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Risk Taking, Preferences, and Beliefs: Evidence from Wuhan

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Risk Taking, Preferences, and Beliefs: Evidence from Wuhan*

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Abstract:

We study risk taking in a panel of subjects in Wuhan, China - before, during the COVID-19 crisis, and after the country reopened. Subjects in our sample traveled for semester break in January, generating variation in exposure to the virus and quarantine in Wuhan. Higher exposure leads subjects to reduce planned risk taking, risky investments, and optimism. Our findings help unify existing studies by showing that aggregate shocks affect general preferences for risk and economic expectations, while heterogeneity in experience further affect risk taking through beliefs about individuals' own outcomes such as luck and sense of control.

JEL Classifications: G50, G51, G11, D14, G41

Keywords: COVID-19, Risk taking, Beliefs, Formative experiences, Expectations, China

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1. Introduction

A growing literature in economics and finance has questioned the presence of time-varying or countercyclical risk taking, a key ingredient in asset pricing models which attempt to match patterns observed in securities markets (Campbell and Cochrane, 1999; Brandt and Wang, 2003; Barberis, Huang, and Santos, 2001). A related number of studies have examined if formative experiences such as financial crises affect future risk taking (Malmendier and Nagel, 2011; Kaustia and Knüpfer, 2008, 2012; Knüpfer, Rantapuska, and Sarvimäki, 2017; Guiso, Sapienza, and Zingales, 2018; Andersen, Hanspal, and Nielsen, 2019; and Brown, Cookson, Heimer, 2019). Most studies that investigate how these shocks affect behavior use observational data on field outcomes and posit through which channels behavior may have been affected. One missing aspect of these studies is how individual risk taking may *acutely* change, in the midst of the experience or crisis itself, and importantly, whether the observed change is driven by changes in individuals' beliefs or preferences.

In this study, we attempt to help bridge these two streams of the literature. We examine time-varying risk taking in the context of the COVID-19 pandemic. Our repeated survey allows us to study risk taking, general preferences for risk, and beliefs about self and the economy before and throughout the pandemic. Our identification strategy allows us to examine how heterogeneous exposure to the pandemic affects these key parameters differently and sheds light upon the link between experiences and time-varying risk taking, and beliefs and preferences. We survey a sample of subjects in Wuhan, China – ground zero of the COVID-19 pandemic. Our first survey wave took place on October 16th 2019, several weeks before initial reports of the virus in mainland China in December 2019 (Holshue *et al.*, 2020). By January 23rd, 2020 all incoming and outgoing public transportation to and from the Hubei province (where Wuhan is the capital) was halted. Gatherings and events inside Wuhan were banned, and quarantine and isolation were established. By February 15th, 2020 Wuhan was in a state of complete and total quarantine. On February 28th 2020, we administered an online follow up survey to the same group of subjects with an 88% retention rate (N = 225/257 in our main sample). On April 8th the lockdowns and quarantine conditions in Wuhan were ended and daily life returned to pre-crisis conditions (Che, 2020). On April 19th we surveyed the same subjects in a third wave of our survey.

Our main sample consists of graduate students from Wuhan University of Science and Technology (WUST).[1] Winter break for the semester started at WUST on January 11th

[1] As part of a separate project, we obtained additional survey data on perceptions of climate risk from both Wuhan and Guizhou, a province of China approximately 1,000 kilometers from Wuhan and one of the least

2020 and students from other provinces were able to return to their homes as planned for the Chinese Lunar New Year celebrations. As the province of Hubei became quarantined and effectively locked down shortly thereafter, students from outside of Wuhan continued their study programs via distance learning (alongside their Wuhan-based peers) and we administered follow up online surveys on WeChat, capturing precise geolocation information from subjects. Wave one of our survey holds constant all subjects in the city of Wuhan, while in waves two and three, 47% of subjects from our main sample are in provinces outside of Hubei, in parts of China with substantially lower exposure to COVID-19.[2] At the time of our follow-up survey, the province of Hubei had 66,300 infection cases, while *all other provinces* across China had 12,600 in total.[3] This variation allows us to explore if individuals who are more closely impacted by the COVID-19 pandemic, as proxied by the province and city of their quarantine location, differ in their preferences and beliefs as the crisis evolves.

We find evidence of time-varying risk aversion and beliefs about the economy and in the stock market, supporting existing studies (e.g., Cohn *et al.*, 2015; Guiso, Sapienza, and Zingales, 2018). Our findings suggest that general preferences for risk and beliefs about tail risk in the stock market are uniformly affected by the COVID-19 pandemic. On the other hand, heterogeneity in experience affects planned risk taking, the allocation of risky assets, and beliefs in individual outcomes such as luck and sense of control. Laboratory studies which exogenously generate affect or variation in experience generally find shifts in risk taking are driven via the preference channel, as beliefs over probabilities can be held constant (e.g., Kuhnen and Knutson, 2011; Knuston *et al.*, 2008). Alternatively, field studies examining risk taking following formative experiences generally argue that beliefs are central to the observed increase in risk aversion (Malmendier and Nagel, 2011). Our findings help unify these differences: preferences and tail-risk beliefs vary over time, *uniformly* by subjects in our sample, and personal experiences accentuate risk aversion and appear to be driven by beliefs individuals' hold about their own outcomes. Such patterns are consistent with the hypothesis that observed changes in risk taking following cohort-level experiences (i.e., Malmendier and Nagel, 2011), aggregate substantial heterogeneity in varying degrees of personal experiences (Andersen, Hanspal, and Nielsen, 2019). Large cohort-level, or aggregate shocks may

affected areas from the COVID-19 pandemic. This survey data was also collected in pre-, during-, and post-crisis waves similar to our main sample. We additionally oversampled additional respondents in Wuhan in waves 2 and 3. Further details about the survey and sampling can be found in Section 3.

[2] Our full sample consists of 1,425 subjects, 853 of which are in other cities in China after Wave 1, 466 are in Hubei outside of the city of Wuhan, and 106 are in Wuhan.

[3] At the time of our third survey wave, Wuhan had all but recovered from the pandemic, while the United States and Europe saw significant growth in cases and deaths and were facing their own lockdowns.

therefore affect risk preferences and beliefs about the economy in the broad population while more direct experience may further affect risk taking via individuals' optimism.

We find three central results related to risk taking. First, exposure has a strong, negative, and persistent effect on *planned* risk taking. Individuals with a higher level of exposure are more likely to state that they plan to take on less risk in the following year. The proportion of subjects who state that they will take less risk in the following year after the onset of the COVID-19 pandemic more than doubles from 46.6% to 89.2%. The entirety of respondents from Wuhan state they will reduce risk taking, and 86% state they will take the lowest level of risk on the survey scale. This effect on planned risk taking is persistent through April 2020, even after the city reopens and quarantine conditions are lifted.

Second, subjects quarantined in Wuhan, with greater subjective (and arguably objective) exposure to the virus allocate significantly less to a hypothetical risky investment option relative to those in other cities within the Hubei province (-88.3 RMB), and those in other provinces of China (-159.5 RMB) and opt for the safe option. This represents an economically significant difference given a mean investment of 317.6 RMB, and constitutes a 45% smaller investment than to subjects in other provinces. As the lockdowns cease, those in Wuhan quickly revert, and increase their allocation to the risky option by 101 RMB (51%).

Third, we administer survey questions on general preferences for risk across waves to test if planned risk taking, and subjects' risky allocations coincide with time-varying generalized preferences for risk. One benefit of such questions is that they are widely used in the literature and have been experimentally validated (Dohmen *et al.*, 2018). We find that, on average, all subjects show a marginal decrease in general preferences for risk regardless of their exposure. The unconditional (conditional) decrease amounts to 12.3% (17.4%) and is highly significant at standard levels.[4] While the decrease in these general measures for those in Wuhan, with higher exposure to the pandemic, is slightly greater, the additional decrease is economically and statistically small.

We then examine several belief measures, including economic expectations, tail-risks in the stock market, and beliefs in individuals' own luck and fortune prior to and during the COVID-19 pandemic, and how they relate to risk taking. Relative to other subjects, those in Wuhan, with higher exposure to the pandemic, show a 9.4 percentage point decrease in beliefs about their own personal luck. For subjects with higher exposure, measures about individuals' sense of control are similarly negatively affected. These measures remain

[4] The unconditional (conditional) effect size is -0.31 (-0.44) relative to a pre-crisis mean scale value of 2.53 on a 5 point scale.

suppressed into April after the reopening of the Wuhan and the rest of the country, reflecting our findings for individuals' planned risk taking. In general, we find that exposure strongly affects individuals' optimism about their own outcomes and this seems to go hand in hand with plans about taking risk.

We find that subjects with higher exposure to the pandemic form more pessimistic beliefs on the economy in general, their own health, and on the environment, relative to subjects in further removed provinces. However, individuals in Wuhan, hold beliefs which quickly *rebound* after the opening up of the city, and in April do not differ from those with less exposure. In part, this rebound effect may be driven by the nature of our survey: respondents may be more likely to say that the economy will improve when they believe it is currently weak, compared to when it is strong and there is less potential for growth. At the same time, the upward adjustment in expectations closely mirrors individuals' reversion in our allocation measure of risk taking. We also measure subjective probabilities in tail events in the stock market (the Shanghai Stock exchange index, or SSE) and find significant time-series, but little cross-sectional variation.

We then relate changes in our various measures of beliefs to time-varying risk taking. We find that individuals' beliefs in self appear to be *at least as important* to changes in risk taking as individuals' economic expectations and beliefs. When we examine changes in risk taking and changes in beliefs by individuals' experience, we find that the relationship is strongest among those with the greatest level of exposure.

Finally, our setting allows us to measure individuals' fear, an ingredient often linked to time-varying risk aversion (e.g., Goetzmann, Kim, and Shiller, 2016; Hoffman, Post, and Pennings, 2012; Guiso, Sapienza, and Zingales, 2019). Importantly, we document that subjects who become quarantined in Wuhan hold subjective beliefs consistent with a higher level of exposure to the pandemic. These subjects believe that they have a higher exposure risk to COVID-19 than those elsewhere. As such, subjects located in Wuhan during the quarantine state higher probabilities that they themselves are likely to be infected, as well as higher exposure to infections and deaths within their families and communities.[5] These subjects also show higher levels of fear in the pandemic in general. Our study not only presents a plausible source of variation in fear, but also the opportunity to control for competing mechanisms such as beliefs in self and the economy. We find these other channels seem to be significantly more important to changes in risk taking, suggesting that fear likely

[5] We refer to these exposures to the virus as subjective perceptions about exposure because we can confirm that no individuals in our sample contracted the virus during our study period.

proxies individuals' beliefs (Guiso, Sapienza, and Zingales, 2018). Taken together, our findings suggest that beliefs about the economy and the stock market may be linked to general shifts in risk preferences, while beliefs about self and optimism more so to observed risk taking from experiences.

Our paper contributes to the literature in economics and finance which examines how events and experiences can shape behavior. In a seminal paper, Malmendier and Nagel (2011) show that experiences with macroeconomic shocks affect financial risk taking well into the future. A further literature has shown that personal experiences make individuals refrain from opportunities to take risk (Knüpfer, Rantapuska, and Sarvimäki, 2017; Guiso, Sapienza, and Zingales, 2018; Giannetti and Wang, 2016; Kaustia and Knüpfer, 2008, 2012; Choi, Laibson, Madrian, and Metrick, 2009; Chiang, Hirshleifer, Qian, and Sherman, 2011; Bucher-Koenen and Ziegelmeyer, 2014; Hoffmann and Post, 2017). Andersen, Hanspal, and Nielsen (2019) highlight the importance of the degree to which individuals make experiences and show that personal first-hand experiences can make individuals actively change their attitudes toward risk. One challenge of this literature, is that in the absence of individuals' forecasts, holding less risky assets may reflect high risk aversion or pessimistic expectations about the future (Malmendier and Nagel, 2011; Cohn *et al.*, 2015). Disentangling these underlying mechanisms are a challenge and a number of studies find evidence of a belief-based channel (Malmendier and Nagel, 2011; Koudijs and Voth, 2016; Kuhnen and Knutson, 2011; Laudenbach *et al.,* 2020), while others find support for a preference based channel (Knuston *et al.*, 2008; Cohn *et al.*, 2015). We contribute to this literature by providing evidence that aggregate shocks can affect general preferences and economic expectations, while heterogeneity in exposure, can acutely, further affect risk taking through beliefs about individual outcomes such as luck and sense of control.

Relatedly, our findings contribute to a literature on time-varying risk aversion (e.g., Campbell and Cochrane, 1999; Brandt and Wang, 2003; Gomes and Michaelides, 2003; Cohn *et al.*, 2015; Chetty and Szeidl, 2016; Brunnermeier and Nagel, 2008). We provide micro-level evidence of changing attitudes towards risk. We document that general risk preferences are uniformly negatively affected by the COVID-19 pandemic, while active risk taking decisions may be more affected by individual level experiences through changing beliefs and optimism.

While a number of recent studies have focused on the importance of subjective beliefs on economic outcomes (e.g., Kuhnen and Miu, 2017; Ameriks *et al.*, 2018; Kuchler and Zafar, 2019; Das, Kuhnen, and Nagel, 2019), less work has focused on how measures of beliefs are linked to different types of risk taking. Andersen *et al.*, (2020) examine this relationship in the cross-section, while Giglio *et al.*, (2019, 2020) focus on portfolio allocations and find minimal active adjustments among higher wealth investors. Knuston *et al.*, (2008) find that changes in risk taking in the lab are attributed to a change in risk preferences rather than by beliefs about probability distributions. Cohn *et al.*, (2015) find evidence supporting a preference rather than expectations channel among financial professionals. One main point of departure from these studies and ours is that the variation is exogenously determined in a lab compared to a real, and very salient systematic shock.

We also contribute to a literature which uses survey or experimental data to measure preferences and how heterogeneity in experiences affect these measures. For example, Callen *et al.* (2013) find that risk aversion is exacerbated by violent wartime experiences, particularly when these memories are made salient with priming. In contrast, Voors *et al.* (2012) and Eckel *et al.* (2009) find large shocks decrease risk aversion in their settings. Relatedly, a growing literature examines the stability of preferences over time, in the absence, or presence of various economic shocks (changes in wealth, income, unemployment, health, household composition) and extreme events (e.g., natural disaster, trauma, or war). While studies in the former generally find a limited effect on individual risk taking (Brunnemeier and Nagel, 2008; Chiaporri and Paiella, 2011), those in the latter find highly conflicting results. For example, Beine *et al.*, (2020) show subjects become more risk averse after experiencing an earthquake. Hanaoka *et al.*, (2018) studies a different earthquake and find that men become more risk loving and gamble at a higher frequency. Many other studies examining various shocks, find similarly contradictory results.[6] One point of departure from these idiosyncratic settings is that the Coronavirus pandemic is unfortunately more of a global and systemic event, thus its effect on individual preferences and behavior may indeed prove to be more robust.

Several challenges are present in this literature. As noted in Chuang and Schechter (2015), preferences are often only measured after an event, and not before, and the construction of an adequate control group is difficult, as various subsets of the population may be affected differentially. Finally, much of this discrepancy may evolve from differences in elicitation, indeed Chuang and Schechter (2015) find that survey questions are more stable than experimental measures (of social preferences) and encourage the use of surveys. Dave *et al.*, (2010) find that experiments using more simple measures of risk aversion reduces noise, Charness and Viceisza (2015) and Cook (2015) also document the complexity arising from risk elicitation methods. Finally, Dohmen *et al.,* (2011) and Lönnqvist *et al.*, (2014) find that

[6] Chuang and Schechter (2015) features a more detailed literature review on the stability of preferences and unexpected events such as war or natural disaster.

survey measures outperform experimental measures of risk aversion. In general, we contribute to this stream of the literature by studying the heterogeneous effect of exposure to a worldwide shock on several survey measures of risk taking and beliefs from a repeated panel of subjects.

