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The social scar of the pandemic: Impacts of COVID-19 exposure on interpersonal trust

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A B S T R A C T

This paper employs a difference-in-differences strategy to examine the causal effect of exposure to the COVID-19 pandemic on interpersonal trust amidst zero-COVID policies in China. Using a nationally representative panel survey, we find that COVID-19 exposure leads to a decrease in the levels of generalized trust. We also show that the change in interpersonal trust varies across domains. Specifically, COVID-19 exposure significantly decreases trust in parents, neighbors, and local government officials, but has small and insignificant effects on trust in doctors, strangers, and Americans. Empirical tests suggest that changes in income and physical health status are not likely to be potential channels. We provide some evidence for the mechanism of deteriorated mental health status and pessimistic expectations.

1. Introduction

The world is now entering the third year of the COVID-19 pandemic. Since the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was first reported from an outbreak in Wuhan in the center of China in December 2019, it has rapidly spread around the world. As of 27 March 2022, it had infected over 480 million people and claimed over 6.1 million lives globally. The pandemic has also brought about severe economic and social disruption worldwide, including the worst global recession in the last eighty years. A better understanding of the medium and long-run effects of the pandemic may lead to more effective post-pandemic economic and social policies.

This paper examines the causal effects of COVID-19 exposure on trust. Trust is an element of virtually every business transaction, especially those that take place over time. A lack of mutual trust is a plausible explanation for much of the economic backwardness in the world (Arrow, 1972). Theoretically, the effect of the COVID-19 pandemic on interpersonal trust is ambiguous. On the one hand, negative income shocks, interfered communication, pessimistic expectations, and mental health issues associated with the pandemic may diminish interpersonal trust (Brodeur, Gray, Islam, & Bhuiyan, 2021; Clemente-Suárez et al., 2021). On the other hand, the experience of external threats and the networks of mutual aid may increase a sense of community and connectedness among the general public (Bonanno, Brewin, Kaniasty, & Greca, 2010; Grundmann, Epstude, & Scheibe, 2021). Although several studies have discussed the changes of interpersonal trust amidst the COVID-19 pandemic (Kye & Hwang, 2020; Li, Zhang, & Niu, 2021; Sibley et al., 2020), our knowledge of the causal effects of COVID-19 exposure on interpersonal trust is limited.

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China provides an attractive setting to study the effects of COVID-19 exposure. China was the first country to implement drastic government interventions (including lockdowns and face mask mandates) and was also one of the fastest countries to bring the outbreak of the virus under control. Since then, China has maintained a dynamic zero-COVID strategy but its sustainability has been a subject of intense debate (Yuan, 2022). The number of COVID-19 cases was minimal when the latest wave of the CFPS was conducted. Therefore, we estimate the persistent effects of COVID-19 exposure amidst zero-COVID policies. Specifically, we quantify COVID-19 exposure as the log of the number of infected cases in a province and the regional and temporal variations of COVID-19 infection allow us to adopt a difference-in-differences (DID) strategy. Our individual-level data on interpersonal trust come from a nationally representative dataset, namely, the China Family Panel Studies (CFPS).

We find that individuals highly exposed to the COVID-19 pandemic exhibit lower levels of generalized trust. Nevertheless, the change in trust is heterogeneous across domains. Specifically, individuals with high COVID-19 exposure become significantly less trusting of parents, neighbors, and local government officials, but have no obvious changes in the levels of trust in strangers, Americans, or doctors. Our main results quantitatively go through several robustness checks, including testing the assumption of parallel trends, controlling for other simultaneous shocks, excluding the Hubei sample, using alternative measures of COVID-19 exposure, and employing an alternative estimation strategy.

We provide some suggestive evidence for the underlying mechanisms. We show that changes in interpersonal trust are not driven by changes in income, physical health status, or interpersonal communication. We provide some evidence that COVID-19 exposure reduces interpersonal trust by deteriorating mental health status and lowering future expectations. In addition, we show limited heterogeneity in the effects of COVID-19 exposure on interpersonal trust across gender, education, and age groups, which suggests that COVID-19 may have inflicted a deep and lasting social scar on the general population.

Our study contributes to two threads of literature. First, it relates to a growing body of literature on the socioeconomic consequences of the COVID-19 pandemic. The spread of COVID-19 has slowed down economic activities considerably. Previous studies have documented that the COVID-19 pandemic produced negative effects on individual health status, educational achievement, and labor market performance (Brodeur et al., 2021; Clemente-Suárez et al., 2021; Vindegaard & Benros, 2020). Our study indicates that the pandemic may also generate long-lasting impacts on economic performance by altering individual economic decision-making.

Second, our study contributes to the literature on social trust (Algan & Cahuc, 2014; Nunn & Wantchekon, 2011). A growing body of literature has revealed that trust can be shaped by past experiences, such as climate changes (Buggle & Durante, 2021), technological advances (Olken, 2009), political movement (Bai & Wu, 2020), natural disasters (Cassar, Healy, & Von Kessler, 2017; You, Huang, & Zhuang, 2020), and civil conflicts (Cassar, Grosjean, & Whitt, 2013; Rohner, Thoenig, & Zilibotti, 2013). Several recent studies have adopted a before-and-after design to examine changes of interpersonal trust amidst the COVID-19 pandemic but yielded mixed results (Kye & Hwang, 2020; Li et al., 2021; Sibley et al., 2020). We adopt a DID strategy to investigate the persistent effects of COVID-19 exposure amidst zero-COVID policies. Our analyses indicate that other simultaneous temporal shocks may contaminate the estimated effects in the before-and-after studies. Therefore, one must be cautious in interpreting the results from the before-and-after studies (Haber, Clarke-Deelder, Salomon, Feller, & Stuart, 2021; Miguel & Mobarak, 2022). In addition, we investigate the underlying mechanisms and heterogeneity in COVID-19 exposure effects which have received limited attention in the previous studies.

