01), although we emphasize that these subjects make up a relatively small fraction of the sample. Female subjects are more risk averse, trusting, altruistic and cooperative than their male counterparts.[19]

In Table A1, we present an additional regression analysis of second-mover behaviour in the Trust and Ultimatum game tasks. For the Trust game, the dependent variable is player 2's return amount and for the Ultimatum game, the dependent variable is player 2's acceptance decision. Since the distribution of first-mover actions varies between the baseline and post-lockdown samples, we interact the amount sent/offered with the post-lockdown sample dummy to check for differential levels of reciprocity. As expected, there is a positive and significant correlation between amounts sent (offered) and return amounts (acceptances). There is no significant difference in either trustworthiness or conditional acceptance decisions between the baseline and post-lockdown samples. There is strong evidence that those subjects based in Wuhan during 2020 are more agreeable during Ultimatum bargaining, although again this observation is based on a small sample of player 2s.

4.2 Post-lockdown transitory effects

An advantage of our repeated cross-sectional wave design is that we can complement the event analysis of the previous sub-section with an investigation of how preferences evolved *within* the six weeks after announcement of the first Covid-19 related lockdown. Differential selection between the five 2020 sampling waves is unlikely to be an issue given the short time horizon involved and since all these waves were elicited in a "post-Covid" world.

In Figure 3, we plot the evolution of mean responses for the decision-making tasks in each experimental sampling wave, with associated 95 percent confidence intervals. There

[19] It has been suggested that the social preferences of women are more malleable (Croson and Gneezy, 2009). We find no significant interaction between gender and pre-/post-lockdown periods in our sample.

Table 3: Regression analysis pre-/post-lockdown.

	Dependent variable							
	Trust	Pro-sociality		Cooperation		Risk		Ambiguity
		DG	UG	SH	PD	Gain	Loss	
	OLS	*OLS*	*OLS*	*Logistic*	*Logistic*	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-lockdown	0.85^{*}	0.27^{*}	0.15	-0.70^{***}	0.63^{***}	0.26^{**}	-0.24^{**}	-0.32^{**}
	(0.45)	(0.14)	(0.21)	(0.27)	(0.21)	(0.12)	(0.11)	(0.13)
Wuhan	-2.35^{***}	-0.26	-0.03	-0.08	-0.76^{*}	-0.16	-0.01	-0.20
	(0.68)	(0.24)	(0.50)	(0.42)	(0.41)	(0.21)	(0.17)	(0.25)
Other Hubei	1.28^{*}	0.20	0.65^{***}	-0.06	-0.33	-0.23	0.10	-0.01
	(0.68)	(0.19)	(0.24)	(0.31)	(0.26)	(0.16)	(0.16)	(0.20)
Female	1.11^{***}	0.35^{***}	0.19	0.19	0.47^{***}	-0.19^{*}	-0.13	-0.10
	(0.40)	(0.12)	(0.19)	(0.22)	(0.18)	(0.11)	(0.09)	(0.12)
Econ. major	0.91^{*}	-0.05	-0.39	-0.15	-0.17	-0.06	0.06	-0.08
	(0.54)	(0.15)	(0.28)	(0.28)	(0.23)	(0.12)	(0.12)	(0.14)
Intercept	3.15	4.09^{***}	5.58^{**}	1.79	-2.74	3.36^{*}	3.28^{**}	0.21
	(6.73)	(1.55)	(2.41)	(2.93)	(2.30)	(1.77)	(1.30)	(1.82)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153	304	151	593	594	565	581	573
R^2	0.16	0.09	0.13			0.03	0.06	0.03
Log Likelihood				-280.50	-382.35			

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Coefficient estimates with robust standard errors in parentheses.

are interesting transitory effects between sampling waves. To formally examine these, we conduct a regression analysis on the post-lockdown data only (see Table 4) and include dummy variables for each independent 2020 sampling wave, along with the full set of control variables in Table 1.[20] We specify the reference wave to be Wave 3; this is the midpoint during post-lockdown sampling and has the benefit of clearly revealing any short-term preference changes in the immediate aftermath of the death of Dr. Li Wenliang.