Finally, we contribute to a growing number of recent studies which look at the effects of the COVID-19 pandemic on households' expectations (e.g., Hanspal, Wohlfart, and Weber, 2020; Binder, 2020; Fetzer *et al.*, 2020; Coibion *et al.*, 2020; among others).[7] Our paper is closest to two other recent studies on risk taking during the COVID-19 pandemic. Angrisani *et al.*, (2020) find that risk preferences remain constant over time across student and professional traders in a UK-based sample after the onset of the Coronavirus pandemic. Huber, Huber, and Kirchler (2020) find a preference-driven increase in risk aversion among financial professionals, echoing our finding that large shocks may affect risk via preferences if experience heterogeneity is unobservable or uniform. Shachat *et al.*, (2020) find an increase in altruism, cooperation, trust and risk *tolerance* across a sample from Wuhan. Our study differs in several dimensions: first our design allows us to examine how heterogeneity in experience and exposure affects risk taking *in addition* to an aggregate effect of the shock; second, our elicitation is survey-based; third, our baseline was measured well before the onset of the Coronavirus crisis rather than shortly after the lockdown in Wuhan. And finally, our study allows us to examine reversion to 'normal' times as China reopened its society and economy. In general, we contribute to this literature by providing evidence of individuals' experienced-based updating of beliefs and preferences throughout the COVID-19 pandemic by using survey data on a repeat panel of subjects.

Understanding how and why individuals' risk taking may change during a crisis is crucial for determining appropriate policy responses, particularly when the persistence of a downturn or crisis is unknown. If, for example, households' tolerance for risk decreases through time-varying beliefs and expectations, it may imply that observed changes in risk taking are temporary (e.g., financial market volatility and the business cycle). Such an expectations-driven shock to risk taking may impact more strongly on consumption and consumer behavior. On the other hand, if changes in observed risk taking come from a more general shift in preferences, policy responses may need to be more structural in nature and may impact long term economic growth. Our study provides evidence that aggregate shocks

[7] Undoubtedly related to the COVID-19 pandemic is a number of studies which examine how beliefs about mortality affect economic decision making. The findings from this literature are mixed and use both individual surveys and life-cycle models (e.g., Hamermesh, 1985; Hurd and McGarry, 2002; Gan et al., 2015; Puri and Robinson, 2007; Cocco and Gomes, 2012; Elder, 2013; Post and Hanewald, 2013; Heimer, Myrseth, and Schoenle, 2019).

may indeed affect individuals' general preferences for risk, and higher exposure or first-hand personal experiences may further shift risk taking through beliefs individuals hold about themselves.

Our study proceeds as follows: the second section provides additional background on the Coronavirus setting in China. In Section 3 we detail our experimental setting, discussing the baseline and follow-up survey along with information about participant selection and the timing of events. In Section 5, we present our main findings along with various other empirical results. Section 6 relates beliefs to the observed changes in risk taking and Section 7 presents robustness checks. We discuss the ramifications of our findings and conclude in the final section.

2. Background

Our study focuses on how differences in exposure to the COVID-19 pandemic affect risk taking and how risk taking may be influenced by changes in preferences and beliefs. An implicit assumption about our empirical approach and identification is that individuals located in different geolocations, i.e., the city of Wuhan, the province of Hubei, and other provinces across China, differ in their exposure to the COVID-19 pandemic. There are two, related, sources of variation by location which are important to discuss. The first is spatial heterogeneity in rates of infection and death caused by COVID-19. Figure 1 plots the cumulative infections (blue, left axis) and deaths (red, right axis) in the Hubei province of China, where the city of Wuhan is located. The dashed red and blue lines represent the cumulative sum of infections and deaths from *all other* provinces in China and are plotted on the same axes. We note that other provinces experienced significantly fewer infection cases and deaths compared to Hubei, and Wuhan, the epicenter of the pandemic, over time. This variation implies that individuals in some provinces of China will not have come into first-hand contact with the virus and are less likely to know people who have been infected or died. On the other hand, individuals in the city of Wuhan or the Hubei province are much more likely to experience COVID-19 either first-hand, or indirectly through family and friends.

Second, and related to the rates of infections and deaths, individuals across provinces and cities in China experienced stark differences in regulations and quarantine conditions during the COVID-19 pandemic. For example, at the epicenter of the pandemic, in all cities across the Hubei province, citizens were not permitted to go outside and leave their living spaces under normal circumstances. Supermarkets, grocery stores, and pharmacies were not open to serve individuals. Rather, the government organized special personnel to purchase living materials for residents and distributed and delivered them throughout communities. All public transportation was completely shut down. Furthermore, the local police patrolled cities vigilantly and individuals found outside without permission were placed in government assigned quarantine stations for 14 days.[8] This aspect of our setting has the advantage in that the effect we find between subjects in Wuhan and in other areas of Hubei should not be driven by quarantine or lockdown effects, as it is effectively held constant across the province.

For individuals in other provinces across China, the quarantine conditions differed substantially. In most areas, each household could assign a family member allowed to make purchases for basic food and living materials every two days. Supermarkets, grocery stores, and pharmacies remained open for individuals. Public transportation was only partially shut down or disrupted for short periods of time in most cities. Finally, citizens were still permitted to leave their communities for limited, necessary, activities. These differences in quarantine conditions are directly related to the severity of the pandemic, however it is likely that individuals experiencing the first-hand effects of the pandemic and the harshest quarantine conditions will be significantly affected compared to those with lower exposure to the virus itself as well as substantially more flexible living conditions.

3. Experimental design

a. Participant selection

In many universities across China students are grouped into cohorts in order to better supervise and manage the large number of incoming students. The size of these cohorts varies at different universities but are normally between 30 and 60 students.[9] Once a cohort is formed, the students generally remain within the same cohort for the entire study period at their respective university. Cohorts differ from classes, and students from the same cohort do not always attend the same lectures or study programs. Each cohort is managed by a supervisor. This supervisor uses social networking apps and tools such as WeChat as a daily communication and management platform for the students. Specifically, supervisors create a WeChat group for each class that they manage where students must join such that everyone can be informed about announcements made by their supervisors. We use these cohorts and

[8] Firsthand accounts suggest that the quarantine measures in the city of Wuhan were a strong deterrent. Video clips circulating on social networking sites display police in Hubei arresting citizens and placing them into forced quarantine.

[9] Also see Bu *et al.*, (2020b) for an additional description of the dormitory and cohort set up common in China and at WUST.

WeChat groups to recruit and segment samples for participation in our study. To encourage students to complete the survey, we offered students a small participation incentive (5 to 10 RMB).

b. Baseline surveys

From October 16, 2019 to October 18, 2019 we conducted a survey based experiment with master students at Wuhan University of Science and Technology (WUST). The survey was conducted primarily for a study on how beliefs about luck and superstition affect risk taking and investment behavior (Bu *et al.*, 2020a). We administered the paper and pencil survey among 257 master's students in a classroom setting. Each postgraduate cohort at WUST typically comprises 30 to 40 postgraduate students. We randomly selected 8 postgraduate cohorts from a pool of more than 90. We collaborated with the cohort supervisors who organized that their students attend our survey sessions.

The survey consisted of several parts. First, students provided demographic information such as age, gender, date of birth, and birth province. After this information students were asked to answer a set of questions aimed to measure individual confidence (or over-confidence). Specifically, subjects answered 10 trivia, fact-based questions and were asked to provide a lower and upper bound for the 90 percent confidence interval of each provided answer. Following these questions, subjects were asked to provide answers to five standard and simple financial literacy questions on compounding interest, inflation, bond and mortgage markets, and diversification.[10]

We then asked 13 questions on beliefs in good luck following Darke and Freedman (1997). We then presented subjects an exercise where we asked individuals to provide probabilities over the next 12 months of Shanghai Stock exchange index. We then asked subjects about gambling and luck behavior with a 10-item questionnaire (Wood and Clapham, 2005). Finally, we questioned subjects on their general preferences for risk following (Dohmen *et al.*, 2018).[11]

From November 25, 2019 to December 3, 2019 we conducted a separate survey among master students at WUST focused on beliefs and preferences related to climate

[10] Refer to Online Appendix A for an English translation of they survey questions.

[11] In our experiment 130 students (51%) received a simple treatment while the other half acted as our control sample. The treated group of students were asked to read a short (approximately five-minute) excerpt from an article about the "Zodiac birth year" superstition, while the control group read a similar length article excerpt with content about the historical origin of Chinese New Year. This was for our original project on beliefs in luck and investment behavior. Controlling for, or studying sub-groups of within-sample have no economic or statistical effect on our results

change. Similar to our main survey above, we administered this climate risk paper and pencil survey among 12 randomly selected post graduate classes comprising 597 participants. The sessions were administered with course counselors similar to described above. The focus of this survey was on perceived climate change risk and pro-environmental behavior. Appendix Table 1 provides a summary of our key survey questions by wave and by survey sample.

c. Follow up surveys

Shortly following the administration of our baseline survey, the city of Wuhan became the epicenter for a worldwide health-crisis, the COVID-19 pandemic. Reports suggest that the Coronavirus began in December 2019 in the Huanan seafood market in downtown Wuhan (WHO, 2020). Winter break for the semester started at WUST on January 11^{th}, 2020. Wuhan was locked down on January 23^{rd}, 2020, and by then most students from regions outside of Wuhan had left the city for holidays to celebrate China's Lunar New Year.

From February 28, 2020 to March 3, 2020, we administered an online follow up survey to the same subject pool as our first survey. The follow up was administered to 225 students from the original 257 student sample. At the same time, we randomly selected 25 new postgraduate cohorts from WUST comprising 605 additional respondents for waves 2 and 3 of the survey. All teaching activities were moved to online distance learning initiatives. We were therefore able to create an online version of our initial survey and students submitted their survey responses similar to their other course work. Again, we collaborated with the managers of the student cohorts, this time to share the survey link to the WeChat groups. The online survey tool allows us to capture precise information about subjects' location. We map the provided geolocation coordinates to cities and provinces across China. A translated screenshot of the online survey is provided in Appendix Figure 2. In addition to the questions from our baseline survey, we also included questions on generalized trust as found in the World Values Survey and Kosse *et al.* (2020) and Falk *et al.* (2018). We also included questions on general uncertainty and subjects' experiences with COVID-19.

On April 8^{th} the lockdowns and quarantine conditions in Wuhan were ended and daily life returned to pre-crisis conditions (Che, 2020). On April 19^{th} we surveyed the same subjects in a third wave of our survey. In this survey wave we repeated all questions from previous waves and additionally asked demographic questions about socioeconomic status and potential sources of heterogeneity.

Table 1 provides descriptive statistics on the subjects in our main sample. Panel B shows the mean values of age, gender, and indicators for the main occupation of the parents for subjects from Wuhan and those from other provinces in wave one of our survey. We note that the sample is highly balanced along these variables.

4. Exposure to and fear of COVID-19

a. Perceptions of exposure to the COVID-19 pandemic

The starting point of our study is to measure how individuals in our sample perceive their exposure to COVID-19. In Figure 2, we plot the mean response to survey questions asking subjects about exposure to infection cases. We compare the mean responses from students who are quarantined in Wuhan with students who are quarantined in the province of Hubei, outside of Wuhan, and with subjects who returned to other provinces during semester break and are quarantined in other, less affected, provinces of China. We largely find that subjects in Wuhan believe that they have a higher exposure to COVID-19 than students located elsewhere. Figure 2 plots this result across panels for confirmed cases in the community where the subject is currently, confirmed cases among family and friends, and confirmed deaths from COVID-19 in the community where the subject is currently. Table 2 presents this results in a regression framework. We note that our main analyses uses OLS linear regressions however our results are robust to nonlinear methods or ordered logit regressions (as many of the survey questions are on ordinal scales).

The differences in subjective beliefs individuals have about their exposure to Coronavirus are likely to be realistic. As noted, Figure 1 plots the cumulative infections (blue, left axis) and deaths (red, right axis) in the Hubei province of China, where Wuhan is located. The dashed red and blue lines represent the cumulative sum of infections and deaths from *all other* provinces in China and are plotted on the same axes. The dashed gray line states the timing of our follow up survey wave. We note that other provinces experienced a significantly fewer infection cases and deaths compared to Hubei, and Wuhan, the epicenter of the pandemic, at the time of our follow up survey.

b. Fear of the COVID-19 pandemic

Given that subjects in our sample have varying levels of exposure to the pandemic, we expect this to result in differences in perceived fear and risk of the virus itself. We test this in Table Columns 4 and 5 of Table 2 and plot the results in Figure 3. Panel A displays the mean values of the question 'do you think you are likely to become infected with COVID-19?' Responses are on a scale between (1) and (5) for 'very unlikely to 'very likely.' Panel B plots the mean values of a question asking if the subject is afraid of the Coronavirus pandemic. Responses are on a scale between (1) and (5) for 'not afraid at all' to 'very afraid.' We find that subjects located in Wuhan during the quarantine state that they are more likely to be infected with COVID-19, and subjects in the provinces of Hubei and Wuhan are equally more afraid of the virus in general compared to those in other provinces. After the main quarantine and lockdown periods end (April 2020) subjective beliefs in infection and general fear of the pandemic decrease significantly (Figure 3), and decrease marginally less for those in Wuhan.

5. Main results: Risk taking, preferences, and beliefs

a. Risk tolerance during the COVID-19 pandemic

Having established that individuals quarantined in Wuhan have higher exposure and more fear of the pandemic, the natural next step is to examine how subjects perceive risk, and if their tolerance to risk is affected due to varying exposure and experiences made during the pandemic.

We first study how differences in exposure affects *planned* risk taking with a survey question asking subjects if they will take more or less risk in the next year compared to the last year. The score ranges from 1 (less risk) to 5 (more risk) and were elicited in all survey waves in our main sample and in waves 2 and 3 in our supplemental survey datasets. As shown clearly in Figure 4 (Panel A), subjects reduce planned risk taking significantly from October to March. The proportion of subjects who state that they will take less risk in the following year after the onset of the Coronavirus pandemic more than doubles from 46.6% to 89.2%. Additionally, individuals with a higher level of exposure from Wuhan, are more likely to state that they plan to take on less risk in the following year. The entirety of respondents from Wuhan state they will reduce risk taking, and 86% state they will take the lowest level of risk on the survey scale. This effect on planned risk taking is persistent through April 2020, even after the city opened up again. In Panel A of Table 3, we present the results in a regression framework for the full sample with and without control variables (Columns 1 and 2), for our total sample (Columns 1-2), and for our main sample (WUST) in Column 4. Columns 1-3 present indicators for each survey wave while in Column 4 we interact exposure with a *post* variable which takes the value of 1 in waves 2 and 3, after the spread of COVID-19. The exposure variables *Hubei subjects* and *Wuhan subjects* are indicators which take the value of one if the subject is located in either the state of Hubei, outside of Wuhan, or in the city of Wuhan, after the COVID-19 outbreak begins. Across columns the table shows that individuals in Wuhan relative to those in other parts of China and those in Hubei are more likely to state that they will reduce risk taking in the next one year, following the onset of the COVID-19 pandemic.