The remaining part of the paper proceeds as follows. Section 2 provides the conceptual framework. Section 3 introduces the data sets and the empirical strategies. Section 4 presents the baseline estimation results for interpersonal trust as well as the robustness checks and the discussion of underlying mechanisms, followed by the heterogeneity analysis. Section 5 compares our findings with previous studies. The last section offers the conclusions.

2. Backgrounds and conceptual framework

2.1. Backgrounds

China was the first country to report an outbreak of COVID-19. In December 2019, hospitals in Wuhan, Hubei Province, China admitted dozens of patients diagnosed with an unknown pneumonia. It was then discovered that the pneumonia was caused by SARS-CoV-2, a new coronavirus. By January 29th, 2020, the virus outbreak had spread to all mainland Chinese provinces. In response to the outbreak, the Chinese government took drastic measures, such as travel restrictions, quarantine, lockdowns, and face mask mandates. By the end of February, all Chinese provinces except Hubei had brought the virus under control. In early April, Wuhan, the hardest-hit city by the virus, lifted its lockdown. According to the statistics reported by the Chinese Center for Disease Control and Prevention (CDC), by April 20th, 2020, the number of confirmed cases in mainland China increased to 82,758, with 4632 related deaths.

From then on, China then has imposed a dynamic zero-COVID strategy. Most new cases came from overseas and several outbreaks had been rapidly controlled by intense public health measures. Typical public health measures included extensive testing, immediate contact tracing, and mandatory quarantine and isolation of infected individuals and their close contacts. Figure A1 plots the number of daily new confirmed COVID-19 cases in China. As shown in the figure, China had largely brought the COVID-19 outbreak under control after a surge in COVID-19 infections in February and March of 2020.

Figure A2 presents the heated map of the cumulative COVID-19 counts (log-transformed) in China on July 1st, 2020. Table A1 examines the correlations between the cumulative COVID-19 counts (log-transformed) and the provincial socioeconomic factors in 2018. The provincial socioeconomic data comes from the National Bureau of Statistics of China. Generally speaking, the COVID-19 counts have statistically insignificant correlations with most socioeconomic factors, including healthcare resources and quality, educational resources, and infrastructure fatalities. Nevertheless, the COVID-19 counts are significantly correlated with GDP per capita, the mortality rate, the areas affected by natural disasters, and the number of higher education students per 10,000 people, and marginally correlated with the after-tax income per capita.

2.2. Conceptual framework

The COVID-19 pandemic may affect interpersonal trust through several channels. One potential channel can be through a negative shock to adult income. To prevent the spread of the pandemic, governments usually adopt a range of public health measures, including containment, isolation, and social distancing. These measures typically require staying at home, shutting businesses, and working from home, which may reduce adults' earning opportunities (Forsythe, Kahn, Lange, & Wiczer, 2020). Low-income people may be less able to absorb the negative consequences of trusting others, thereby exhibiting lower levels of trust (Alesina & La Ferrara, 2002).

The second channel may entail a negative shock to mental health. During the pandemic and post-pandemic period, individuals may experience stress, anxiety, depression, and insomnia for a long period (for reviews, see Clemente-Suárez et al., 2021). These are a range of potential stressors associated with the pandemic, including confinement, confusion, uncertainty, fear of contagion, loss of routine, reduced concentration, decreased physical activity, diminished sunlight exposure, recurrent sleep disorders, heavy use of digital media, alternations in eating routines, and excessive consumption of COVID-19 information on news and media. Poor mental health may lead to poor-quality social relationships, including high frequencies of domestic violence (Leslie & Wilson, 2020). The worsened social relationship may also make individuals less trusting.

The third channel may be related to the interfered communication. Wearing face masks in public places is recommended as a public health measure to reduce the spread of the COVID-19 pandemic. When communicating with masked people, individuals must imagine, pretend to recognize, and intuit facial expressions. Face masks may interfere with emotion recognition and perception of closeness, which may be worrisome when certain emotion recognition is essential (Grundmann et al., 2021). For example, individuals may have a feeling of cognitive and emotional discomfort when greeting masked strangers. The interfered communication may lead to reduced trust and trustworthiness.

The fourth channel may involve an increase in the perceived probability that negative events will occur. Individuals are constantly making trust decisions and may have uncertainty about whom to trust and to what extent. During and after the COVID-19 pandemic, individuals may be worried about getting the virus, the length of the pandemic, and the future. When people feel particularly vulnerable or worried, they may find it hard to place confidence in someone else (Li et al., 2021). In addition, the pandemic may affect interpersonal trust through affecting physical health. The pandemic may lead to poor physical health status by inducing unhealthy lifestyles and crowding out non-COVID-19-related health care demands (Brodeur et al., 2021). Uncertainty and vulnerability associated with poor health may then make individuals less trusting (Rocco, Fumagalli, & Suhrcke, 2014).

The channels mentioned above may make individuals exposed highly to the COVID-19 pandemic exhibit lower levels of trust. Nevertheless, there are several channels through which the COVID-19 pandemic increases interpersonal trust. For example, getting help from family members and neighbors during the COVID-19 pandemic may strengthen the faith that others are trustworthy (Bonanno et al., 2010). In addition, suffering in wake of an epidemic may give rise to an enhanced sense of personal strength, a shift in priorities, and more meaningful interpersonal interactions (Greenaway & Cruwys, 2019). Several studies have documented that the external threat and the display of mutual aid may stimulate increased connectedness and a sense of community in the general population (Cassar et al., 2013; Whitt & Wilson, 2007).