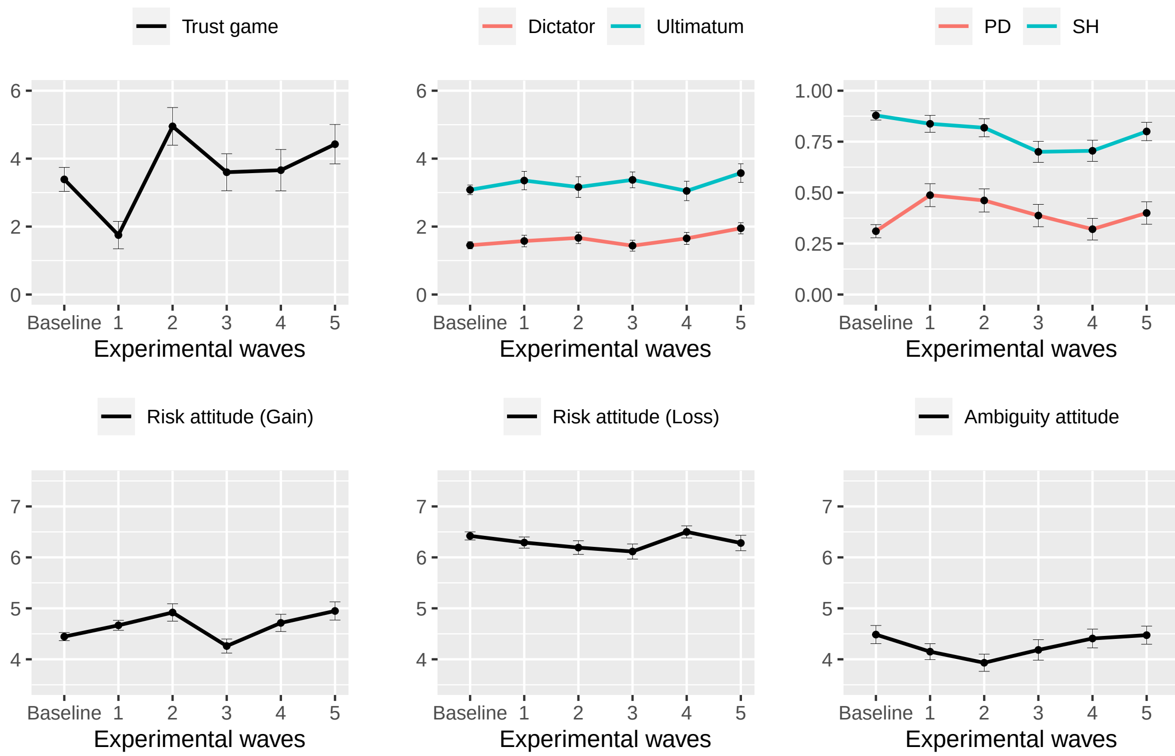

Figure 3: Time series of economic behaviours and preferences

Notes. Mean values with error bars +/- 1 standard error. For Trust game and Ultimatum game, series is amount sent/offered by first mover. PD = cooperation in Prisoner's Dilemma game, SH = cooperation in Stag Hunt game.

This analysis suggests several acute preference perturbations. Wave 3 is strongly associated with lower trust and increased risk aversion in gains, versus Wave 2 (both p-values < 0.01). Moreover, these effects are short-lived: by Waves 5, both measures return to their

[20]Non-parametric test results for the comparisons discussed in this sub-section are contained in Table A4 and confirm the main results.

Table 4: Regression analysis of the post-lockdown sampling waves only.

	Dependent variable:							
	Trust	DG	UG	SH	PD	Risk+	Risk-	Ambiguity
	OLS	*OLS*	*OLS*	*Logistic*	*Logistic*	*OLS*	*OLS*	*OLS*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wave 1	-1.85^{***}	0.16	-0.11	0.71^{*}	0.50	0.43^{**}	0.22	-0.04
	(0.64)	(0.22)	(0.36)	(0.40)	(0.35)	(0.17)	(0.18)	(0.25)
Wave 2	1.47^{**}	0.29	-0.18	0.67^{*}	0.34	0.67^{***}	0.18	-0.25
	(0.66)	(0.22)	(0.38)	(0.40)	(0.34)	(0.23)	(0.20)	(0.26)
Wave 4	0.28	0.17	-0.39	0.02	-0.34	0.44^{**}	0.38^{**}	0.25
	(0.81)	(0.23)	(0.33)	(0.36)	(0.34)	(0.21)	(0.18)	(0.27)
Wave 5	0.18	0.51^{**}	-0.03	0.64	0.11	0.70^{***}	0.20	0.31
	(0.71)	(0.22)	(0.29)	(0.40)	(0.33)	(0.23)	(0.20)	(0.27)
Intercept	-12.77^{*}	2.84	3.32	-1.50	-4.59	0.62	2.18	-2.23
	(7.72)	(1.96)	(3.47)	(3.52)	(2.95)	(2.52)	(1.75)	(2.56)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	99	196	97	388	389	366	378	370
R^2	0.38	0.15	0.26			0.06	0.07	0.05
Log Likelihood				-199.71	-252.30			