One question which arises is if the change in risk taking may be driven by changes in wealth or financial constraints stemming from the COVID-19 crisis. Our ability to examine the underlying assets of subjects in our sample is limited, however we do ask subjects about the labor market activity of their families which we use to proxy for wealth or potential financial constraints. We examine this as part of our analysis on heterogeneity in Panel A of Table 4. To study heterogeneity in subjects' characteristics we run separate regressions by subgroup of interest within our main sample (WUST). Column 1 (2) conditions the sample to men (women) and Column 3 (4) examines low (high) socioeconomic status subjects as measured by main employment of their parents. Low socioeconomic employment categories are those who indicate that their parents main occupation is jobless, factory work, peasantry, or in support services. It is likely that these groups would face greater challenges in the face of income shocks, and those in the services industry may be particular affected by a shutdown. The high socioeconomic status group consists of the remainder of individuals. The change in risk taking for those with higher exposure is slightly stronger for women, although not statistically different from men. We also note that those from lower socioeconomic status seem to decrease planned risk taking significantly more than other individuals, echoing recent work documenting differences in risk taking behavior by socioeconomic status (Das, Kuhnen, and Nagel, 2019). This effect is marginally significant, and as we note in the following, does not appear to be a particularly robust finding across our measures of changes in risk taking.

We next examine a financial measure of risk taking by eliciting subjects' allocation to a risky investment from a hypothetical gamble. This measure of financial risk taking was elicited in our survey during the COVID-19 pandemic in March 2020 as well as in wave 3 (April 2020). Subjects can chose an amount (0-1000 RMB) to be invested with 50% probability of a higher return (3000 RMB if all invested) or 50% probability of a loss (0 RMB if all invested). The alternative investment is a risk free payment (1000 RMB if all invested).[12] We differentiate between students who are quarantined in Wuhan, versus those who are quarantined at home in Hubei, and those in different provinces in China. Panel B of Figure 4 shows that subjects in Wuhan, with greater exposure to the pandemic, allocate significantly less to the risky gamble. The mean (median) investment across the entire sample in March 2020 is 317.7 (300) RMB. Panel B of Table 3 highlights cross-sectional differences in exposure in the amount invested. The variables of interest are indicators for where the

[12] 100 RMB = approximately 14.25 USD in March 2020.

subjects are located during wave 2 (March 2020 in Column 1) and wave 3 (April 2020 in Column 2). In Column 3 we pool both waves and interact individuals' exposure (measured by their location) with an indicator for wave 3 and include individual fixed effects. In general the results show that individuals in Wuhan allocate less to the risky investment compared to those in other regions of China during the peak of the COVID-19 pandemic, the effect is economically and statistically significant and represents a 45% (31%) decrease in investment relative to subjects in other provinces (other cities of Hubei). They also increase their financial risk taking significantly after the end of the lockdowns in Wuhan. They increase risk taking by approximately 120 RMB more than those in other regions.

In Panel B of Table 5 we examine heterogeneity in our lottery measure of risk taking. We note that women with greater exposure to the pandemic in our sample allocate even less to the risky investment compared to those with further removed experiences and seem to revert to a higher value as compared to men, however this is not statistically significant at standard levels. We also find that higher socioeconomic status subjects from Wuhan increase risk taking by a higher degree following the reopening of the city. The heterogeneity in risk taking by gender is in line with previous findings (Croson and Gneezy, 2009; Charness and Gneezy, 2012; Andersen *et al.*, 2020), and complements recent findings about how gender norms and experiences affect economic outcomes and forecasts (D'Acunto *et al.*, 2019; D'Acunto, Malmendier and Weber, 2020).

b. General preferences for risk during the COVID-19 pandemic

We next examine how general preferences for risk evolved through the COVID-19 pandemic. In Panel C of Figure 4, we plot the score from an established survey question on general attitudes to risk. The survey question is a direct translation of the general risk preference question validated by Falk *et al.,* (2016, 2018), 'In general, how willing are you to take risks?' Subjects are asked to respond on a scale of 1 (low willingness to take risk) to 5 (high willingness to take risk). These risk questions are elicited in each survey wave. The figure shows that the total sample of subjects elicited first in Wuhan and later at the place of the quarantine show a large and significant decrease in risk appetite (an increase to risk aversion). We examine these differences statistically in Panel C of Table 3. The decrease amounts to -0.44 on the 5 point scale and is significant at standard levels (t-stat = -9.76, *Wave 2* in Column 2). Given a mean value in wave 1 of 2.53, this constitutes a substantial 17.4% decrease. In Columns 3-5 we interact the exposure measures with the time-trend as in previous tables to consider if subjects in Wuhan compared to those in other regions further removed from the pandemic, reduce general preferences from risk. We find that all groups seem to decrease *equally* in their preferences of risk. Our generalized measures of risk do not seem to vary more for subjects with higher exposure to the pandemic compared to those outside of the most affected province. This suggests that the observed differences in risk taking, as measured by planned risk and allocation decisions, may not be driven solely by changes in general risk preferences.[13] We also note in Panel C of Table 4, that there seems to be no significant heterogeneity in these results by gender or socioeconomic status.

Our results show a large increase in risk aversion from before the COVID-19 pandemic to its peak in Wuhan. It is plausible that this effect is partially driven by an increase in fear as attributed to risk taking following the financial crisis of 2007-2009 (Guiso, Sapienza, and Zingales, 2018). However, as shown in Figures 2 and 3, higher fear and second-hand experiences (exposure to COVID-19 via family and community) are concentrated among individuals with higher levels of exposure. We further examine the link between fear and risk taking in Section 6.c. Two additional, and related channels which we first wish to examine are how optimism, beliefs about luck and sense of control, and beliefs about the economy can influence risk taking. We first explore the time variation in these measures in the following subsection, and the link to risk taking in Section 6.

c. Beliefs about luck and individuals' sense of control

As our initial study was formulated to study optimism, beliefs in individuals' own luck, and investment decisions, we elicited several measures of these behavioral traits prior to and during the COVID-19 pandemic. In Table 5 we explore how these measures evolved over time, and how experience with the pandemic may affect them. Figure 5 presents the results visually. In Panel A we plot the mean values of an index of optimism created based on individuals' belief in good luck from Darke and Freedman (1997),[14] which ranges from 0 (low belief in their own personal luck) to 1 (high belief in their own personal luck). The score was elicited across all survey waves in our main sample. As previously, we plot the values for both periods based on subjects' exposure, proxied by location in the lockdown. The variables of interest are *Hubei subjects*, an indictor variable which takes the value of one if subjects are quarantined in the Hubei province, *Wuhan subjects,* which takes the value of one if subjects

[13] To further elaborate on this point, in Appendix Table 3, we present Panels A and B from Table 3 while controlling for time-varying general risk preferences. We note that the experience effect on risk taking remains econmically and statistically signifcant and the point estimates increase slightly.

[14] The index is created based on statements that subjects agree or disagree with such as 'I consider myself to be a lucky person;' 'I believe in luck;' and 'I often feel like it's my lucky day.' Further information about the survey can be found in Online Appendix A.

are quarantined in the city of Wuhan, and the interaction of the two location variables with the time trend (an indicator for post-lockdown which takes the value of one for both wave 2 and wave 3. We find a large decrease for subjects in Wuhan in their beliefs about how lucky they are personally, while prior to the pandemic their belief in luck was statistically equivalent to subjects from other provinces. This is best shown in Column 2 with interaction the *Wuhan* dummy with the *post* variable. The effect in both post-periods is -9.5 percentage points, highly statistically significant, and similar when we use only the full sample and include individual fixed effects (Columns 3 and 4). The size of the effect is also economically important, give pre-COVID the mean scale value for all subjects was 0.55, thus the treatment effect is approximately 17%.

In Panel B of Figure 5 we plot the mean value of an index on beliefs about subjects' sense of control over their own outcomes and luck. The survey questions are based on the Drake Beliefs about Chance (DRC) Inventory (Wood and Clapham, 2005) and contain a battery of statements such as 'If I concentrate hard enough I might be able to influence whether I win when I play (game),' and 'If I am well prepared, I have very large likelihood to win a gamble.' We find that subjects from Wuhan show lower beliefs in their individual sense of control as measured by the DRC survey statements from pre-pandemic to its peak, relative to subjects in other provinces. In Columns 5-8 of Table 5, we note that Wuhan subjects in the post-period, decrease their beliefs about their own sense of control by approximately 5.8 percentage points. Again, an economically relevant decrease given a pre-pandemic mean scale value of 0.43, corresponding to a 13.3% effect.

In general, our findings suggest that higher exposure to the COVID-19 pandemic, and therefore more direct and acute experiences, have a strong negative effect on individuals' beliefs in optimism, and sense of individual control.

d. Beliefs and expectations on economic indicators

A number of recent studies have focused on the importance of subjective beliefs on economic outcomes (Kuhnen and Miu, 2017; Ameriks *et al.*, 2018; Giglio *et al.*, 2019; Kuchler and Zafar, 2019; Das, Kuhnen, and Nagel, 2019; Andersen *et al.*, 2020; Hanspal, Wohlfart, and Weber, 2020). In this section we examine how exposure to the pandemic may affect such expectations in the stock market, and broader beliefs about future economic activity and social conditions.

We study expectations in two ways: first we measure scale-based survey questions on future economic outcomes, i.e., 'compared to last year, China's economy (your health;

China's natural environment) will become better in the next 12 months.' The scale ranges from (1) to (5) for 'strongly disagree' to 'strongly agree.' Secondly we ask subjects to assign probabilities to market returns from 6 scenarios and form a probability distribution. We create indicator variables for probabilities of tail events of these probability bins for the Shanghai Stock Exchange index (SSE).[15]

In Figure 7 we plot the mean values of these two types measures of beliefs for subjects quarantined in Wuhan, subjects in Hubei outside of the city of Wuhan, and for subjects in other provinces of China. We note in Panels A, B, and C, that subjects more closely experiencing the COVID-19 pandemic largely form more pessimistic beliefs in the general economy, social conditions, and financial market indices, relative to subjects in provinces further removed from the pandemic. This is clearly displayed by the elicited lower level of expectations in the March 2020 wave of the survey. On the right of each plot, we note that expectations for those in Wuhan and Hubei revise upwards significantly in April 2020, after the province reopens and the local risk of the pandemic dissipates. In part, this rebound effect may be driven by the nature of our survey: respondents may be more likely to say that the economy will improve when they believe it is currently weak, compared to when it is strong and there is less potential for growth.

These results are also shown conditional on individual fixed effects and control variables in Panel A of Table 6. As previous, the coefficients of interest are the interaction terms between individuals' location (exposure) and the post-period. We note that in Panel A, *post* represents the change from wave 2 to wave 3 of the survey.

In Panels D and E of Figure 7, we measure subjective probabilities in tail events in the stock market. Panel D (Panel E) plots the probability weight subjects placed in bin corresponding with the outcome of market returns of less than -20% (greater than +20%) in the Shanghai Stock Exchange index. These figures correspond to Columns 1 and 2 of Panel B in Table 6. In Columns 3 and 4 the dependent variable is an indicator taking the value of one for individuals who placed more than 25% weight in these probability bins. In general both the figure and the table suggest there is significant variation in the time-series. Subjects strongly increase (decrease) their belief in the probability of large losses (gains) in the stock market following the onset of the COVID-19 pandemic. As the pandemic largely resolves in China, individuals slightly upwards revise their beliefs. However, we find little

[15] We prefer to examine tail probabilities rather than mean expected returns because of a potential data loss from our survey provider in wave 3 of the survey, omitting elicited probabilities in a number of mid-range bins.

cross-sectional variation. Personal experiences with the COVID-19 pandemic, do not seem to further affect individuals' beliefs and expectations in tail-risks in the stock market.[16]

As these expectations are forward looking, we cannot ascertain if individuals with more acute experiences provide more *accurate* responses, perhaps because they have more local and relevant information, or if they are more likely to provide biased forecasts. In the first wave of our survey we note that individuals from different locations (prior to their exposure and experience to the pandemic) did not differ statistically in their responses either for tail risks or expected mean returns. Recent evidence suggests experience may cause subjects to provide more imprecise forecasts (Goldfayn-Frank and Wohlfart, 2019; Kuchler and Zafar, 2019). In general, our results show that subjects with higher exposure to the pandemic form more pessimistic beliefs on the economy, the stock market, their own health, and on the environment, relative to subjects in further removed provinces.

6. Beliefs and time-varying risk taking

Thus far, our findings suggest both significant time-series variation in risk taking and beliefs, and cross-sectional differences based on individuals' experience and exposure to the COVID-19 pandemic. A central question our study aims to answer is through which mechanisms do contemporaneous experiences affect risk taking? A body of work has documented heterogeneity over the life-cycle and stability in general preferences (Dohmen *et al.*, 2017; Falk *et al.,* 2018). Recent literature has focused on potential explanations for changing observed measures of risk taking. Time-varying risk aversion may be a function of changing preferences (Kuhnen and Knutson, 2011; Knutson *et al.*, 2008), emotions, e.g., fear (Loewenstein *et al.,* 2001; Lerner *et al.*, 2003; Goetzmann, Kim, and Shiller, 2016; Hoffman, Post, and Pennings, 2012; Guiso, Sapienza, and Zingales, 2019), or potentially time-varying beliefs or expectations. The latter has been discussed broadly, (e.g., Malmendier and Nagel, 2011), however are difficult to pinpoint empirically. In this section we specifically examine the link between various measures of beliefs on changes in risk taking.

a. Economic expectation, beliefs about self, and risk taking

In Table 7 we examine how changes in risk taking are affected by various measures of expectations and beliefs. Recall in the previous section that almost 90% of individuals in our main sample stated that they would take less risk in the next 12 months when asked during

[16] We provide a similar heterogeneity analysis on these belief measures in Appendix Table 4.

the peak of the lockdowns in March. Nearly 65% of individuals *reduce* the stated amount of risk they plan to take in the next 12 months from October to March. Given the substantial number of subjects decreasing planned risk taking, particularly those exposed to the COVID-19 pandemic, it seems relevant to understand if this decrease in planned risk taking may be linked to heterogeneity in expectations about the future.

In Panel A the dependent variable is an indicator we create for *decreasing* planned risk taking from wave 1 of the survey (October 2019) to wave 2 (March 2020). We analyze how our various measures of individuals' expectations affected the probability that individuals reduced stated planned risk taking. In Columns 1-4, the variable *Economy improve* is the Likert scaled based question asking subjects if they believe the economy will be better in 12 months compared to now (scale 1-5, 1 = strongly disagree, 5 = strongly agree). The variables *⊿ Optimism* and *⊿ Sense* of control are the change in individuals' beliefs in their own optimism and their sense of control from wave 1 to wave 2, while the variable *⊿ P(High mkt returns)* allows us to measure individuals' beliefs in tail events in the stock market, as it measures the change in probability of expected annual returns greater than 20% in the Shanghai Stock exchange index. We bring these various measures to the same scale in Columns 5-8 by creating indicators which measure if subjects *decreased* their belief in the economy, their own optimism, or in their own sense of control from wave 1 to wave 2. While the related literature has documented a link between beliefs and risk taking (Andersen *et al.*, 2020; Giglio *et al.*, 2020; Giglio *et al.*, 2019; Hanspal, Weber, and Wohlfart, 2020), these recent studies either examine this relationship in the cross-section, or focus on risk taking in the field, i.e., portfolio allocations, and highlight minimal active adjustments. Table 7 in our study highlights that changes in beliefs go hand-in-hand with stated measures of planned risk taking. In addition, we note that the focus of extant literature has been macroeconomic expectations, or beliefs on the aggregate stock market. Panel A provides evidence that beliefs in other domains, such as beliefs about optimism and self, seem to be at least as important for determining changes in risk taking as more economic expectations. Subjects who decreased their level of individual optimism were 12 percentage points more likely to have reduced planned risk taking, those who reduced their sense of control, almost 30 percentage points more likely. These effects from beliefs in self contrast with our measures of economic expectations which do not correlate directly to changes in risk taking.