3. Data and empirical strategy

3.1. Data sources and descriptive statistics

The CFPS is an ongoing biennial longitudinal survey initiated by the Institute of Social Science Survey of Peking University, China. The baseline survey was conducted in 2010, covering 42,590 individuals from 14,960 households. In the subsequent wave, members who left or became members of their original family were also surveyed. The attrition rate of the longitudinal survey is around 25% biennially. The survey gathers information on a range of topics, including demographic characteristics, physical and mental health status, social preference, and labor market performance. The sample is nationally representative of Chinese communities, families, and individuals. Xie et al. (2017) show that statistical characteristics of many demographic and socioeconomic factors (e.g., gender, age, marital status, household size, educational level, family income, and health) in the CFPS dataset are similar to those in other nationally representative datasets.

Trust outcomes — Our primary measure of trust is generalized trust. It is derived from a hypothetical question, which has appeared in many large-scale surveys, such as the General Social Survey and the World Value Survey. Specifically, the CFPS asks respondents: "In general, would you say that most people can be trusted or that you need to be very careful in getting along with people?" We define a dummy variable with a value of 1 if they report most people can be trusted, and 0 otherwise. This measure of trust is routinely employed in previous studies when laboratory measures of trust are unavailable. Previous studies have validated that the general measure of trust predicts behavior in the trust game (Fehr, Fischbacher, von Rosenbladt, Schupp, & Wagner, 2002; Sapienza, Toldra-Simats, & Zingales, 2013).

In addition, we employ measures of group-specific trust (Kye & Hwang, 2020). The CFPS asks respondents how much they trust their parents, neighborhoods, local government officials, doctors, strangers, and Americans. Respondents can choose answers from a scale of 0 (extremely untrustworthy) to 10 (extremely trustworthy). These measures sometimes operate independently or even in opposition to one another. For example, people who highly trust neighbors in a tight-knit community may still hold xenophobic views about outsiders or distrust health advice from government officials and health workers.

Health status — We examine the effects of COVID-19 exposure on health outcomes in the mechanism analysis. We leverage two questions in the CFPS to measure respondents' physical health status. The CFPS asks respondents to evaluate their health status as poor, fair, good, very good, or excellent. Accordingly, we construct an ordered variable "health status" with 1 representing poor and 5 representing excellent. Moreover, the CFPS asks respondents whether they have gotten sick in the past two weeks. We define a dummy variable "illness" for having gotten sick in the past two weeks. Previous studies have shown that self-reported health outcomes are robust and significant predictors of morbidity and mortality (Doiron, Fiebig, Johar, & Suziedelyte, 2015; Wu et al., 2013).

The CFPS also contains several measures of mental health and subjective well-being. The first is the 8-item Centre for Epidemiological Studies Depression Scale (CES-D), which is widely used to evaluate depressive symptoms in the general population (Missinne, Vandeviver, Van de Velde, & Bracke, 2014, 2009; Van de Velde, Levecque, &).[1] The CES-D score ranges from 0 to 24, with higher scores representing greater severity of depression. The second measure is life satisfaction. The CFPS asked respondents to rate their levels of life satisfaction on a scale from 1 (very unsatisfied) to 4 (very satisfied). A respondent's level of life satisfaction indicates how closely his experiences match his expectations and long-term goals. The third measure is short-run hedonic happiness. Specifically, the CFPS asks respondents about their levels of happiness on a scale from 0 (extremely unhappy) to 10 (extremely happy).

Other mechanism variables — We employ two questions in the CFPS to measure respondents' expectations. The first is about expectations about others' helping behavior. The CFPS asks respondents: "Do you think that most people are willing to help, or selfish?" We define a dummy variable for perceiving that most people are willing to help. The second question is about respondents' expectations in the future. The CFPS asks respondents: "How confident do you feel about your future?" The answer is an ordinal scale ranging from 1 to 5, with higher scores indicating stronger confidence.

The CFPS also collects information on respondents' labor market performance. We use an employment dummy and the log of income to measure labor market performance.

COVID-19 exposure — Information on the COVID-19 pandemic comes from the Chinese Center for Disease Control and Prevention. It has been widely used in scientific research related to the COVID-19 pandemic (Fang, Wang, & Yang, 2020; Jia et al., 2020; Lai et al., 2020). Individuals' perceived intensity of the epidemic is largely shaped by COVID-19 case counts reported on news media (Agüero & Beleche, 2017). Because the distribution of the COVID-19 case counts is highly right-skewed, with a small number of provinces taking on large values, we use the log-transformed case count in each province to quantify COVID-19 exposure. In the robustness tests, we use the ranking of the COVID-19 case count and the COVID-19 infection rate in each province as alternative measures of COVID-19 exposure.

The 2020 CFPS was conducted in the second half year of 2020. There had already been a large-scale COVID-19 outbreak in China before the 2020 CFPS was conducted. Under the strict management of the Chinese government, the large-scale epidemic had got controlled and the number of newly infected cases in China was almost zero in the second half year of 2020. In the empirical analysis, we use the cumulative number of confirmed COVID-19 cases on July 1st, 2020 to construct the proxy variable for the COVID-19 intensity. Our estimates remain robust if we use COVID-19 information on different dates.

Regression sample — We use the 2016, 2018, and 2020 waves of the CFPS. We restrict the sample to adults born between 1965 and 2000 so that young children and retirees are not included. We further exclude individuals with less than three observations to make the panel balanced. Our final sample covers 10,996 individuals, which corresponds to 32,988 individual-year observations. Table 1 shows the summary statistics. Because of data availability, sample sizes differ across main outcome variables. The respondents are 37 years old on average and their average total years of education is 9.1 years. About 49% of the respondents are male and about 58.4% believe that most people can be trusted. The levels of group-specific trust increase with the closeness of the relationship: individuals have the highest levels of trust in parents (about 9.5 on average) and the lowest levels of trust in strangers and Americans (about 2.4 on average).