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.
Coefficient estimates with robust standard errors in parentheses.

levels recorded in Wave 2. While we cannot definitively identify these effects with the death of Dr. Li Wenliang, the data provides compelling evidence that temporary changes in public sentiment may have marked behavioural implications. The other notable finding is that generalized trust is at a very low level in the first few days after the Wuhan lockdown, but recovered quickly in the second Wave.

With this in mind, recall that our earlier finding as to the impact of the Covid-19 outbreak and associated measures on risk attitudes contrasts with Bu et al. (2020), who report a generalized increase in risk aversion in a separate population of Wuhan-based subjects. Aside from differences in dates of the baseline sample for comparison (May versus October 2019) and risk elicitation measures (incentivized lottery choices in our study versus hypothetical allocation and self-reported attitudes in theirs), one explanation for the discrepancy may be that their follow-up survey was conducted in late February 2020, after the death of Dr. Li Wenliang.

4.3 Baseline re-sampling and selective participation

In our final empirical analysis, we present results from a wave of 92 subject who participated in our original baseline study and then again in a wave conducted February 15-16 2020. We conducted this re-sampling to evaluate whether any changes in their paired responses matched the treatment effects observed in our pre- and post-Covid announcements. We provide further evaluation by comparing the re-sampling responses to the immediately preceding and succeeding waves. We view these evaluations as a second check, in addition to previous multivariate regression analyses, for potential selective subject participation in our experiment.

In Table 5, we report the averages of the sub-sample's Baseline and Re-sample responses to the two risk preference and the ambiguity tasks.[21] Comparing their baseline and re-sample choices via Wilcoxon signed-rank tests we don't find treatment effects for the Risk attitude task both in the gain and loss domain. On the other hand we do find a significant increase (p-value < 0.01) in average ambiguity aversion; consistent with our previous findings.

We next compare the responses of the Re-sample to those of Waves 3 and 4. If there isn't a substantive issue of selective participation we should find no differences. When comparing average responses from individual waves to the Re-sample the only significant difference is for risk attitude for losses in Wave 3. These null results could arise from low power from the small samples. In response, we pool the responses from Waves 3 and 4 before comparing to the Re-sample responses. Hypothesis tests fail to reject a difference in the

[21] Due to the Re-sample subjects having the opportunity to learn in the game tasks after from their previous play and feedback we don't report those results.

mean response between the Re-sample and the pooled data. In conclusion, we believe this resampling exercise combined with the previous multivariate regression analysis provides evidence against selective participation bias for our five waves.

Table 5: Descriptive statistics and hypothesis tests for the baseline re-sample.

	Baseline 2019 May		Re-sample 2020 Feb 15-16		2020 new subjects Wave 3		Wave 4		Wave 3 & 4	
	mean	sd.	mean	sd.	mean	sd.	mean	sd.	mean	sd.
Risk attitude, gain {1,2,...,10}	4.49	0.92	4.51	1.06	4.26	1.18	4.71	1.42	4.48	1.32
Risk attitude, loss {1,2,...,10}	6.31	0.97	6.49	1.02	6.12^{A}	1.31	6.50	1.00	6.30	1.19
Ambiguity attitude {1,2,...,10}	4.50	1.13	$4.05^{\mathbf{D}}$	1.15	4.18	1.75	4.41	1.55	4.29	1.66
Number of subjects	92		92		80		78		158	

${}^{a}p$ <0.1, ${}^{A}p$ <0.05, ${}^{\mathbf{A}}p$ <0.01 for comparison of means unpaired sample Wave versus Re-sample;
${}^{d}p$ <0.1, ${}^{D}p$ <0.05, ${}^{\mathbf{D}}p$ <0.01 for comparison of means paired Re-sample versus Baseline.
For unpaired sample comparisons, two-tailed Wilcoxon rank-sum tests.
For paired sample comparisons, two-tailed Wilcoxon signed-rank tests.