In Panel B the dependent variable is an indicator for decreasing risk allocation based on a hypothetical lottery from wave 2 of the survey (March 2020) to wave 3 (April 2020). This specification allows us to examine the link between beliefs and quantitative measures of risk taking from peak to trough. The variables are defined as in Panel A with the exception that all variables are coded as changes from wave 2 to wave 3. Recall from Table 4 that the mean allocation to the risky lottery stays about the same from wave 2 to wave 3 (mean of 318 to 321 RMB), however underlying this mean effect there is significant heterogeneity. As highlighted in Figure 4, individuals from Wuhan were likely to increase their allocation to the risky asset in April relative to March, and approximately 44% of all subjects decreased risk taking by allocating less to the risky lottery. In general Panel B shows that individuals' expectations play an important role in this heterogeneity in risk taking. A one-point change on the scale of individual optimism (sense of control) expectations results in a 25 (35) percentage point decrease in the probability of reducing risk allocations. The effect of beliefs in the economy shows an unexpected sign and becomes marginally significant as an indicator variable (Column 8). In general, the table suggests that subjects' beliefs in self play more of an important role in risk taking than their expectations about the economy.[17]

b. Experiences, beliefs, and risk taking

One important question which arises is if the individuals who had the largest exposure to the virus, are those who shift beliefs in their own luck and outcomes alongside the observed shifts in risk taking. This is indeed the case and best shown visually. In Panel A of Figure 7, we plot the unconditional mean values in changes in beliefs in optimism (left panel), beliefs in sense of control (middle panel), and planned risk taking (right panel), by individuals' experience as measured by their location and their exposure to the COVID-19 pandemic. These values confirm previous results showing that those in Wuhan, show the largest decreases in their planned risk taking alongside measures of beliefs in self.

What Panel A lacks however, is a direct link between changes in beliefs, changes in risk taking, and individuals' experiences. In Panel B, we plot the coefficient values from a regression of changes in beliefs in optimism and beliefs in sense of control on an indicator for lower planned risk taking from wave 1 to wave 2. Each bar is the coefficient value from a regression conditional on experience, i.e., we regress beliefs on risk taking for individuals in all other provinces in China, for those in other cities of Hubei, and finally for those in Wuhan, while controlling for demographic variables. We note that individuals in Wuhan show a stronger association between beliefs and changes in risk taking compared to those with further removed experiences. In total, Figure 7 provides evidence that experiences

[17] In this section we focus on changes in planned risk and the risky allocation as previously we have shown that changes in general risk preferences do not vary significantly with heterogeneous experiences.

generate greater changes in both beliefs in self and in planned risk taking, and that the correlation between reduced risk taking and changes in beliefs is strongest for those with closer exposure to the COVID-19 pandemic.

Table 8 provides additional support. Individuals from Wuhan compared to those from other provinces in China are more than 20 percentage points more likely to decrease planned risk taking, and 39 and 40 percentage points more likely to revise downward their beliefs on their own luck and sense of control, respectively. We also note that these individuals hold slightly more pessimistic beliefs in the stock market, by placing 3 percentage points higher weight into the bin corresponding to less than 20% returns of the market index. As a note of caution, we do not place great weight onto a differences analysis of expectations in the economy improving variable as this is cross-sectional given that we do not have an observation from the pre-COVID-19 period. Another point that we wish to highlight in the Table is the relative fraction of subjects who downward adjust beliefs in self. Columns 3 and 4 show, that conditional on stating a lower planned risk taking during March compared to October, 93.6% subjects in Wuhan reduce beliefs in optimism, and 75% reduce beliefs in sense of control, almost twice that of their peers quarantined in other cities across China. In general, Table 8 confirms our hypothesis that general preferences in risk and economic expectations do not vary considerably by experience, while cross-sectional differences in exposure to the COVID-19 pandemic greatly underlie planned risk taking via differences in beliefs about subjects' own outcomes.[18]

c. Individuals' perceptions of fear and risk taking

Time-varying risk aversion has been hypothesized to be an outcome of varying emotions such as fear, and has been the focus of previous studies, in particularly those relating risk taking to financial crises (e.g., Goetzmann, Kim, and Shiller, 2016; Hoffman, Post, and Pennings, 2012; Guiso, Sapienza, and Zingales, 2019). As such, an important aspect of our study is to understand how heterogeneity and *changes* in fear may affect changes in risk taking. Our study has therefore two significant advantages. First, we can examine fear in an arguably realistic manner, as individuals are exposed to a deadly virus, which at the time of our study, was not well understood and garnered significant attention. Secondly, we can control for, and compare the effect of fear to, individual beliefs in self and in economic outcomes.

[18] Appendix Table 5 also provides the differences in these outcome variables between subjects in Wuhan and those in other cities of Hubei.

In Table 9 we follow our approach in Table 7 and add individual measures of fear and risk of infection to the analysis. Specifically, Columns 1-4 the dependent variable is the change in planned risk taking from October to March (as in Panel A, Table 7), while in Columns 5-8 it is the change in the risky allocation from March to April (as in Panel B, Table 7). Columns 1, 3, 5, and 7 relate our two measures of fear to the change in risk taking while control for standard covariates. Columns 2, 4, 6, and 8 also control for the previously described measures of individual beliefs. *Fear* and *risk of infection* are scale based measures elicited during March about fear in the pandemic, and how likely individuals belief they may become infected. In Columns 3 and 4 we create indicators based on these measures if individuals state a high level of fear or risk of infection (i.e., greater than 3 on a 5-point scale). In Columns 5 and 6, *⊿ Fear* and *⊿ Risk of infection* relate the change in these measures from wave 2 to wave 3 to risk taking, and in Columns 7 and 8 we create indicators for a positive change from wave 2 to wave 3 (i.e., increased fear of the pandemic or risk of infection). While one may not expect that fear or risk of infection necessarily increases as the pandemic effects wane from March to April as the country reopens, we do note that approximately 32% (29%) of subjects reported higher levels of fear (risk of infection). This construction of variables, also allows us to keep our scale with expectations constant between analyses.

In general, we find unconditionally, fear and individuals' subjective beliefs over risk of infection indeed are positively associated with greater increases in risk aversion. However, once we control for individual beliefs in self and on the economy and stock market we find these effects to be economically and statistically insignificant. At the same time, our measures of beliefs remain relatively unchanged from Table 7. While we find in the cross-section, exposure to the COVID-19 pandemic indeed effects individuals' fears and subjective risks of being infected (Figure 2 and 3 and Table 3), we note that these measures do not predict changes in risk taking, compared to our measures of beliefs. In sum, our analysis of the relationship between emotions such as fear and changes in risk taking shows that individuals' beliefs in self remain to be an important aspect of changes in risk taking while fear does not seem to play a role in our setting.

7. Additional analysis and discussion

a. Use of VPNs (Virtual Private Networks)

One cause for concern is in our measure of location based exposure. If individuals in China use VPNs, for example to avoid firewall restrictions as has been documented in previous studies (Chen and Yang, 2019; Roberts *et al.*, 2010), this could pose a problem for our identification strategy. Essentially individuals would appear in our dataset to be in one location, however actually be located elsewhere. We believe that this is not a concern in our sample for two reasons. First, the first wave of the survey was administered in person in Wuhan. In this wave we asked individuals which province in China they are from. In following waves we use the geolocation data to measure individuals' location. When we examine if the text stated response matches up to the location data we find that the information perfectly aligns. Second, the surveys were administered alongside online teaching to students by teaching assistants as part of standard classroom instruction. We believe that in this setting, students are much more likely to adhere to standard procedures and conduct and perhaps refrained from using a VPN during these sessions. This is also reflected in our high retention rate. If students in our sample use a VPN, which indeed is possible, it seems likely that they do so aside from university associated activities, our survey included.

b. Differences in individual and household characteristics

Our identification strategy relies on the assumption that individuals are assigned to exposure or experience groups in a manner that is as good as random. Thus, it is important to confirm that our sample is well-balanced across observable characteristics. In Panel B of Table 1 we confirm that individuals by location do not systematically differ, statistically or economically, in observable characteristics which may be correlated to differences in risk taking and beliefs, such as gender and socioeconomic status which have both been highlighted in recent related studies (Das, Kuhnen, and Nagel, 2019; D'Acunto *et al.*, 2019; D'Acunto, Malmendier and Weber, 2020). In Appendix Table 2, we also confirm that observable characteristics are highly similar across survey samples. Nonetheless, we control for these covariates as well as survey sample and survey wave in our empirical specifications where individual fixed effects are not included. In general, we note that subjects from Wuhan or the region of Hubei, seem to appear rather similar to those from other areas of China and differences in characteristics are unlikely to bias our results in any specific direction.

c. External validity

Our study has several important, yet unique, features. It is important to discuss if our findings, which may be in part a function of such design aspects, can be applied to other settings as well. First, we argue that large shocks can affect preferences and expectations, and experience effects may also compound changes in risk taking via individuals' beliefs. The shock in question, and experience heterogeneity, derives from the COVID-19 pandemic, arguably one of the largest, unexpected, events of recent history. On one hand, the COVID-19 crisis is unique in that global pandemics in the modern world constitute a very rare event, on the other hand, all financial and natural crises will have their own unique features (Giglio *et al.*, 2020b). Second, our study is among university students in China rather than adult investors. While examining market participants or professional traders would surely be of interest, recent work has shown similarities between student samples and professionals in experimental tasks, particularly in the absence of rank incentives (Kirchler, Lindner, and Weitzel, 2018). At the same time, our setting allows us to generate variation in experience which likely would not be as cleanly identifiable in a non-university sample. Finally, our study is survey based, generating concerns about incentive compatibility. We believe that this is of limited concern as our preference measure is experimentally validated (Dohmen *et al.*, 2018) and recent studies have shown that incentives play less of an important role as previously suggested (see Hackethal *et al.*, 2020 for recent discussion, evidence, and literature review). Additionally, we believe that students in our sample provided reasonable and as close to accurate responses as possible, as the survey was administered alongside official university related curriculum.

In general, while we acknowledge that our study is focused on a unique setting and sample, we believe there are many several features that allow us to learn about the link between large shocks, personal experiences, and risk taking. Furthermore, our survey allows us to investigate the mechanisms which underlie time-varying risk taking, a relatively robust finding across the literature.

8. Conclusion

In this paper, we study time-varying risk taking and its foundations in experiences, preferences, and beliefs. We study how risk taking evolves from normal times to the peak of a worldwide health-crisis with repeated survey data from a panel of subjects based in Wuhan, China. Our identification strategy exploits the fact that winter break for the semester started on January 11th 2020 and students from other provinces were able to return to their homes as planned for the Chinese Lunar New Year celebrations, providing quasi-random variation in the exposure to the pandemic and quarantine conditions individuals experience across China.

We find that subjects in Wuhan, with objectively higher exposure to the COVID-19 pandemic, also believe that they have a higher exposure risk to the virus than those elsewhere. They state higher probabilities that they are likely to be infected, and show higher levels of fear in the pandemic in general. At the same time, our results are unlikely to be driven by quarantine conditions alone, as these are effectively held constant between subjects in Wuhan and subjects in other cities of Hubei.

We then show that subjects more closely experiencing the pandemic in Wuhan, reduce planned risk taking and allocate less risk to investment decisions. At the same time, while we find significant time-series variation in general preferences for risk, we find that experience does not differentially affect these general preferences. On average, subjects surveyed first in Wuhan and later at their place of quarantine show a large and significant decrease in general risk appetite. Our measures of beliefs also show similar sensitivity to time-series and cross-sectional variation. We argue that general preferences and economic expectations seem to be impacted significantly by aggregate shocks, while additional changes in risk taking stemming from experiences are explained by changes in optimism and beliefs about individuals' own luck and sense of control. It seems likely that large shocks may affect risk via preferences if experience heterogeneity is unobservable or uniform.

Our results therefore help unify existing studies by providing a framework which fits with findings suggesting that changes in risk taking are driven by beliefs, as well as others suggesting that underlying preference changes affect risk taking. At the same time, our results also align with, and provide micro-level evidence for, theoretical contributions of time-varying risk aversion. We also present an important contribution to a large literature on risk taking behavior after large shocks and formative experiences. In general, our results help explain why individual-level experiences have a more pronounced effect on behavior than further removed experiences. Finally, our findings provide important supporting evidence for policy decision making. If observed risk taking of households changes via time-varying beliefs and expectations, the effects may only be temporary. On the other hand, changes in household risk taking from more of a general shift in preferences may require policy that are larger, and more structural, and may reflect a larger impact on long term economic growth.

Our work is a relatively early study on the large consequences we expect to occur from the global COVID-19 pandemic. Future work in our field and within our own research agenda will study how these beliefs and preferences further evolve over time, link these measures to field behavior, and exploit further heterogeneity in personal experiences.

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Figure 1: COVID-19 infection cases and deaths in the Hubei province and across China

In the following figure we plot the cumulative infections (blue, left axis) and deaths (red, right axis) in the Hubei province of China, where Wuhan is located. The dashed red and blue lines represent the cumulative sum of infections and deaths from *all other* provinces in China and are plotted on the same axes. The dashed gray line states the timing of our follow up survey wave.