3.2. *Empirical strategy*

We adopt a DID strategy to investigate the effects of COVID-19 exposure on interpersonal trust. We exploit the temporal and geographic variations of COVID-19 exposure and compare the changes of interpersonal trust in provinces with different levels of COVID-19 exposure before and after the COVID-19 outbreak.[2] Instead of using a standard dummy treatment measure, we employ a continuous measure of treatment intensity (i.e. COVID-19 exposure), which utilizes more variations in the data (Chen & Zhou, 2007; Nunn & Qian, 2011). Specifically, we estimate the following econometric model:

$$Y_{ipt} = \beta_1 \bullet COVID19_p * Post + X_{ipt}\gamma + \delta_p + \alpha_i + \lambda_t + \varepsilon_{ipt} \tag{1}$$

where i indexes individual, p province, and t survey wave. Y represents a given measure of interpersonal trust. *COVID-19* is a proxy variable for COVID-19 intensity, which is the log of the number of COVID-19 cases in the province in our main analysis. Post is an

[1] The 8-item CES-D scale includes six items that measure negative feelings ("I felt depressed", "I felt lonely", "I felt sad", "Everything I did felt like an effort", "I felt restless", and "I could not get going") and two items that measure positive feelings ("I was happy" and "I enjoyed life"). Respondents are required to rate the frequency of certain feelings during the past week on a scale from 0 (rarely or none of the time) to 3 (most or all of the time). The CES-D score is computed by adding up responses from the 8 items, taking reverse coding of positive feelings into consideration.

[2] We have data before and after the outbreak of the COVID-19 pandemic. The 2016 and 2018 waves of CFPS were collected before the COVID-19 pandemic. The 2020 CFPS was conducted after the first large-scale outbreak of COVID-19 in China. In the 2020 CFPS, some samples were strongly influenced by COVID-19 (there is a large number of COVID-19 cases in the province), while some samples were not.

Table 1
Summary statistics of main variables.

VARIABLES	(1) Observation	(2) Mean	(3) Standard deviation	(4) Minimum	(5) Maximum
Trust outcomes					
Generalized trust	31,717	0.584	0.493	0	1
Trust in parents	31,746	9.487	1.213	0	10
Trust in neighbors	31,759	6.600	2.063	0	10
Trust in government officials	31,690	5.037	2.565	0	10
Trust in doctors	31,756	6.845	2.280	0	10
Trust in Americans	31,435	2.363	2.474	0	10
Trust in strangers	31,734	2.382	2.158	0	10
Mechanism variables					
Log of income	11,630	10.09	1.733	0	13.53
Employment	30,267	0.873	0.333	0	1
Health status	32,933	2.813	1.155	1	5
Illness	31,766	0.247	0.431	0	1
CES-D score	21,204	5.536	3.836	0	24
Hedonic happiness	21,549	7.398	2.060	0	10
Life satisfaction	31,773	3.788	0.993	1	5
Future expectations	31,763	4.094	0.929	1	5
Perceived kindness	31,682	0.732	0.443	0	1
COVID-19 variables					
COVID-19 counts	31	2683	12155	1	68135
COVID-19 cases per ten thousand people	31	0.480	2.046	0.003	11.50
Other variables					
Male	32,988	0.490	0.500	0	1
Age	32,988	37.43	10.45	16	55
Birth year	32,988	1981	10.35	1965	2000
Wave	32,988	2018	1.633	2016	2020
Years of education	32,889	9.072	4.631	0	22

Note: The data come from the 2016, 2018, and 2020 waves of the CFPS.

indicator for observations being observed after the COVID-19 outbreak. α_i stands for individual fixed effects. These fixed effects control for the influences of all observed and unobserved individual characteristics that have a stable effect on interpersonal trust during the sample period. δ_p denotes province fixed effects, which capture all observed and unobserved characteristics of a province. These provincial characteristics may include natural environments, social norms, and cultural spheres. Since respondents might migrate across provinces during the sample period, the individual fixed effects do not absorb the province fixed effects. λ_t means survey wave fixed effects, which account for time trends in the outcome variables that are common to all provinces. The vector X represents a set of individual-level time-varying covariates, including age fixed effects. ε_{ipt} is an error term. To account for arbitrary correlations in social preference outcomes of residents in the same province, we cluster the standard errors at the provincial level (Bertrand, Duflo, & Mullainathan, 2004).

The parameter of interest is β_1, which captures the change in COVID-19 exposure effects before and after the COVID-19 outbreak. We hypothesize that, in the absence of the COVID-19 outbreak, the time trends in interpersonal trust of individuals would have been the same among provinces with different intensities of the COVID-19 pandemic. The COVID-19 pandemic induced deviations from these parallel trends.

The significant correlations between COVID-19 intensity and some socioeconomic factors may lead to spurious estimates of the COVID exposure effects if the same socioeconomic factors are associated with differential trends in interpersonal trust. In the sensitivity analysis, we include interaction terms of these pretreatment provincial socioeconomic factors with survey wave dummies to control for potential differences in trends across provinces that are spuriously associated with the COVID exposure effects.

As the measurements of interpersonal trust are categorical, several estimation methods are available. In our baseline specification, we simply treat the measures of trust as continuous variables and run linear regressions. This strategy is desirable due to a large number of individual fixed effects in our baseline model. In the sensitivity analysis, we maintain the categorical nature of the trust outcomes and estimate a fixed-effects logit model. As we discuss below, this alternative approach produces qualitatively identical estimates.