5 Discussion & Conclusion

In this study, we compare incentivized choice data on pro-social and economic preferences from a baseline sample of Wuhan University students collected pre-Covid, with five independent samples elicited from the same subject population over the six weeks following stringent Covid-related lockdown measures were introduced in China at the beginning of 2020. Our experimental design affords a consistent response medium between samples and instruments. We also use geo-location data to exploit the quasi-random variation in subjects' exposure to the virus and test for differences in behaviour among those subjects who remained in Wuhan and the wider Hubei province during the post-lockdown period.

We propose that the time and place of our sample gives us a unique opportunity to shed light on this question. Hubei province, during those early days of 2020, is an ideal domain to test the impact of lockdown measures not only because it was the first (and so most unexpected) lockdown, but also because it was the "harshest of lockdowns".[22] To this extent, the uniqueness of our setting is a strength; it cleanly isolates the preference shock under study (List, 2020).

The experimental results suggest that social and risk-related preferences are liable to be influenced by formative events associated with a public health crisis. We find high levels of altruism, cooperation and aversion to risk taking under ambiguity in the immediate aftermath of the lockdown, while trust is significantly lower. Subjects also exhibit greater sensitivity to risk in both gain and loss domains. We go further and uncover significant transitory effects on trust and risk aversion within the post-lockdown sample. In particular, we observe temporary falls in these measures in our third sampling wave, which was conducted during the days that followed the death of a high-profile Chinese whistleblower.

At this point, it is important to compare our findings to those of Lohmann et al. (2021), who also experimentally investigate the short-term impact of the Covid-19 pandemic on pro-social and economic preferences in China. Unlike Lohmann et al. (2021), we find significantly lower risk aversion in gains during the post-lockdown period. One explanation for this discrepancy is differences in the respective sampling periods. Whereas we elicit a series of independent preference measurements between late January and early March, Lohmann et al. (2021) collected their post-Covid data on March 14-17, by which time the most stringent lockdown measures in China were easing.[23] Thus, at the time of our sampling, the risks associated with the novel coronavirus were less well-defined.

An interpretation consistent with our data is that individuals were more cautious when the probabilities associated with their actions were unknown (e.g., in risking exposure to the new and unfamiliar virus), but more willing to seek out risk in situations where those probabilities were well-defined (e.g., in seeking out established medical treatments). Since Lohmann et al. (2021) implemented a longitudinal design, it is further possible that attri-

[22] E.g., https://www.bbc.co.uk/news/world-asia-china-52197054.

[23] For example, on March 13, Huangshi became the first Hubei city to lift local travel restrictions: https://news.sina.com.cn/c/2020-03-13/doc-iimxyqwa0259279.shtml.

tion in their sample is masking some differences; they found that attrited individuals were significantly less risk averse than non-attrited individuals (see their Table B3).

Lohmann et al. (2021) also find no significant changes in trust or pro-social preferences between their pre- and post-Covid samples. Aside from differences in the saliency of outcomes (the trust game and public good game implemented in Lohmann et al. (2021) were not incentivized in any wave), we again believe differences in sampling dates to be important. Whereas we observe no significant aggregate effect on trust in our post-lockdown sample, we do see a sharp fall in trust within the first sampling wave conducted in late January, a time when the Chinese government's response to the virus lagged behind public awareness.[24]

Moreover, in China mortality was largely concentrated in Hubei province. Whereas 42% of subjects in our post-lockdown sample are located in Hubei, this is true of less than 2% of subjects in Lohmann et al. (2021); indeed, half of the cities inhabited by subjects in their dataset had yet to report a death by the time of their survey in mid-March. Thus, exposure to the worst effects of the virus was likely higher in our sample. A related driver of differences could stem from the subject population itself. Subjects in our study were recruited from a database of Wuhan University students; Lohmann et al. (2021) conducted experiments on a sample drawn from a population of students in Beijing. Students of Wuhan University may reasonably be expected (on average) to have closer academic and social ties to Wuhan city, which may have further increased the saliency of events early on.