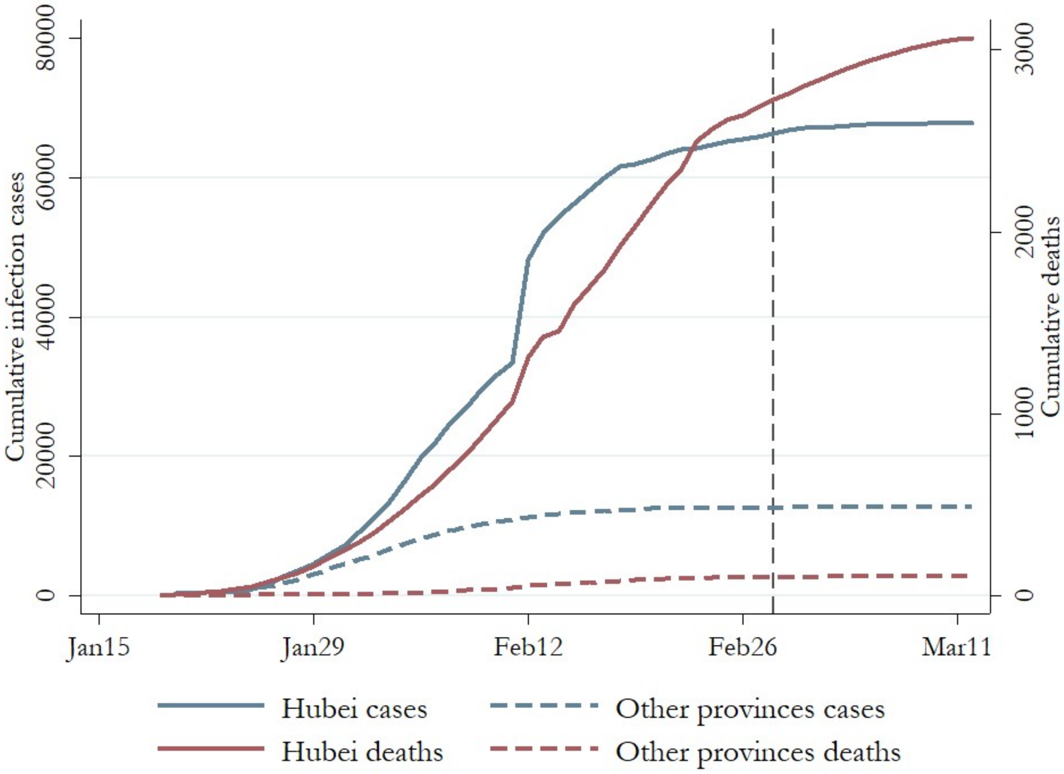
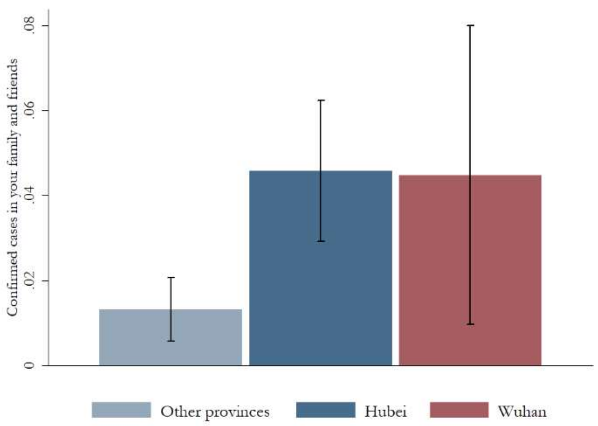


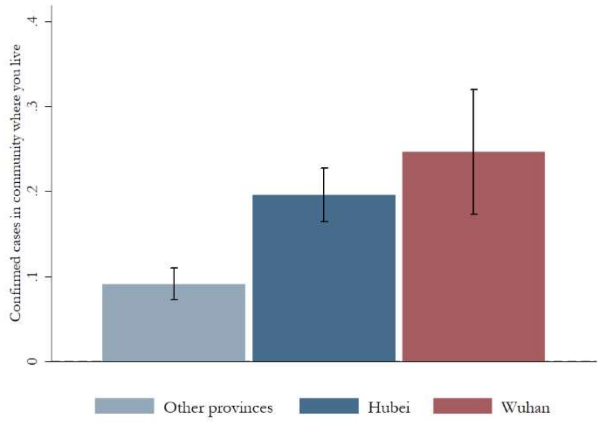
Figure 2: Subjects' perceptions of exposure to COVID-19

In the following figures we plot the mean response to survey questions asking subjects about exposure to COVID-19 cases. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China. In Panel A (top left) we plot the mean value to a question if there are confirmed cases among family and friends (yes/no). In Panel B (top right), if there are confirmed cases in the community where the subject is currently (yes/no), Panel C asks if there are confirmed deaths from COVID-19 in the community where the subject is currently. The responses are pooled between survey waves 2 (March 2020) and 3 (April 2020). 95% confidence intervals are displayed.

Panel A:



Panel B:



Panel C:

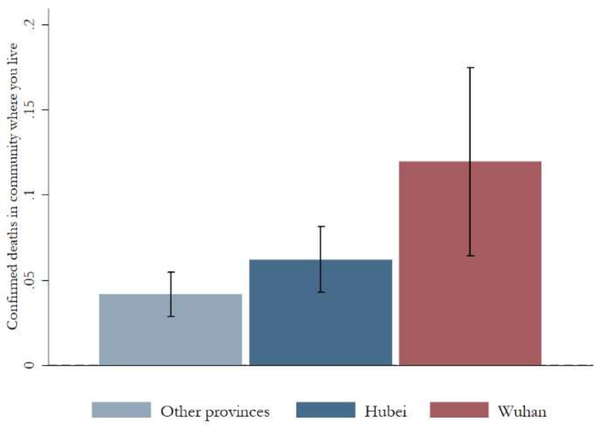
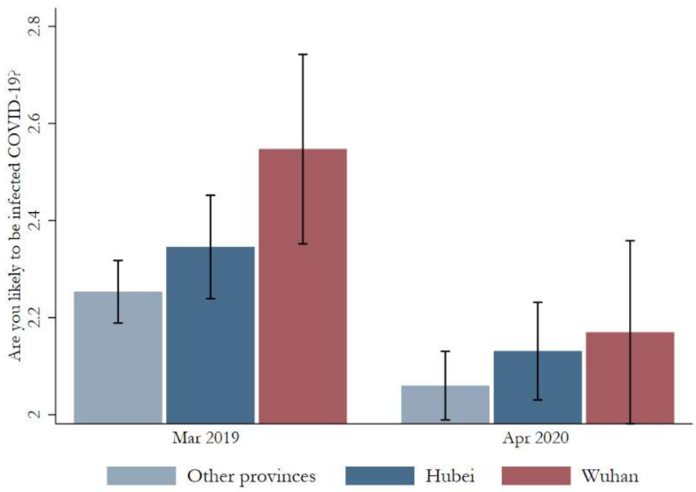


Figure 3: Subjects' self-perceived fear of the COVID-19 pandemic

In the following figure we plot subjects' self-perceived fear of COVID-19. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China In Panel A we plot the mean values of the question 'do you think you are likely to be infected with COVID-19?' Responses are on a scale between (1) and (5) for 'very unlikely to 'very likely.' The *x*-axis plots the response by survey waves 2 (March 2020) and 3 (April 2020). Panel B plots the mean values of a question asking if the subject is afraid of the Coronavirus pandemic. Responses are on a scale between (1) and (5) for 'not afraid at all' to 'very afraid.' 95% confidence intervals are displayed.

Panel A:



Panel B:

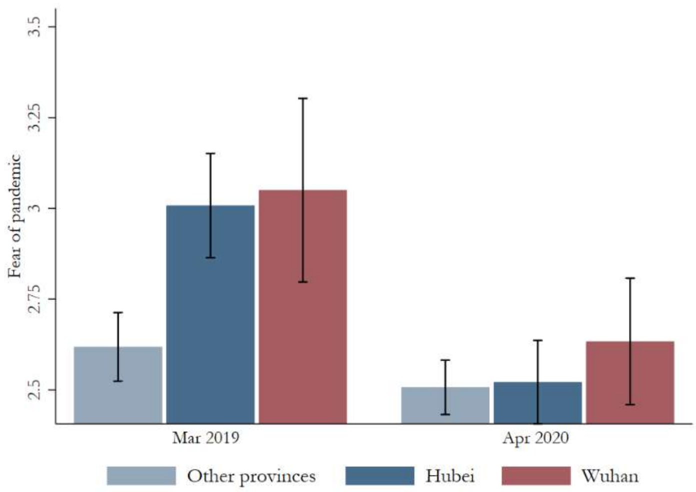
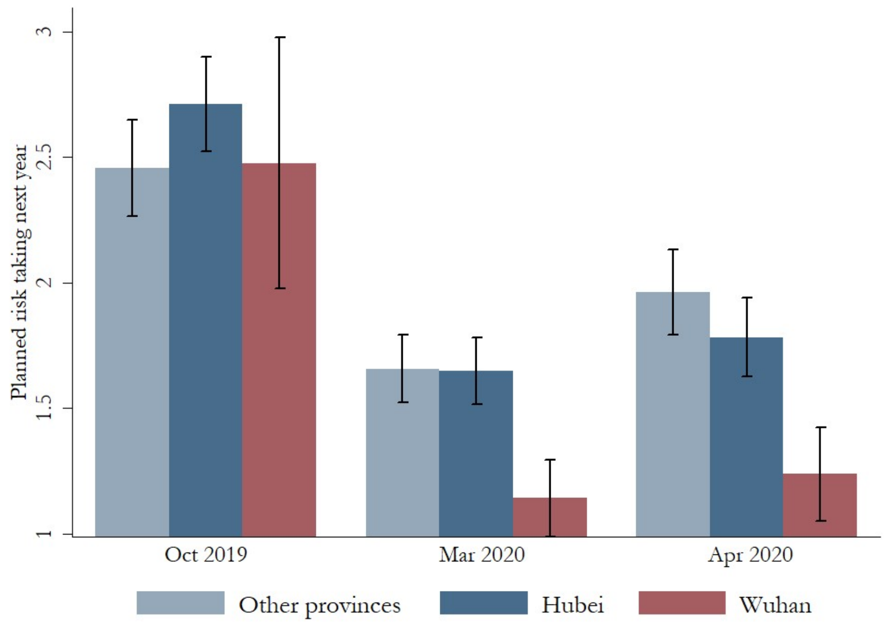


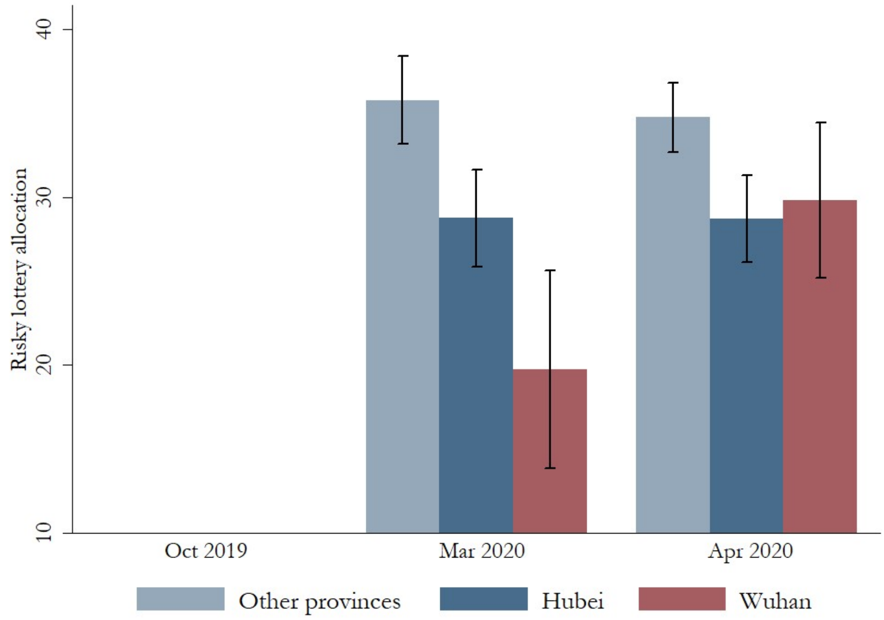
Figure 4: Risk taking during the COVID-19 pandemic

In the following figures we plot survey measures of risk tolerance. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China. In Panel A, we plot the mean score from a survey question on planned risk taking in the next year. The question asks if subjects will take more or less risk in the next year compared to the last year. The score ranges from 1 (less risk) to 5 (more risk) and were elicited in all survey waves. In Panel B we plot the allocation to a risky investment from a hypothetical gamble (0-1000 RMB) elicited in survey waves 2 (March 2020) and 3 (April 2020). In Panel C we plot the mean score from a survey question on general risk preferences motivated by Falk *et al.* (2018). The score ranges from 1 (low willingness to take risk) to 5 (high willingness to take risk) and were elicited in all survey waves. 95% confidence intervals are displayed.

Panel A: Planned risk taking



Panel B: Risky lottery allocation



Panel C: General preferences for risk

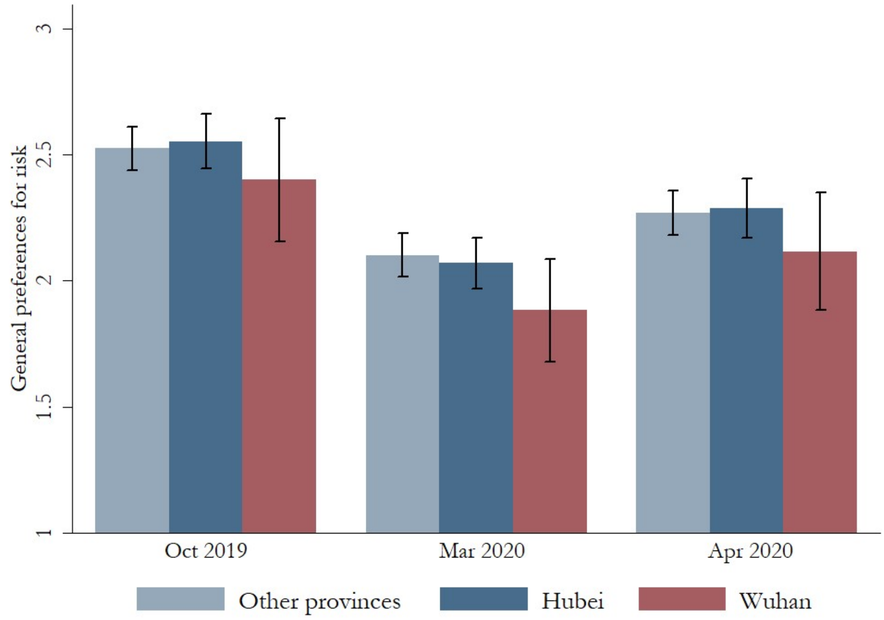
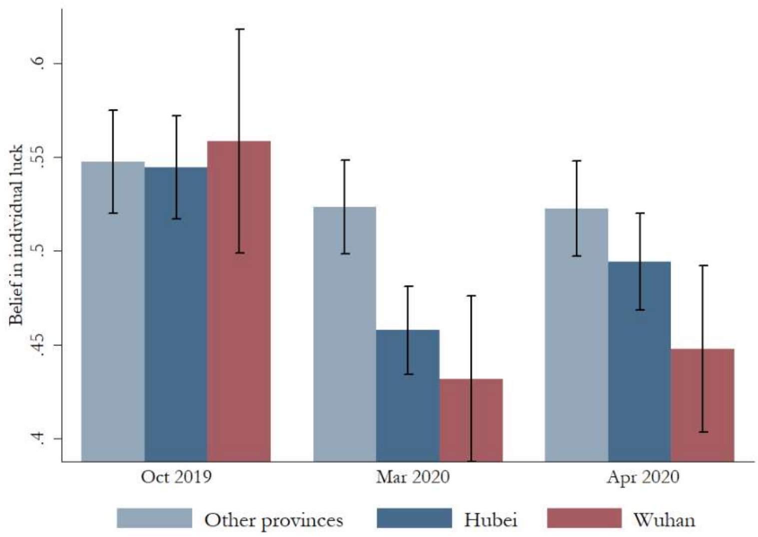


Figure 5: Subjects' beliefs in optimism during the COVID-19 pandemic

In the following figure we plot subjects' beliefs about self. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China. In Panel A we plot the mean values of an index of belief in individual luck based on Darke and Freedman (1997), which ranges from 0 (low belief in individual luck) to 1 (high belief in individual luck). Panel B plots mean values of an index on beliefs about subjects' sense of control based on the Drake Beliefs about Chance Inventory (Wood and Clapham, 2005). Both scores were elicited in all survey waves. 95% confidence intervals are displayed.