4. Empirical results

4.1. Baseline results

Table 2 presents the estimation results for interpersonal trust. Column (1) presents the estimate for general social trust. The estimates indicate that COVID-19 exposure significantly decreases trust. The following example gives some idea of its magnitude. The COVID-19 count in Jilin Province (155) is at the 25th percentile. The COVID-19 count in Jiangxi Province (932) is at the 75th percentile. The COVID-19 count in Jiangxi Province is about six times as many as that in Jilin province. The estimated coefficient indicates that the individuals residing in Jiangxi Province are 2.0% points less likely to have confidence in most people than those

Table 2
Baseline results.

VARIABLES	(1) General	(2) Parents	(3) Neighbors	(4) Officials	(5) Doctors	(6) Strangers	(7) Americans
COVID-19 exposure	-0.014 * *	-0.026 *	-0.068 * **	-0.053 * *	-0.019	0.028	0.004
	(0.006)	(0.014)	(0.015)	(0.026)	(0.023)	(0.023)	(0.035)
Observations	31,580	31,612	31,626	31,549	31,622	31,598	31,275
R-squared	0.573	0.567	0.608	0.63	0.62	0.623	0.622
Province FE	YES	YES	YES	YES	YES	YES	YES
Survey wave FE	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES	YES	YES

Note: Standard errors are clustered at the provincial level. ***significant at 1% level, **at 5%, *at 10%.

residing in Jilin Province after the COVID-19 pandemic. This represents 3.4% of the sample average.

Trust is a multidimensional concept and segmenting trust may help us to gain a better understanding of popular opinions and behaviors after the COVID-19 outbreak. Columns (2) to (7) of Table 2 report the estimates for different forms of trust. The estimates indicate that COVID-19 exposure significantly decreases trust in parents, neighborhoods, and local government officials, but has small and insignificant effects on trust in strangers, Americans, and doctors. The pandemic may deteriorate social relationships among family and neighbors. In addition, individuals may doubt the ability of the local government officials because they fail to limit the spread of the virus. Therefore, we observe the significant effects of COVID-19 exposure on trust in parents, neighborhoods, and local government officials. Amidst zero-COVID policies, individuals exposed highly to COVID-19 may stay at home for a long period. The public health measures may have limited effects on individual interaction with strangers and Americans. Consequently, COVID-19 exposure has no obvious effects on trust in strangers and Americans. Meanwhile, doctors are responsible for treating COVID-19 patients rather than curbing the spread of COVID-19. Therefore, people are unlikely to blame doctors for the rapid spread of the virus and decrease trust in doctors.[3]

4.2. Sensitivity analysis

Thus far, the evidence has suggested that COVID-19 exposure significantly reduces the levels of interpersonal trust, especially trust in parents, neighbors, and government officials. In this subsection, we conduct a range of robustness and sensitivity checks. Specifically, we demonstrate that our baseline DID results are not driven by (i) differential trends in interpersonal trust prior to the COVID-19 outbreak, (ii) the influence of other simultaneous shocks, (iii) the sample selection process, (iv) the measurement biases of COVID-19 exposure. We report the corresponding estimates in the appendix.

Parallel trends – The assumption of parallel trends is critical to ensure the internal validity of DID models. It requires that in the absence of the pandemic, the differences in interpersonal trust among provinces with different intensities of the pandemic would have been constant over time. A relevant question is therefore whether the DID estimates confound the dynamic effects of COVID-19 exposure with pre-existing differential time trends across provinces. In other words, individuals may have experienced deterioration in their interpersonal trust due to the continued differences in the provincial time trends that precede the pandemic. We adopt three approaches to address this issue.

First, we employ a flexible event-study framework to evaluate the effect of COVID-19 exposure. The econometric specification is as follows:

$$Y_{ict} = \sum_{k\in[2012,2020]} \delta_k \bullet COVID19_p * 1(t = k) + X_{ipt}\gamma + \delta_p + \alpha_i + \lambda_t + \varepsilon_{ipt} \tag{2}$$

where $1(t = k)$ is an indicator for being surveyed in year k and $COVID19_p$ is the log of the number of COVID-19 cases in the province p. The core explanatory variables are the interaction terms between the survey year dummies and the provincial COVID-19 intensity. The omitted interaction term is the interaction term between the year of 2018 dummy and the COVID-19 intensity. The other control variables are the same as those in Eq. (1). This specification allows us to examine the effects of pandemic exposure on interpersonal trust before and after the COVID-19 outbreak. We add the 2012 and 2014 waves of the CFPS to increase the statistical power of the pre-trend test.

Figure A3 presents the event-study estimates from Eq. (2). Consistent with the parallel trends assumption, we observe no obvious effects of COVID-19 exposure on interpersonal trust before the COVID-19 outbreak. The estimated coefficients for the pre-pandemic period have different signs and are statistically insignificant. In addition, generalized trust, and trust in parents, neighbors, and government officials begin to decrease significantly relative to those of the baseline group after the COVID-19 outbreak. The fact that the trend break coincides with the timing of the COVID-19 outbreak is reassuring that the COVID-19 outbreak itself is responsible for

[3] Amidst zero-COVID policies, high COVID-19 exposure is always associated with a long period of quarantine. Therefore, we estimate the overall effect of COVID-19 exposure (including quarantine experience). We can not further exclude the influence of quarantine policies due to data availability. Future studies may use more detailed information on individual epidemic experience to investigate this issue.

the observed changes in interpersonal trust.