Next, we comment on possible policy implications of our findings. Many non-pharmaceutical interventions designed to reduce the spread of respiratory diseases rely on initial, short-term behavioural responses among community members. Survey data collected during the SARS 1 outbreak of the early 2000s suggested the importance of behavioural and psycho-social factors in the adoption of protective measures (Leung et al., 2003). Recent evidence on measures implemented to mitigate the transmission of Covid-19 have uncovered a positive correlation between an individual's propensity to engage in precautionary behaviour and his

[24] https://www.scmp.com/news/china/politics/article/3047230/wuhan-mayor-under-pressure-resign-over-response-coronavirus.

or her level of pro-sociality and risk aversion (Campos-Mercade et al., 2021; Müller and Rau, 2021), and between generalized trust levels and perceptions of the appropriateness of media coverage (Müller and Rau, 2021).

Our results imply an additional confound in this relationship. That is, the onset of a public health crisis *itself* may have unintended consequences for economic preferences that determine population compliance with interventions designed to reduce the spread of a novel coronavirus. For example, if greater risk aversion is associated with an increased propensity to avoid public gatherings, then a shift towards greater risk tolerance in the population will make deterring such behaviours more difficult. Conversely, if individuals become less willing to take risk under ambiguity, then governments can harness this knowledge by openly communicating to the public uncertainties surrounding scientific estimates and rapidly emerging evidence (see OECD, 2020, for policy recommendations in this vein).

A related implication concerns pro-social preferences. Many Western governments have appealed to the public's notions of pro-sociality in their pandemic response (the slogan 'Stay Home, Protect the NHS, Save Lives' in the UK is but one example). If crises induce greater cooperative tendencies, then such an approach is more likely to pay social dividends. Similarly, if generalized trust correlates positively with perceptions of media coverage on the virus, then a negative shock to trust will reduce individuals' willingness to engage with a government's messaging about the virus and in turn their likelihood of complying with recommended personal protective measures. This underscores the requirement that governments take measures to actively promote the public's trust in their actions. The UK government, for example, has recently recognised the role of data transparency underpinning decisions.[25]

Finally, there are some important limitations of our study that we want to emphasize. As discussed in detail in the previous section, differential selection into the baseline and post-lockdown samples is a potential confound. While we took steps to mitigate sample imbalances in our analysis, we cannot rule out that unobserved factors influenced subjects'

[25] See parliamentary committee report available at: https://publications.parliament.uk/pa/cm5801/cmselect/cmpubadm/803/80302.htm.

selection into the post-lockdown sample and that these may also correlate with the deep economic parameters of interest. Second, we use a student sample. While student samples are not representative of the full population, their behaviours display reduced measurement error and correlate positively with non-student samples (Snowberg and Yariv, 2018). They are also a demographic that has received attention in the West regarding compliance with lockdown policies (Moore et al., 2020). Third, we cannot observe the underlying channels driving the observed preference effects. For example, Lohmann et al. (2021) provide evidence to suggest that psychological and emotional factors were important behavioural mediators in China during the pandemic. Finally, our study is context-specific and we cannot generalize to other populations. We thus view our study as adding to a collective body of evidence on the behavioural impact of the Covid-19 pandemic.