Panel A: Belief in individual luck



Panel B: Sense of control

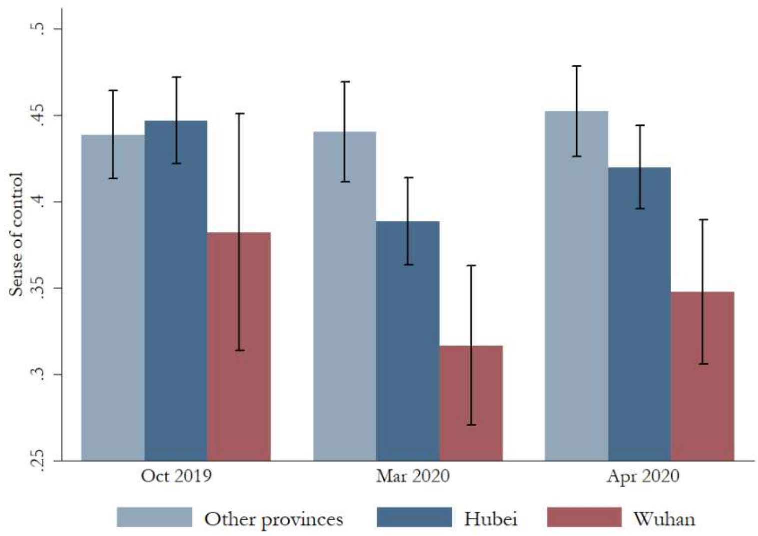
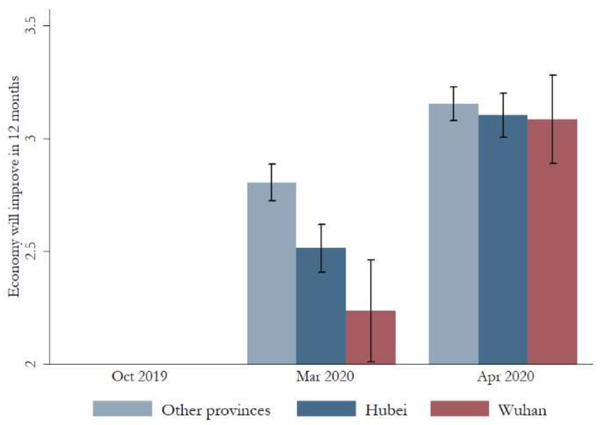


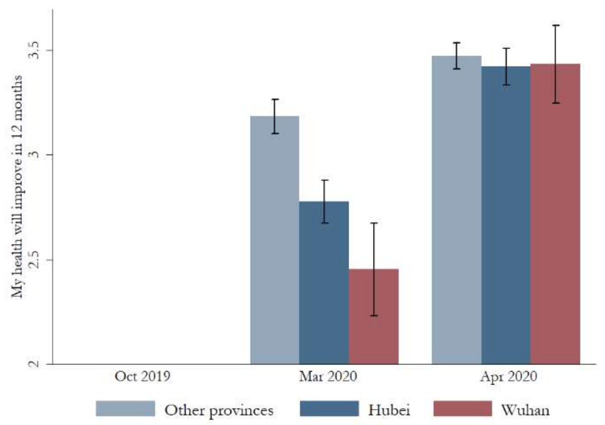
Figure 6: Expectations and beliefs during the COVID-19 pandemic

In the following figures we plot survey measures of beliefs and expectations on economic and social indicators. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China. We measure Panels A, B, and C with scale based survey questions, i.e., 'compared to last year, China's economy (your health; China's natural environment) will become better in the next 12 months.' The scale ranges from (1) to (5) for 'strongly disagree' to 'strongly agree.' These beliefs were elicited in survey waves 2 (March 2020) and 3 (April 2020). In Panel D (E) we plot the subjective probability subjects place in market returns of less than -20% (greater than +20%) in the Shanghai Stock Exchange index (SSE) in the following year. These beliefs were elicited in all three survey waves. 95% confidence intervals are displayed.

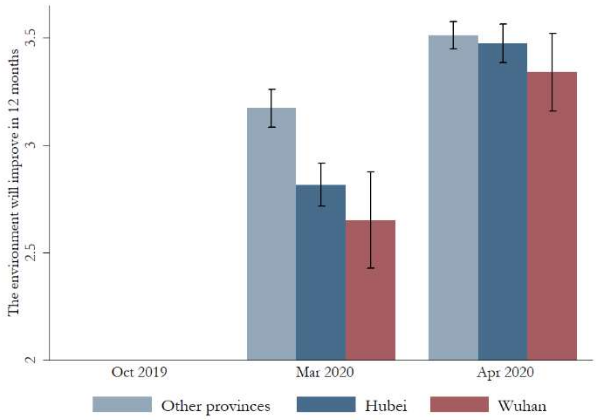
Panel A: Economy



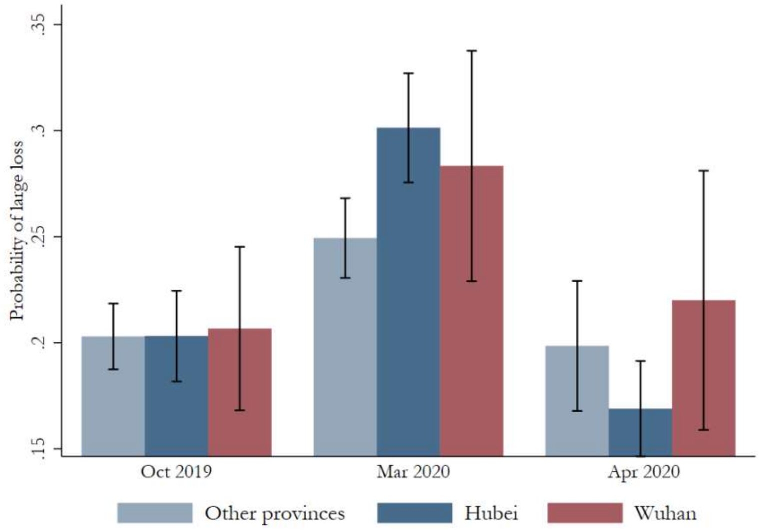
Panel B: Health



Panel C: Environment



Panel D: Probability of large loss in the Shanghai Stock exchange index



Panel E: Probability of large gain in the Shanghai Stock exchange index

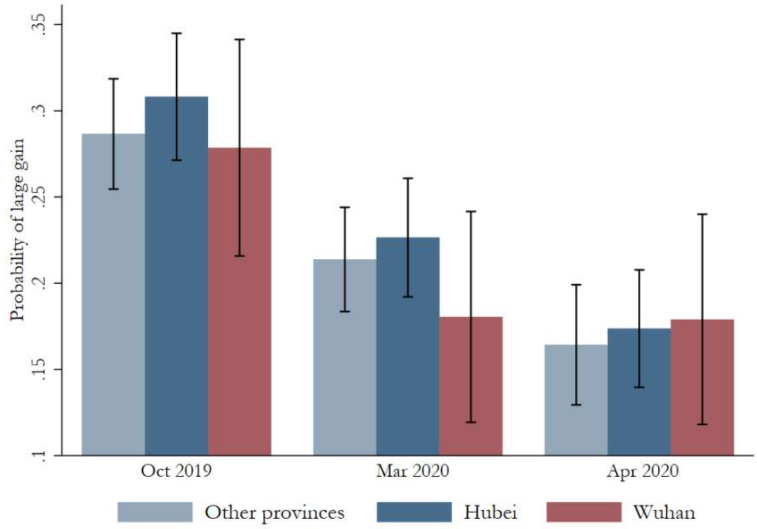
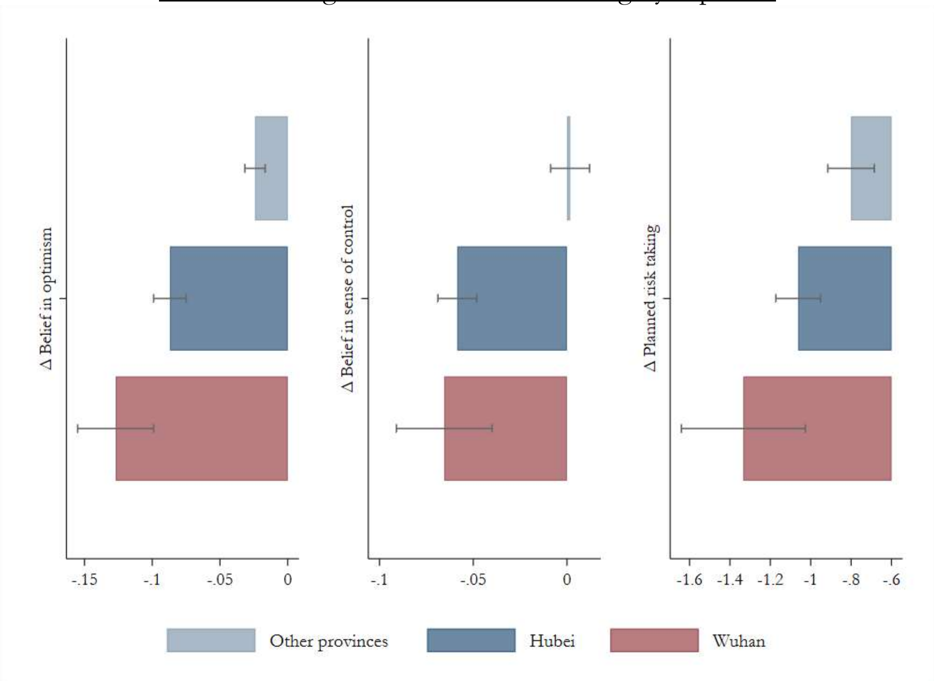


Figure 7: Changes in beliefs on changes in risk taking by experience

In the following figures we plot changes in subjects' beliefs and risk taking by their level of experience. We plot responses by subjects who are quarantined in Wuhan, subjects who are quarantined in the province of Hubei (but outside of Wuhan), and subjects in different provinces in China. In Panel A we plot the unconditional mean values in changes in beliefs in optimism (left), beliefs in sense of control (middle), and planned risk taking (right). Panel B plots the coefficient values of standardized measures of changes in beliefs in optimism and sense of control on an indicator for lower planned risk taking from wave 1 to wave 2. Each bar is the coefficient value from a regression conditional on experiences (All other provinces, Hubei, Wuhan) and demographic variables. Standard errors are clustered at the individual level. 95% confidence intervals are displayed.

Panel A: Change in beliefs and risk taking by exposure



Panel B: The effect of changes of beliefs on changes in risk taking

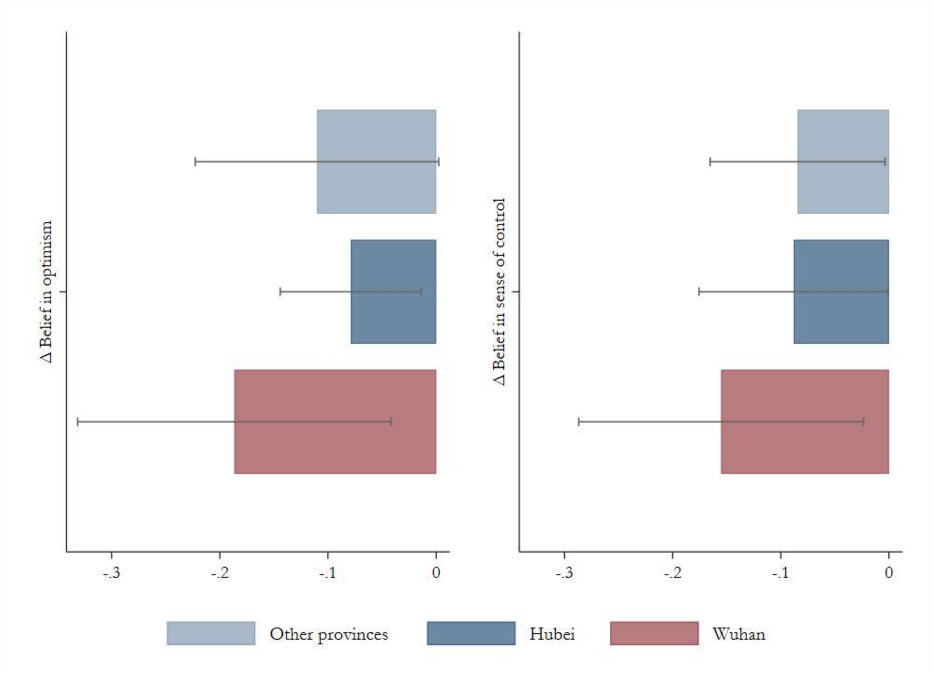


Table 1: Summary statistics

In Panel A, we report descriptive statistics: mean, median, min, and max for all subjects included in wave two and three of the survey questionnaire. For each individual, we observe demographic characteristics detailed below from March 2020. *Age* is the age in years of subjects, *Male* is an indicator for male gender, *Low SES* is an indicator for subjects' parents' main occupation as laborer/peasant, unemployed, or factory worker. *Government* is an indicator for subjects' parents' main occupation as public servant, military, or state owned enterprise. *Wuhan subjects* indicates subjects located in Wuhan. Panel B reports characteristics by subjects who are quarantined in Wuhan (4), subjects who are quarantined in the province of Hubei (but outside of Wuhan) (3), subjects in different provinces in China (2), and a *t*-test of differences between subjects in Wuhan and other provinces in China. Standard errors are in parenthesis and t-stats are in brackets. * $p < .1$, ** $p < .05$, *** $p < .01$

Panel A:

	Mean (1)	Median (2)	Min (3)	Max (4)
Age	23.24	22.0	18.0	60.0
Male	0.65	1.0	0.0	1.0
Low SES	0.23	0.0	0.0	1.0
Government	0.22	0.0	0.0	1.0
Wuhan subjects	0.07	0.0	0.0	1.0
Subjects	1,396			

Panel B:

	Full sample (1)	Other provinces (2)	Hubei (3)	Wuhan (4)	*t*-test (4)-(1)
Age	23.24	23.89	22.21	22.26	1.06
	(5.41)	(5.79)	(4.44)	(5.17)	[1.89]
Male	0.65	0.66	0.63	0.61	0.04
	(0.48)	(0.47)	(0.48)	(0.49)	[0.76]
Low SES	0.23	0.24	0.24	0.19	0.05
	(0.42)	(0.43)	(0.43)	(0.39)	[1.07]
Government	0.22	0.23	0.22	0.18	0.05
	(0.41)	(0.42)	(0.42)	(0.39)	[1.08]
Wuhan subjects	0.07	0.00	0.00	1.00	-
	(0.26)	(0.00)	(0.00)	(0.00)	-
Subjects	1,396	853	443	100	

Table 2: Subjects' perceptions of exposure and fear to the COVID-19 pandemic

The following table reports regression results analyzing how subjects' perceptions of exposure and fear to the COVID-19 pandemic differ by experience. *Hubei subjects* is an indictor variable which takes the value of one if subjects are quarantined in the Hubei province, outside of the city of Wuhan. *Wuhan subjects* takes the value of one if subjects are quarantined in Wuhan. The dependent variable in Column 1 an indicator variable for a survey question if there are confirmed cases among family and friends (yes/no). In Column 2 it indicates if there are confirmed cases in the community where the subject is currently (yes/no), and in Column 3, if there are confirmed deaths from COVID-19 in the community where the subject is currently. In Column 4 the dependent variable is an ordinal variable for the survey question 'do you think you are likely to be infected with COVID-19?' Responses are on a scale between (1) and (5) for 'very unlikely to 'very likely.' In Column 2 it is a question asking if the subject is afraid of the Coronavirus pandemic. Responses are on a scale between (1) and (5) for 'not afraid at all' to 'very afraid.' Data is pooled between survey waves 2 and 3 (March and April 2020). Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

Dependent variable:		Exposure		Fear	
	Family	Community	Deaths	Risk infection	Fear pandemic
	(1)	(2)	(3)	(4)	(5)
Hubei subjects	0.03	0.09***	0.03***	0.07	0.01
	(0.02)	(0.03)	(0.01)	(0.05)	(0.05)
Wuhan subjects	0.09**	0.13***	0.03	0.19**	0.02
	(0.04)	(0.05)	(0.02)	(0.08)	(0.07)
Controls	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.05	0.03	0.02	0.01
Observations	1,628	1,628	1,628	2,820	2,820