Second, we allow the provincial trends to vary with the predetermined provincial socioeconomic factors associated with the intensity of the COVID-19 pandemic. Specifically, we add to our baseline specification the interaction terms of the provincial socioeconomic factors and the survey wave dummies. These provincial socioeconomic factors include GDP per capita, the after-tax income per capita, the mortality rate, the areas affected by natural disasters, and the number of higher education students per 10,000 people. Panel A of Table A2 presents these estimates, which are similar to our baseline estimates.

Third, we perform a permutation test (Rosenbaum, 2007). Specifically, we randomly assign the effective COVID-19 counts to provinces and calculate "placebo" COVID-19 exposure by interacting the simulated COVID-19 counts with the dummy for the post-outbreak period. We then estimate the placebo treatment effects on interpersonal using the baseline models. We repeat this process 1000 times and report the distributions of the placebo estimates in Figure A4. The dashed line represents the estimated effect of actual COVID-19 exposure. As shown in the figure, the placebo effects are significantly different from the true estimated effects for generalized trust and trust in parents, neighbors, and government officials, whereas the differences are not obvious for trust in strangers, Americans, and doctors. In the permutation test, the p-value is the proportion of placebo estimates that are above or equal in absolute value to the estimated effect of actual COVID-19 exposure. The corresponding p-values confirm our visual impression, which suggests that the sign and significance of our baseline estimates are not merely driven by provincial differences unrelated to the effects of COVID-19 exposure. Overall, the three robustness checks provide support to our identification strategy.

Other confounding factors – Our research design exploits an exogenous pandemic shock. Our interpretation of COVID-19 exposure effects may be problematic if there were some other exogenous shocks other than the COVID-19 pandemic influencing interpersonal trust during the sample period. One potential policy candidate is travel restrictions (Fang et al., 2020; Lai et al., 2020). Local governments usually implemented travel restrictions to control the spread of the virus. Travel restrictions may reduce social contacts and thereby make people less trusting. This may bias our baseline estimates.

To examine this possibility, we control for population migration across provinces (Lai et al., 2020). Information on population migration comes from the Gaode website. If travel restrictions during the pandemic and post-pandemic period were primarily responsible for the deterioration of trust, the estimates shall decrease after controlling for population migration across provinces. Panel B of Table A2 reports the estimates with the average daily population migration flows across provinces in the first half year of 2020 controlled for. The estimated effects of COVID-19 exposure are almost unchanged, which indicates minimal bias caused by the changes in travel restrictions.

Sample selection – One may wonder whether our results are driven by some outliers. The province with the highest number of COVID-19 cases was Hubei Province, followed by Guangdong Province. The number of COVID-19 cases in Hubei Province was 41 times greater than that of Guangdong Province. We exclude the Hubei sample to assess whether our estimates are sensitive to the inclusion of the Hubei sample. The estimates are reported in Panel C of Table A2. Removing the Hubei Province results in point estimates that are qualitatively similar to our baseline estimates. As a result of the reduced sample size, the significance levels of the estimates are a bit lower.

Model specifications – First, we examine whether our results are robust to alternative functional forms of COVID-19 exposure. In the previous analysis, we have quantified exposure to the COVID-19 pandemic as the log of the total number of COVID-19 confirmed cases. As a robustness test, we use the ranking of the COVID-19 counts and the infection rate to measure COVID-19 exposure. Panels D and E of Table A2 present the corresponding estimates. We continue to find significant negative effects of COVID-19 exposure on interpersonal trust, especially trust in parents, neighbors, and government officials. The estimate in Column (6) of Panel E indicates that increased infection rates may be associated with enhanced trust in strangers. This may be due to the fact that individuals received informational and emotional support from strangers online during the pandemic. Nevertheless, we should interpret this finding with caution because the estimate is insignificant in most cases. Moreover, we use the number of infected cases by the time points of the questionnaires to proxy for the COVID-19 intensity. The estimates reported in Panel F of Table A2 produce quantitatively similar results.

We then investigate whether measurement errors associated with provincial COVID-19 exposure may bias our estimation results. Individuals may be more concerned about COVID-19 infection in their city. Within the same province, COVID-19 exposure may differ significantly and local governments may respond to the spread of the virus in different ways. In addition, provincial COVID-19 exposure may be correlated with some unobserved provincial characteristics, such as traditional Chinese medicine culture, religious beliefs, and property right institutions.

To examine potential biases associated with provincial level data, we use the log of the cumulative number of COVID-19 cases at the city level to measure COVID-19 exposure.[4] We control for city and survey wave dummies and cluster standard errors at the city level. The estimates are reported in Panel G of Table A2. The estimation results remain qualitatively similar.

Next, we examine whether the decrease in trust is due to the COVID-19 shock or government pandemic prevention policies. More severe epidemics are often accompanied by more stringent epidemic prevention policies, such as city and district lockdowns. These

[4] To protect private information of respondents, the CFPS public-use datasets do not contain the names of surveyed counties. Users should apply for the use of geographic information. We applied for the usage of geographic information and processed the data in the security room of Peking University. For details, see https://www.isss.pku.edu.cn/cfps/en/data/restricted/index.htm.

epidemic prevention policies may also decrease interpersonal trust. Following previous studies, we divide cities into three categories based on the intensity of epidemic prevention and control measures: completed lockdown, partial lockdown, and others (Fang et al., 2020).[5] The estimates reported in Panel H of Table A2 use city-level COVID-19 exposure and additionally control for the interaction terms between survey year dummies and epidemic control policy dummies. The estimated effects of COVID-19 exposure are almost unchanged. Therefore, city lockdowns are unlikely to bias our results.

Finally, we examine whether our results are robust to alternative estimation methods. Panel I of Table A2 presents the estimation results from a fixed effect logit model. Using the alternative estimation method does not alter our baseline conclusion. We continue to find that COVID-19 exposure significantly reduces interpersonal trust.