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Appendix

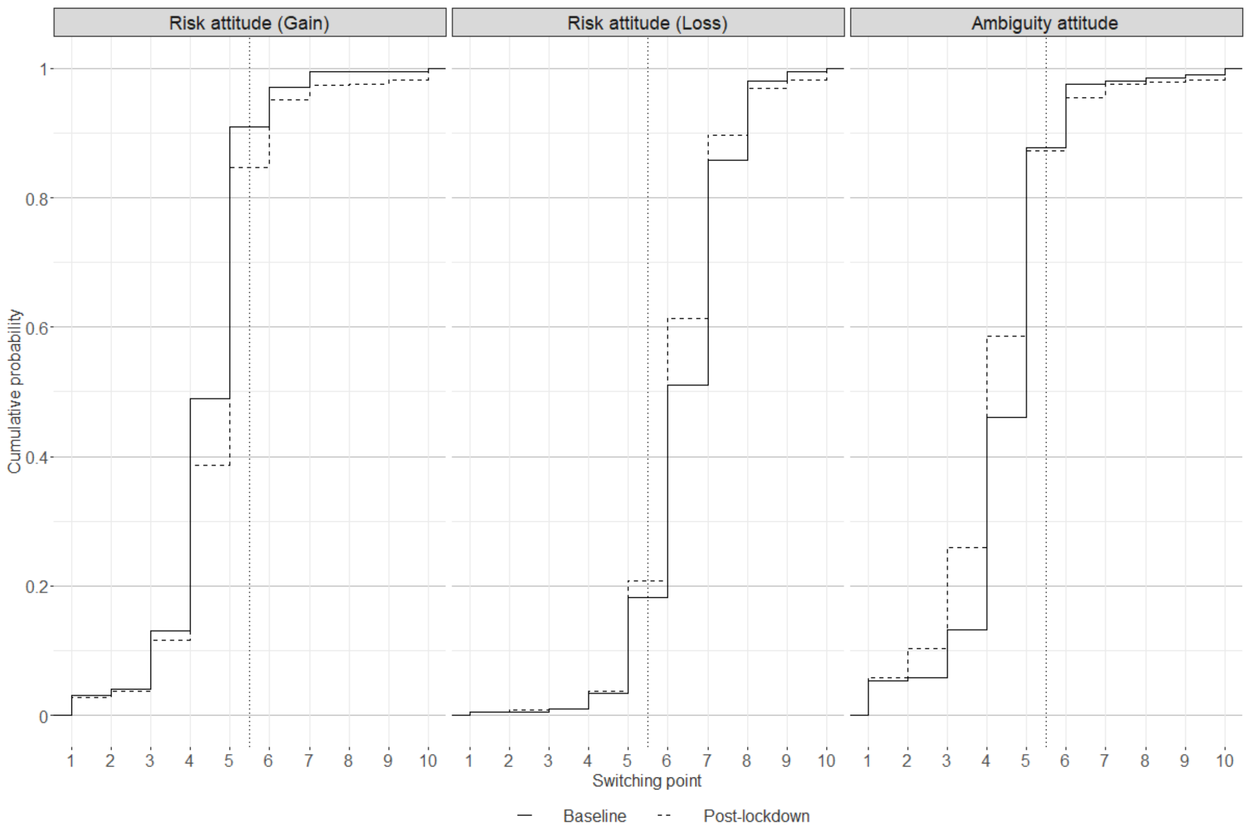

Figure A1: Comparison of c.d.f.s for switching points in the risk and ambiguity attitude elicitation tasks; the vertical dotted line corresponds to risk neutrality.

Table A1: Second-mover regression analysis pre-/post-lockdown.

	Dependent variable:	
	TG return	UG accept
	OLS	*logistic*
	(1)	(2)
Send/offer	1.28***	2.76*
	(0.15)	(1.48)
Post-lockdown	−0.12	2.45
	(0.54)	(4.12)
Wuhan	−0.74	15.53***
	(0.54)	(1.48)
Other Hubei	−0.75	−0.27
	(0.78)	(1.37)
Female	−0.65*	−0.58
	(0.37)	(0.77)
Econ	0.26	−1.04
	(0.46)	(0.74)
Send/offer*Post-lockdown	0.23	−0.72
	(0.19)	(1.41)
(Intercept)	7.21	−14.54
	(5.63)	(11.76)
Control Variables	Yes	Yes
Observations	144	146
R^2	0.74	
Log Likelihood		−27.18

Note: *p<0.1; **p<0.05; ***p<0.01.
Coefficient estimates with robust standard errors in parentheses.

Table A2: Censored (Tobit) regression analysis pre-/post-lockdown

	Dependent variable:					
	Trust	DG	UG	Risk+	Risk-	Ambiguity
	(1)	(2)	(3)	(4)	(5)	(6)
Post-lockdown	1.47**	0.31*	0.15	0.27**	−0.23**	−0.32**
	(0.67)	(0.18)	(0.21)	(0.13)	(0.11)	(0.14)
Wuhan	−3.79***	−0.33	−0.10	−0.16	−0.01	−0.20
	(1.22)	(0.33)	(0.55)	(0.21)	(0.17)	(0.26)
Other Hubei	1.81*	0.26	0.65***	−0.25	0.10	−0.03
	(1.01)	(0.23)	(0.24)	(0.17)	(0.17)	(0.22)
Female	1.60***	0.45***	0.18	−0.18	−0.13	−0.11
	(0.60)	(0.16)	(0.20)	(0.11)	(0.10)	(0.13)
Econ	1.58*	−0.04	−0.41	−0.07	0.06	−0.08
	(0.83)	(0.19)	(0.29)	(0.12)	(0.12)	(0.15)
(Intercept)	1.28	4.29**	5.46**	3.31*	3.19**	−0.28
	(10.08)	(1.94)	(2.45)	(1.86)	(1.35)	(1.97)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	153	304	151	565	581	573
Log Likelihood	−322.52	−466.37	−228.00	−954.51	−909.21	−1,053.97
Wald Test	38.44***	173.02***	23.75*	16.57	33.11***	26.22*

Note: *p<0.1; **p<0.05; ***p<0.01.
Coefficient estimates with robust standard errors in parentheses.