Table 3: Risk tolerance during the COVID-19 Pandemic

The following table reports regression results analyzing how risk tolerance is affected by exposure to the COVID-19 pandemic. In Panel A, we measure planned risk taking in the next year. The dependent variable is a score from a survey question which asks if subjects will take more or less risk in the next year compared to the last year. The score ranges from 1 (less risk) to 5 (more risk) and was elicited in all survey waves. The explanatory variables are *Hubei subjects*, an indictor variable which takes the value of one if subjects are quarantined in the Hubei province outside of Wuhan. *Wuhan subjects* takes the value of one if subjects are quarantined in the city of Wuhan. *Wave two* indicates the timing of March 2020 from our second survey wave and *Wave three* indicates April 2020 for our third survey wave. In Column 4 the variable *Post* indicates the time trend after March 2020 and the interaction term provides the difference in the outcome for those in Wuhan (Hubei) relative to those in other provinces in the post period. In Panel B, the dependent variable is the allocation to a risky investment from a hypothetical gamble (0-1000 RMB) elicited in survey waves 2 (March 2020) and 3 (April 2020). The *Post* variable in this specification therefore indicates April 2020. In Panel C, the dependent variable is the score from a survey question on general risk preferences motivated by Falk *et al.* (2018). The score ranges from 1 (low willingness to take risk) to 5 (high willingness to take risk) and were elicited in all survey waves. The *Post* variable therefore indicates the post-March 2020 period. We control for standard demographic characteristics and individual fixed effects as noted. Standard errors are clustered at the individual level. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Panel A:

Dependent variable	**Planned risk in the next year**			
	Full sample		Survey 1	
	(1)	(2)	(3)	(4)
Hubei subjects	-0.11**	-0.14***	0.02	
	(0.04)	(0.04)	(0.09)	
Wuhan subjects	-0.30***	-0.32***	-0.41***	
	(0.06)	(0.06)	(0.11)	
Wave two		-0.86***	-0.96***	
		(0.07)	(0.07)	
Wave three		-0.86***	-0.75***	
		(0.07)	(0.08)	
Post				-0.64***
				(0.14)
Hubei subjects *x* Post				-0.35*
				(0.18)
Wuhan subjects *x* Post				-0.64*
				(0.34)
Controls	No	Yes	Yes	Yes
Individual fixed effects	No	No	No	Yes
R^2	0.01	0.13	0.22	0.65
Observations	3,073	3,043	669	669

Panel B:

Dependent variable:	Risky investment allocation		
	Surveys 1 & 3		
	Wave 2	Wave 3	Pooled
	(1)	(2)	(3)
Hubei subjects	-67.69***	-57.08***	
	(20.89)	(17.72)	
Wuhan subjects	-161.35***	-45.33*	
	(32.92)	(25.98)	
Post			-4.78
			(22.83)
Hubei subjects *x* Post			4.58
			(36.25)
Wuhan subjects *x* Post			119.66**
			(52.15)
Controls	Yes	Yes	Yes
Individual fixed effects	No	No	Yes
R^2	0.04	0.02	0.58
Observations	800	828	1,628

Panel C:

Dependent variable	General preferences for risk				
	Full sample				Surveys 2 & 3
	(1)	(2)	(3)	(4)	(5)
Hubei subjects	-0.00	-0.01	0.02		
	(0.04)	(0.04)	(0.07)		
Wuhan subjects	-0.10	-0.11	-0.13		
	(0.07)	(0.07)	(0.13)		
Wave two		-0.44***			
		(0.04)			
Wave three		-0.27***			
		(0.05)			
Post			-0.35***	-0.34***	-0.35***
			(0.06)	(0.08)	(0.07)
Hubei subjects *x* Post			-0.04	-0.04	-0.05
			(0.08)	(0.12)	(0.12)
Wuhan subjects *x* Post			0.03	-0.06	-0.06
			(0.14)	(0.20)	(0.19)
Controls	No	Yes	Yes	Yes	Yes
Individual fixed effects	No	No	No	Yes	Yes
R^2	0.00	0.04	0.03	0.54	0.55
Observations	3,670	3,639	3,639	3,639	2,457

Table 4: Heterogeneity in risk taking and experience

The following table reports regression results heterogeneity in how risk tolerance is affected by exposure to the COVID-19 pandemic. The explanatory and dependent variables in Panels A, B, and C are defined as in Table 4. For each specification we run regressions where we Column 1 (2) conditions the sample on Men (Women), and Columns 3 (4) conditions the sample on those from low (high) socioeconomic status households. We control for standard demographic characteristics and individual fixed effects as noted. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

Panel A:

Dependent variable	**Planned risk in the next year**			
	Male	Female	Low SES	High SES
	(1)	(2)	(3)	(4)
Post	-0.64***	-0.65***	-0.63***	-0.66***
	(0.19)	(0.21)	(0.19)	(0.21)
Hubei subjects *x* Post	-0.20	-0.63**	-0.26	-0.41*
	(0.22)	(0.29)	(0.28)	(0.23)
Wuhan subjects *x* Post	-0.53	-0.93	-0.98*	-0.46
	(0.39)	(0.68)	(0.54)	(0.41)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.66	0.65	0.66	0.64
Observations	429	240	264	405

Panel B:

Dependent variable:	**Risky investment allocation** Surveys 1 & 3			
	Male	Female	Low SES	High SES
	(1)	(2)	(3)	
Post	1.44	-20.98	12.31	-10.13
	(26.38)	(45.83)	(47.71)	(26.09)
Hubei subjects *x* Post	2.78	11.64	-43.01	20.13
	(45.28)	(61.80)	(67.05)	(42.97)
Wuhan subjects *x* Post	107.16*	150.47	107.05	122.98**
	(61.08)	(101.39)	(103.99)	(60.49)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.57	0.61	0.58	0.58
Observations	1,153	475	383	1,245

Panel C:

Dependent variable	General preferences for risk			
	Samples 2 & 3			
	Male	Female	Low SES	High SES
	(1)	(2)	(3)	(4)
Post	-0.34***	-0.36***	-0.31**	-0.36***
	(0.10)	(0.11)	(0.13)	(0.09)
Hubei subjects *x* Post	-0.01	-0.11	-0.22	0.02
	(0.16)	(0.17)	(0.22)	(0.14)
Wuhan subjects *x* Post	-0.01	-0.12	-0.29	-0.01
	(0.24)	(0.31)	(0.26)	(0.22)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.57	0.53	0.55	0.55
Observations	1,440	1,017	672	1,785

Table 5: Beliefs in optimism and sense of control during the COVID-19 pandemic

The following table reports regression results analyzing how beliefs in self are affected by exposure to the COVID-19 pandemic. The dependent variable in Columns 1-4 is an index of belief in individual luck based on Darke and Freedman (1997), which ranges from 0 (low belief in individual luck) to 1 (high belief in individual luck). In Columns 5-8 it is an index on beliefs about subjects' sense of control based on the Drake Beliefs about Chance Inventory (Wood and Clapham, 2005). The explanatory variables are *Hubei subjects*, an indictor variable which takes the value of one if subjects are quarantined in the Hubei province. *Wuhan subjects* takes the value of one if subjects are quarantined in the city of Wuhan. *Post* indicates the timing of March and April 2020 from our second and third survey waves. Columns 1, 2, 5, and 6 are limited to our main Sample 1 consisting of WUST students, while Columns 3, 4, 7 and 8 include the full sample. These questions were asked in all three waves of the survey. We control for standard demographic characteristics and individual fixed effects as noted. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

Dependent variable:	Beliefs in individual luck				Beliefs in sense of control			
	Survey 1		Full sample		Survey 1		Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hubei subjects	-0.03*	-0.00	-0.00		-0.03	0.01	0.01	
	(0.02)	(0.02)	(0.02)		(0.02)	(0.02)	(0.02)	
Wuhan subjects	-0.05**	0.01	0.01		-0.10***	-0.06	-0.06	
	(0.02)	(0.03)	(0.03)		(0.03)	(0.04)	(0.04)	
Post		-0.03***	-0.03**	-0.04***		-0.00	0.03***	-0.02
		(0.01)	(0.01)	(0.01)		(0.01)	(0.01)	(0.01)
Hubei subjects *x* Post		-0.04***	-0.02	-0.04**		-0.05***	-0.05***	-0.05***
		(0.01)	(0.02)	(0.02)		(0.01)	(0.02)	(0.02)
Wuhan subjects *x* Post		-0.09***	-0.05*	-0.09***		-0.06**	-0.02	-0.06*
		(0.03)	(0.03)	(0.03)		(0.03)	(0.03)	(0.03)
Individual fixed effects	No	No	No	Yes	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.07	0.06	0.61	0.07	0.07	0.14	0.63
Observations	669	669	1,851	1,851	669	669	1,851	1,851

Table 6: Economic and social beliefs during the COVID-19 pandemic

The following table reports regression results analyzing how expectations and beliefs on the economy, social conditions, and the stock market returns differ by experience. *Hubei subjects* is an indictor variable which takes the value of one if subjects are quarantined in the Hubei province, outside of the city of Wuhan. *Wuhan subjects* takes the value of one if subjects are quarantined in Wuhan. In Panel A, the dependent variable in Column 1 (2) (3) are scale-based survey questions, i.e., 'compared to last year, China's economy (your health; China's natural environment) will become better in the next 12 months.' The scale ranges from (1) to (5) for 'strongly disagree' to 'strongly agree.' Beliefs were elicited in survey waves 2 (March 2020) and 3 (April 2020). In Panel B the dependent variable is the elicited probability of market returns of less than -20% (greater than +20%) in the Shanghai Stock Exchange index (SSE) in the following year in Column 1 (2). In Column 3 (4) it is an indicator for providing a probability estimate of more than 25% associated with less than -20% declines (greater than +20% returns). These beliefs were elicited in all three survey waves. Standard errors are clustered at the individual level. $^{*}\ p < .1$, $^{**}\ p < .05$, $^{***}\ p < .01$

Panel A:

Dependent variable:	Economy	Health	Environment
	(1)	(2)	(3)
Post	0.38^{***}	0.30^{***}	0.35^{***}
	(0.08)	(0.08)	(0.08)
Hubei subjects *x* Post	0.22	0.33^{***}	0.30^{**}
	(0.14)	(0.13)	(0.13)
Wuhan subjects *x* Post	0.49^{**}	0.71^{***}	0.36
	(0.24)	(0.24)	(0.23)
Individual fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
R^2	0.53	0.54	0.50
Observations	2,820	2,820	2,820

Panel B:

Dependent variable:	Subjective probability		I: Probability>25%	
	Loss <-20%	Gain >+20%	Loss <-20%	Gain >+20%
	(1)	(2)	(3)	(4)
Post	0.04^{***}	-0.09^{***}	0.10^{*}	-0.24^{***}
	(0.02)	(0.02)	(0.06)	(0.06)
Hubei subjects *x* Post	0.01	-0.01	0.06	-0.08
	(0.02)	(0.02)	(0.08)	(0.08)
Wuhan subjects *x* Post	0.02	-0.00	0.04	-0.09
	(0.03)	(0.03)	(0.15)	(0.15)
Individual fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
R^2	0.55	0.58	0.52	0.56
Observations	1,781	1,782	1,781	1,782

Table 7: The effect of individuals' beliefs on risk taking

The following table reports regression results analyzing how changes in risk taking are affected by different types of expectations and beliefs. In Panel A the dependent variable is an indicator for decreasing planned risk taking based on a survey question from wave 1 of the survey (October 2019) to wave 2 (March 2020). The variable *Economy improve* is the Likert scaled based question asking subjects if they believe the economy will be better in 12 months compared to now (scale 1-5, 1 = strongly disagree, 5 = strongly agree). The variables Δ Optimism and Δ Sense of control are the change in individuals' beliefs in their own optimism and their sense of control from wave 1 to wave 2. The variable Δ P(High mkt returns) is the change in the probability associated with annual returns over 20% in the Shanghai Stock exchange index. In Columns 5-8 we create indicator versions of these variables which indicate that subjects decreased their belief in the economy, their own optimism, or in their own sense of control from wave 1 to wave 2. In Panel B the dependent variable is an indicator for decreasing risk allocation based on a hypothetical lottery from wave 2 of the survey (March 2020) to wave 3 (April 2020). The variables are defined as in Panel A with the exception that Column 1 presents the change in economic expectations from wave 2 to wave 3 and all other variables are coded as changes from wave 2 to wave 3. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

Dependant variable	Reduced planned risk taking (Oct 2019 to Mar 2020)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Economy improve	-0.06**				-0.04					
	(0.03)				(0.03)					
Δ Optimism		-1.32***			-0.76**					
		(0.29)			(0.34)					
Δ Sense of control			-1.33***		-0.89**					
			(0.31)		(0.35)					
Δ P(High mkt returns)				-1.94**	-1.41					
				(0.75)	(0.88)					
Economy worsen (d)						0.06				0.02
						(0.07)				(0.06)
Lower optimism (d)							0.18***			0.12*
							(0.07)			(0.07)
Lower sense control (d)								0.28***		0.28***
								(0.06)		(0.06)
Lower mkt returns (d)									-0.02	-0.10
									(0.07)	(0.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.04	0.08	0.09	0.04	0.13	0.06	0.06	0.04	0.02	0.12
Observations	223	223	223	223	223	223	223	223	223	223

Dependant variable	Reduced risk allocation (Mar 2020 to Apr 2020)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ Economy will improve	0.02**				0.03**					
	(0.01)				(0.01)					
Δ Optimism		-0.32***			-0.25**					
		(0.11)			(0.12)					
Δ Sense of control			-0.37***		-0.35***					
			(0.10)		(0.10)					
Δ P(High mkt returns)				0.05	0.07					
				(0.08)	(0.08)					
Economy worsen (d)						-0.06*				-0.06*
						(0.04)				(0.04)
Lower optimism (d)							0.10***			0.09**
							(0.04)			(0.04)
Lower sense control (d)								0.05		0.04
								(0.04)		(0.04)
Lower mkt returns (d)									-0.03	-0.02
									(0.04)	(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.01	0.01	0.02	0.00	0.03	0.01	0.01	0.00	0.00	0.02
Observations	828	828	828	828	828	828	828	828	828	828

Table 8: The effect of experience on changes in beliefs and changes in risk taking

The following table reports regression results analyzing how changes in risk taking are affected by different types of expectations and beliefs by individuals in Wuhan compared to those in other regions of China. Each coefficient represents the indicator variable *Wuhan subjects* in individual regressions where the dependent variable is defined on the left column. Column 1 presents the coefficient in an unconditional regression, Column 2 controls for standard covariates listed previously. In Columns 3 and 4 we describe the conditional probability of the variables listed at left for those in Wuhan and those in other cities in China, conditional on reducing planned risk taking from wave 1 to wave 2. Standard errors are clustered at the individual level. * p < .1, ** p < .05, *** p < .01

	Difference in … between Wuhan subjects and those in other regions of China		Probability of … conditional on lower planned risk taking between subjects in…	
	Unconditional	Conditional	Other cities in China	Wuhan
	(1)	(2)	(3)	(4)
a) Lower general risk preferences (d)	-0.04 (0.07)	-0.02 (0.07)	38.6%	31.3%
b) Lower planned risk taking (d)	0.22* (0.12)	0.21* (0.12)	-	-
c) Lower optimism (d)	0.39*** (0.12)	0.41*** (0.12)	43.9%	93.6%
d) Lower sense of control (d)	0.40*** (0.11)	0.42*** (0.11)	35.1%	75.0%
e) Probability of <-20% returns	0.03** (0.01)	0.03** (0.01)	35.8%	75.0%