4.3. Mechanism analysis

We have established that COVID-19 exposure causes individuals to become less trusting. In this subsection, we explore the possible channels through which COVID-19 exposure affects interpersonal trust.

We first examine the hypothesis that COVID-19 exposure effects are driven by deteriorated labor market outcomes. Previous studies have revealed that individual income is an important determinant of interpersonal trust (Alesina & La Ferrara, 2002). It is possible that the COVID-19 pandemic generates long-lasting negative consequences on labor market performance and thereby alters interpersonal trust. Columns (1) and (2) of Table 3 report the estimation results for employment and income. The estimated coefficients are almost zero and statistically insignificant. Therefore, deteriorated labor market outcomes are unlikely to be the underlying mechanism.

Another hypothesis is that the changes in interpersonal trust reflect the changes in physical health status. The COVID-19 pandemic may have negatively impacted individual physical health status for a long time, thus detrimentally affecting interpersonal trust. Columns (3) and (4) of Table 3 report the estimation results for self-reported health outcomes. The estimated coefficients are small and statistically insignificant. Therefore, deteriorated physical health status outcomes are also unlikely to be the underlying mechanism.

We then investigate whether the changes in interpersonal trust reflect the changes in communication. If interfered communication (e.g. face masking) plays a role in driving COVID-19 exposure effects, we expect that individuals exhibit lower levels of trust in strangers and weaker belief in others' trustworthiness. Our baseline estimates indicate minimal effects of COVID-19 exposure on trust in strangers. In addition, the estimate reported in Columns (1) of Table 4 suggests that COVID-19 exposure has a small and insignificant effect on belief in others' kindness. Overall, there is little evidence for the channel of interfered communication.

COVID-19 exposure may also undermine people's sense of trust by deteriorating their mental health status. Columns (2) to (4) of Table 4 report the estimation results for mental health and subjective well-being. Consistent with the mechanism of worsening mental health status, the estimates indicate that individuals exposed highly to the pandemic display higher levels of depression and lower levels of happiness and life satisfaction. These findings are also in line with previous research reporting high levels of anxiety and depression among the general population during the pandemic (Qiu et al., 2020). Moreover, COVID-19 exposure may affect interpersonal trust by influencing confidence in the future. The estimates reported in Table 4 reports confirm this possibility: individuals with high COVID-19 exposure have a poorer evaluation of possible futures.

4.4. Heterogeneity analysis

Previous studies have documented that the COVID-19 pandemic has been affecting some socio-demographic groups particularly adversely, both in terms of health conditions and economic outcomes (Brodeur et al., 2021). Do the effects of COVID-19 exposure on interpersonal trust vary across socio-demographic groups? We investigate this issue in this subsection. We adopt a fully interacted regression model. Specifically, we add interaction terms between a dummy for a specific group and all baseline covariates to our baseline specification. The flexible specification is equivalent to split-sample regressions and allows us to compare two groups for statistical significance. However, the precision of parameter estimates may decrease due to estimating a large number of parameters.

COVID-19 exposure may have differential effects on males and females. Previous studies have documented that women are more susceptible to gender-based violence and psychological stressors associated with the COVID-19 pandemic than men (Clemente-Suárez et al., 2021). We interact a male dummy with all baseline covariates and report the estimation results of the interacted model in Panel A of Table 5. Although COVID-19 exposure seems to have larger effects on women than men in several cases, the differences are statistically insignificant.

The effects of COVID-19 exposure may vary with educational attainment. Less educated people have been hit harder by the COVID-19 pandemic both in terms of health and economic outcomes (Brodeur et al., 2021). We define a dummy variable for receiving at least middle school education and interact the dummy variable with all baseline covariates. Panel B of Table 5 reports the corresponding estimates from the interacted model. We observe that COVID-19 exposure has larger effects on trust in government officials and doctors among less educated people. A potential explanation is that less educated people lack knowledge about how to prevent and control infectious diseases and are therefore more likely to blame government officials and doctors for the spread of the virus. Nevertheless, COVID-19 exposure has no significant differential effects on other trust measures of the highly and less educated people.

The effects of COVID-19 exposure may depend on age. The COVID-19 pandemic has been hitting older cohorts much more than

[5] When a city is under complete lockdown, all public and private transportation are forbidden and all residential buildings are locked down with no residents allowed to leave. When a city is under partial lockdown, most public transportation is shut down and checkpoints are set up to control population mobility.

Table 3
Employment and health outcomes.

VARIABLES	(1) Employment	(2) Log income	(3) Health status	(4) Illness
COVID-19 exposure	0.001	0.006	0.015	-0.004
	(0.004)	(0.028)	(0.016)	(0.005)
Observations	29,899	9285	32,932	31,635
R-squared	0.612	0.655	0.649	0.517
Province FE	YES	YES	YES	YES
Survey wave FE	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Age FE	YES	YES	YES	YES

Note: Standard errors are clustered at the provincial level. ***significant at 1% level, **at 5%, *at 10%.

Table 4
Psychological outcomes.

VARIABLES	(1) Perceived kindness	(2) CES-D score	(3) Hedonic happiness	(4) Life satisfaction	(5) Future expectations
COVID-19 exposure	-0.004	0.121 * *	-0.066 * *	-0.043 * **	-0.037 * *
	(0.005)	(0.049)	(0.025)	(0.015)	(0.014)
Observations	31,543	20,612	21,030	31,642	31,633
R-squared	0.562	0.744	0.722	0.591	0.577
Province FE	YES	YES	YES	YES	YES
Survey wave FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
Age FE	YES	YES	YES	YES	YES

Note: Standard errors are clustered at the provincial level. ***significant at 1% level, **at 5%, *at 10%.