Table A3: Count data (Poisson) regression analysis of attitudes towards risk and ambiguity pre-/post-lockdown.

	Dependent variable:		
	Risk+	Risk-	Ambiguity
	(1)	(2)	(3)
Post-lockdown	0.06^{**}	-0.04^{**}	-0.07^{**}
	(0.03)	(0.02)	(0.03)
Wuhan	-0.03	-0.002	-0.05
	(0.04)	(0.03)	(0.06)
Other Hubei	-0.05	0.02	-0.002
	(0.03)	(0.03)	(0.05)
Female	-0.04^{*}	-0.02	-0.02
	(0.02)	(0.01)	(0.03)
Econ	-0.01	0.01	-0.02
	(0.03)	(0.02)	(0.03)
(Intercept)	1.25^{***}	1.36^{***}	0.51
	(0.39)	(0.20)	(0.42)
Control Variables	Yes	Yes	Yes
Observations	565	581	573
Log Likelihood	$-1{,}049.87$	$-1{,}134.67$	$-1{,}087.14$

Note: *p<0.1; **p<0.05; ***p<0.01.
Coefficient estimates with robust standard errors in parentheses.

Table A4: Descriptive statistics by independent sampling wave.

	Baseline		Wave 1		Wave 2	
	mean	*sd.*	*mean*	*sd.*	*mean*	*sd.*
Dictator game $[0, 5]$	1.45	1.08	1.58	1.07	1.67	1.05
Stag Hunt game {0,1}	0.88	0.33	0.84	0.37	0.82	0.39
Prisoner's Dilemma game {0,1}	0.31	0.46	$0.49^{\mathbf{A}}$	0.50	0.46^{A}	0.50
Trust game sent $[0, 8]$	3.39	2.59	1.75^{A}	1.80	4.95^{A}	2.48
Ultimatum game offer $[0, 8]$	3.08	1.04	3.36	1.21	3.16	1.31
Risk attitude, gain {1,2,...,10}	4.45	1.13	4.67^{a}	0.86	$4.92^{\mathbf{A}}$	1.47
Risk attitude, loss {1,2,...,10}	6.42	1.14	6.29	0.98	6.19^{A}	1.18
Ambiguity attitude {1,2,...,10}	4.49	1.33	4.15^{A}	1.4	$3.93^{\mathbf{A}}$	1.46
Number of subjects	206		80		78	

	Wave 3		Wave 4		Wave 5	
	mean	*sd.*	*mean*	*sd.*	*mean*	*sd.*
Dictator game $[0, 5]$	1.44	1.01	1.65	1.12	1.95^{A}	1.04
Stag Hunt game {0,1}	$0.70^{\mathbf{A}}$	0.46	$0.71^{\mathbf{A}}$	0.46	0.80	0.40
Prisoner's Dilemma game {0,1}	0.39	0.49	0.32^{c}	0.47	0.49	0.50
Trust game sent $[0, 8]$	3.6^{c}	2.44	3.66	2.73	$4.43^{\mathbf{B}}$	2.59
Ultimatum game offer $[0, 8]$	3.38	1.04	3.05	1.28	3.58^{A}	1.23
Risk attitude, gain {1,2,...,10}	$4.26^{\mathbf{C}}$	1.18	4.71	1.42	$4.95^{\mathbf{A}}$	1.58
Risk attitude, loss {1,2,...,10}	6.12^{A}	1.31	6.50^{c}	1.00	6.28	1.34
Ambiguity attitude {1,2,...,10}	$4.18^{\mathbf{A}}$	1.75	4.41	1.55	4.47^{C}	1.55
Number of subjects	80		78		80	

The following tests are two-tailed Wilcoxon rank-sum tests.
Note: $^{a}p<0.1$, $^{A}p<0.05$, $^{\mathbf{A}}p<0.01$ for comparison of means Wave versus Baseline;
$^{b}p<0.1$, $^{B}p<0.05$, $^{\mathbf{B}}p<0.01$ for comparison of means Wave 5 versus Wave 1.
$^{c}p<0.1$, $^{C}p<0.05$, $^{\mathbf{C}}p<0.01$ for comparison of means Wave 3/4/5 versus Wave 2.