Table 9: The effect of individuals' fear and risk of infection on risk taking

The following table reports regression results analyzing how changes in risk taking are affected by different types of expectations and beliefs. In Panel A the dependent variable is an indicator for decreasing planned risk taking based on a survey question from wave 1 of the survey (October 2019) to wave 2 (March 2020). The variable *Economy improve* is the Likert scaled based question asking subjects if they believe the economy will be better in 12 months compared to now (scale 1-5, 1 = strongly disagree, 5 = strongly agree). The variables Δ Optimism and Δ Sense of control are the change in individuals' beliefs in their own optimism and their sense of control from wave 1 to wave 2. The variable Δ P(High mkt returns) is the change in the probability associated with annual returns over 20% in the Shanghai Stock exchange index. In Columns 5-8 we create indicator versions of these variables which indicate that subjects decreased their belief in the economy, their own optimism, or in their own sense of control from wave 1 to wave 2. In Panel B the dependent variable is an indicator for decreasing risk allocation based on a hypothetical lottery from wave 2 of the survey (March 2020) to wave 3 (April 2020). The variables are defined as in Panel A with the exception that Column 1 presents the change in economic expectations from wave 2 to wave 3 and all other variables are coded as changes from wave 2 to wave 3. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .0$

Dependent variable	Reduced planned risk taking (Oct 2019 to Mar 2020)				Reduced risk allocation (Mar 2020 to Apr 2020)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fear	-0.01	-0.02						
	(0.03)	(0.03)						
Risk of infection	0.05*	0.04						
	(0.03)	(0.03)						
Higher fear (d)			0.02	0.04			0.07*	0.06
			(0.08)	(0.08)			(0.04)	(0.04)
Higher risk of infection (d)			-0.09	-0.04			0.01	0.01
			(0.07)	(0.07)			(0.04)	(0.04)
Δ Fear					0.01	0.01		
					(0.01)	(0.01)		
Δ Risk of infection					-0.00	-0.00		
					(0.01)	(0.01)		
Economy improve		-0.05						
		(0.03)						
Economy worsen (d)				0.04				-0.06*
				(0.06)				(0.04)
Δ Optimism						0.03**		
						(0.01)		
Δ Sense of control		-0.76**				-0.25**		
		(0.34)				(0.12)		
Δ P(High mkt returns)		-0.87**				-0.36***		
		(0.35)				(0.10)		
Lower optimism (d)		-1.40				0.08		
		(0.88)				(0.08)		
Lower sense control (d)				0.13*				0.09**
				(0.07)				(0.04)
Lower mkt returns (d)				0.25***				0.04
				(0.06)				(0.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.03	0.14	0.03	0.13	0.00	0.03	0.01	0.02
Observations	223	223	223	223	828	828	828	828

Appendix for

"Risk Taking, Preferences, and Beliefs: Evidence from Wuhan"

Appendix Figure 1: October 2019 survey sessions in Wuhan, China

The figures below show pencil and paper survey wave one sessions at WUST in October 2019.

Appendix Figure 2: Online survey conducted in March 2020

The figures below shows an example screen from the online wave two survey (translated into English) while subjects are in quarantined.

* **48. Compared with last year, China's economy will become better in the next 12 months: 1 ~ 5 i ncrease in approval degree**

A. 1 B. 2 C. 3 D. 4 E. 5

* **49. Compared with last year, my health will be better in the next 12 months: 1 ~ 5 increase in ap proval degree**

A. 1 B. 2 C. 3 D. 4 E. 5

* **50. Compared with last year, China's natural environment will become better in the next 12 mon ths: 1 ~ 5 increase in approval degree**

A. 1 B. 2 C. 3 D. 4 E. 5

* **51. Age**

* **52. Gender**

A. Male

B. Female

* **53. Horoscope**

* **Please select province city and region:**

Appendix Table 1: Overview of selected survey questions, survey sample, and survey wave

The following table provides a summary of key survey questions asked of subjects corresponding to the three waves of the survey and the three different survey samples. S1 = Survey 1, S2 = Survey 2, S3 = Survey 3. Sample 1 correspond to our main sample from WUST, Sample 2 derives from the environmental study which included a number of related survey questions, and Sample 3 is our additional sampling of students from WUST.

	Survey wave and Survey sample		
Survey question:	Wave 1	Wave 2	Wave 3
General risk preferences	S1, S2	S1, S2, S3	S1, S2, S3
Planned risk taking	S1	S1, S2, S3	S1, S2, S3
Risky lottery allocation		S1, S3	S1, S3
Beliefs in self	S1	S1, S3	S1, S3
Sense of control	S1	S1, S3	S1, S3
Economy/Heath/Environment 12 month forecast		S1, S2, S3	S1, S2, S3
Tail-risks in SSE	S1	S1, S3	S1, S3

Appendix Table 2: Summary statistics by survey sample

We report mean values for all subjects included in wave two of the survey questionnaire. For each individual, we observe demographic characteristics detailed below from March 2020. *Age* is the age in years of subjects, *Male* is an indicator for male gender, *Low SES* is an indicator for subjects' parents' main occupation as laborer/peasant, unemployed, or factory worker. *Government* is an indicator for subjects' parents' main occupation as public servant, military, or state owned enterprise. *Wuhan subjects* indicates subjects located in Wuhan. Column 1 presents the full sample, while the subsequent columns provides mean values and standard deviations for each individual sample. Sample 1 correspond to our main sample from WUST, Sample 2 derives from the environmental study which included a number of related survey questions, and Sample 3 is our additional sampling of students from WUST.

	Full sample (1)	Sample 1 (2)	Sample 2 (3)	Sample 3 (4)
Age	23.24	23.24	22.79	23.72
	(5.41)	(0.93)	(3.82)	(7.42)
Male	0.65	0.64	0.57	0.74
	(0.48)	(0.48)	(0.50)	(0.44)
Low SES	0.23	0.39	0.23	0.18
	(0.42)	(0.49)	(0.42)	(0.38)
Government	0.22	0.17	0.11	0.35
	(0.41)	(0.37)	(0.32)	(0.48)
Wuhan subjects	0.07	0.09	0.07	0.07
	(0.26)	(0.29)	(0.25)	(0.25)
Subjects	1,396	223	596	577

Appendix Table 3: Heterogeneity in economic beliefs

The following table reports regression results analyzing how risk tolerance is affected by exposure to the COVID-19 pandemic. In Column 1, we measure planned risk taking in the next year. The dependent variable is a score from a survey question which asks if subjects will take more or less risk in the next year compared to the last year. The score ranges from 1 (less risk) to 5 (more risk) and was elicited in all survey waves. The explanatory variables are *Hubei subjects*, an indictor variable which takes the value of one if subjects are quarantined in the Hubei province outside of Wuhan. *Wuhan subjects* takes the value of one if subjects are quarantined in the city of Wuhan. *Wave two* indicates the timing of March 2020 from our second survey wave and *Wave three indicates April 2020* for our third survey wave. The variable *Post* indicates the time trend after March 2020 and the interaction term provides the difference in the outcome for those in Wuhan (Hubei) relative to those in other provinces in the post period. In Columns 2-4, the dependent variable is the allocation to a risky investment from a hypothetical gamble (0-1000 RMB) elicited in survey waves 2 (March 2020) and 3 (April 2020). The *Post* variable in this specification therefore indicates April 2020. In all specifications we control for time-varying general risk preferences. We control for standard demographic characteristics and individual fixed effects as noted. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

Dependent variable	Planned risk	Risky allocation		
	(1)	(2)	(3)	(4)
Hubei subjects		-67.67***	-59.83***	0.00
		(20.90)	(17.01)	(.)
Wuhan subjects		-160.25***	-46.65*	0.00
		(32.97)	(25.90)	(.)
Post	-0.56***			-9.75
	(0.14)			(22.58)
Hubei subjects *x* Post	-0.36**			3.58
	(0.17)			(35.94)
Wuhan subjects *x* Post	-0.71**			115.64**
	(0.32)			(52.32)
General preferences for risk	0.31***	11.97	65.49***	36.05**
	(0.06)	(12.16)	(7.51)	(14.16)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.69	0.04	0.11	0.59
Observations	669	800	828	1,628

Appendix Table 4: Heterogeneity in economic beliefs

The following table reports regression results heterogeneity in individuals' economic beliefs. In Panel A, the dependent variable is a scale-based survey questions, i.e., 'compared to last year, China's economy will become better in the next 12 months.' The scale ranges from (1) to (5) for 'strongly disagree' to 'strongly agree.' Beliefs were elicited in survey waves 2 (March 2020) and 3 (April 2020). In Panel B the dependent variable is an indicator for providing a probability estimate of more than 25% subjective probability of less than -20% declines in the SSE. These beliefs were elicited in all three survey waves. For each specification we run regressions where Column 1 (2) conditions the sample on Men (Women), and Columns 3 (4) conditions the sample on those from low (high) socioeconomic status households. We control for standard demographic characteristics and individual fixed effects as noted. Standard errors are clustered at the individual level. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$

Panel A:

Dependent variable	**Economy improve in next 12 months**			
	Male	Female	Low SES	High SES
	(1)	(2)	(3)	(4)
Post	0.37***	0.38***	0.38**	0.37***
	(0.10)	(0.13)	(0.17)	(0.09)
Hubei subjects *x* Post	0.03	0.56***	0.57**	0.11
	(0.17)	(0.21)	(0.27)	(0.16)
Wuhan subjects *x* Post	0.51	0.48	0.46	0.50*
	(0.32)	(0.37)	(0.50)	(0.27)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.50	0.59	0.51	0.54
Observations	1,827	993	655	2,165

Panel B:

Dependent variable	**Expected large loss in SSE next 12 months**			
	Male	Female	Low SES	High SES
	(1)	(2)	(3)	(4)
Post	0.06	0.16*	-0.06	0.17**
	(0.08)	(0.09)	(0.09)	(0.07)
Hubei subjects *x* Post	0.12	-0.04	0.17	-0.02
	(0.11)	(0.13)	(0.12)	(0.11)
Wuhan subjects *x* Post	0.16	-0.22	-0.01	0.06
	(0.18)	(0.26)	(0.25)	(0.19)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
R^2	0.51	0.54	0.55	0.52
Observations	1,246	535	458	1,323

Appendix Table 5: The effect of experience on changes in beliefs and changes in risk taking

The following table reports regression results analyzing how changes in risk taking are affected by different types of expectations and beliefs by individuals in Wuhan compared to those in other regions of China. Each coefficient represents the indicator variable *Wuhan subjects* in individual regressions where the dependent variable is defined on the left column. Column 1 presents the coefficient in an unconditional regression, Column 2 controls for standard covariates listed previous and Columns 3 and 4 condition the sample to compare individuals in Wuhan to those in other cities in Hubei. Standard errors are clustered at the individual level. * $p < .1$, ** $p < .05$, *** $p < .01$

	Difference in … between *Wuhan subjects* and those in …			
	Other regions of China		Other cities of Hubei	
	Unconditional	Conditional	Unconditional	Conditional
	(1)	(2)	(3)	(4)
a) Lower general risk preferences (d)	-0.04	-0.02	-0.08	-0.08
	(0.07)	(0.07)	(0.07)	(0.07)
b) Lower planned risk taking (d)	0.22*	0.21*	0.03	0.03
	(0.12)	(0.12)	(0.11)	(0.11)
c) Lower optimism (d)	0.39***	0.41***	0.06	0.07
	(0.12)	(0.12)	(0.10)	(0.10)
d) Lower sense of control (d)	0.40***	0.42***	0.06	0.07
	(0.11)	(0.11)	(0.12)	(0.12)
e) Probability of <-20% returns	0.03**	0.03**	-0.02	-0.02
	(0.01)	(0.01)	(0.02)	(0.02)

Online Appendix A: Sample survey questions translated into English

<u>Belief on good luck</u>
Darke and Freedman (1997)

Likert-scale which ranges from strongly disagree (1) … strongly agree (5).

Some people are consistently lucky, and others are unlucky.
I consider myself to be a lucky person.
I believe in luck.
I often feel like it's my lucky day.
Nobody can win at games of chance in the long-run.
I consistently have good luck.
It's a mistake to base any decisions on how lucky you feel.
Luck works in my favour, especially this year.
I don't mind leaving things to chance because I'm a lucky person.
Even the things in life I can't control tend to go my way because I'm lucky.
In general I am lucky.
There is such a thing as luck that favours some people, but not others.
Luck is nothing more than random chance.

<u>Beliefs about luck</u>

If you make investment on stocks this year, what percentage of other investors have better luck than you at investing stocks with above average performance?
(Please give a number between 0% and 100%)

If you make investment on stocks this year, what percentage of other investors had higher returns than you?
(Please give a number between 0% and 100%)

<u>Control over luck</u>
Drake Beliefs about Chance Inventory; Wood and Clapham (2005)

Participants indicate the extent of their agreement using Likert-scale which ranges from strongly disagree (1) … strongly agree (5).

If I well prepared, I would have very large likelihood to win a gamble.
Some gamblers are just born lucky.
The longer I've been losing, the more likely I am to win.
The chances of winning a substantial amount of money at the Casino are quite high
I think I'll win a good prize in sport lottery (over $10,000) one day
One day I'm going to strike it lucky at gambling
If I concentrated hard enough I might be able to influence whether I win when I play the pokies
I can/could stick to a budget when/if I gamble

<u>Risk taking</u>
Falk et al., (2018)

Risk measures were elicited through two qualitative questions and one quantitative question:

In general, how willing are you to take risks?
    On a scale of 1(not willing at all) - 5(very willing to)

Will you take more risk this year compared to last year?
    On a scale of 1(less risk) - 5 (more risk)

Imagine you have an extra 1,000 yuan in your pocket, and you have to options with how to use it:

a. Use an amount of the money to invest in a lottery (with a 50% chance that you can win up to 2,000 yuan (including the principal of 1,000 yuan), and a 50% chance of zero additional winnings)
b. Don't make any investment.

Please fill in the following boxes how you will allocate the 1,000 yuan in these two options:

_____Yuan in lottery investments
_____ Yuan in keep in cash

Economy expectations

All questions on scale of strongly disagree (1) … strongly agree (5).

Compared to last year, China's economy will become better in the next 12 months
Compared with last year, my health will be better in the next 12 months
Compared with last year, China's natural environment will become better in the next 12 months

Stock market expectations

Stock market expectations: in the following we present you with 6 scenarios of how the annual percentage change of stock indices could be during this year (between Nov 2020-Nov 2021). Please indicate how likely you think the individual scenarios are. Assign a probability to each of the scenarios, and make sure the sum of the probability to be 100%.

Shanghai Stock exchange index
-20%
-10-20%
0-10%
0 +10 %
10-20%
+20%

Questions on trust
WVS; Kosse *et al.*, (2020)
All questions on scale of strongly disagree (1) … strongly agree (5).

In general, the vast majority of people in the society can be trusted
In general, no one else can be trusted, I can only rely on myself
We'd better stay vigilant when dealing with strangers
Others treat me with good intentions

Additional questions

Are there confirmed COVID-19 cases among your family member and friends?
Yes/no
Are there any confirmed COVID-19 cases in the community where you currently live?
Yes/no
Are there any suspected cases in the community where you currently live?
Yes/no
Has anyone in your community died from the COVID-19?
Yes/no

Are you afraid of this epidemic?
1)Not afraid at all …… 5)Very afraid
Do you think you are likely to be infected with COVID-19?
1)Very unlikely …… 5)Very likely

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