Table 5
Heterogeneity analysis.

VARIABLES	(1) General	(2) Parents	(3) Neighbors	(4) Officials	(5) Doctors	(6) Strangers	(7) Americans
Panel A. Gender							
COVID-19 exposure	-0.017 * *	-0.040 *	-0.064 * **	-0.036	-0.021	0.022	0.005
	(0.008)	(0.023)	(0.020)	(0.029)	(0.034)	(0.047)	(0.044)
COVID-19 exposure *Male	0.006	0.031	-0.011	-0.034	0.003	0.014	0.001
	(0.007)	(0.023)	(0.026)	(0.035)	(0.039)	(0.064)	(0.063)
Observations	31,580	31,612	31,626	31,549	31,622	31,598	31,274
Panel B. Education							
COVID-19 exposure	-0.023 * *	-0.043	-0.057 *	-0.144 * *	-0.109 * *	0.033	-0.002
	(0.009)	(0.036)	(0.031)	(0.057)	(0.053)	(0.032)	(0.039)
COVID-19 exposure *Highly Educated	0.012	0.024	-0.010	0.121 * *	0.125 * *	-0.005	0.020
	(0.011)	(0.046)	(0.038)	(0.058)	(0.052)	(0.038)	(0.037)
Observations	31,579	31,611	31,625	31,548	31,621	31,597	31,275
Panel C. Cohorts							
COVID-19 exposure	-0.009	-0.022	-0.097 * **	-0.077 *	-0.047	0.035	-0.029
	(0.010)	(0.015)	(0.018)	(0.043)	(0.040)	(0.028)	(0.038)
COVID-19 exposure *Young cohorts	-0.010	-0.006	0.059 * *	0.046	0.059	-0.017	0.067
	(0.012)	(0.024)	(0.024)	(0.045)	(0.058)	(0.045)	(0.040)
Observations	31,580	31,612	31,626	31,549	31,622	31,598	31,275

Note: Other control variables include fixed effects for individuals, provinces, survey waves, and age and their interactions with a grouping dummy variable. Standard errors are clustered at the provincial level. ***significant at 1% level, **at 5%, *at 10%.

younger cohorts (Brodeur et al., 2021). We define a dummy variable for being born after 1985 and interact it with all baseline covariates. Panel C of Table 5 presents the estimates. The results indicate that the effects of COVID-19 exposure on old and young groups are similar in most cases. There is one exception: the negative effect of COVID-19 exposure on trust in neighbors is more pronounced for older cohorts.

All in all, there is limited evidence for differential effects of COVID-19 exposure on interpersonal trust across gender, education, and age groups. These results suggest that the COVID-19 pandemic may have left a great social scar on the general population.

5. Discussions

Our results differ from several recent studies examining the change of interpersonal trust amidst the COVID-19 pandemic. These studies typically adopt a before-and-after design. The idea is that any changes in the outcomes are attributed to the pandemic. Kye and Hwang (2020) find that adults display higher levels of trust in society, people, and the government but lower levels of trust in the judiciary, the press, and religious organizations during the COVID-19 pandemic in South Korea. Sibley et al. (2020) reveal that New Zealanders exhibit higher levels of trust in science, politicians, and police during the COVID-19 pandemic. Li et al. (2021) conduct an online experiment among Chinese students and show that trust behaviors significantly decreases during the COVID-19 pandemic.

It is possible that other common temporal shocks contaminate the estimated effects in the before-and-after studies (Haber et al., 2021). To shed light on this possibility, we also conduct a before-and-after study. Table A3 presents the estimation results controlling for individual fixed effects. The core explanatory variable is a dummy variable for being after the COVID-19 outbreak, whose coefficient measures the change of trust after the COVID-19 outbreak. We find inconsistent changes in trust across domains after the COVID-19 outbreak. Specifically, the levels of generalized trust and trust in doctors, officials, and strangers increase significantly during the sample period, whereas the levels of trust in neighbors and Americans decrease significantly. These estimates stand in sharp contrast to our baseline estimates in Table 2, which implies significant biases stemming from other common temporal shocks.

Another potential explanation for the discrepancy between our results and those of the previous studies is different pandemic stages investigated. The number of newly diagnosed cases in China was almost zero when the latest wave of the CFPS was conducted in our study. However, previous studies focus on a period when the number of diagnosed cases kept rising among the study population. Interpersonal trust may be unstable in the midst of the COVID-19 pandemic (Li et al., 2021). Another possible reason is different sample compositions. Our study employs a nationally representative dataset with a large sample size, which is less likely to be biased by outliers.

6. Conclusions

Trust is an important component of social capital and plays a vital role in economic development. An increasing number of studies have documented that trust can be shaped by the current environment (Algan & Cahuc, 2014). Using data from the 2016–2020 CFPS, this paper employs a difference-in-differences approach to examine the effects of COVID-19 exposure on interpersonal trust. We show that individuals highly exposed to the COVID-19 pandemic exhibit lower levels of trust in general. The effect is mainly caused by a loss of trust in parents, neighbors, and local government officials. One potential explanation is that COVID-19 exposure increases mental health issues and induces pessimistic expectations about the future, thereby reducing the quality of social relationships.

The COVID-19 pandemic has posed an exceptional challenge in almost every part of the world. A better understanding of the potential effects of the COVID-19 pandemic may lead to more effective management of the pandemic. Future studies may be directed at ascertaining whether the effects on interpersonal trust that we report here persist over the longer run and whether and how potential policy interventions may enhance interpersonal trust. These results may produce useful information for governments to stimulate economic growth after the pandemic.

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Conflict of interest statement

The authors declare that they have no conflict of interest.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.asieco.2023.101609.

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