Mental Health and COVID-19 Citywide Lock-down A Case Study on Shanghai 2022

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Abstract. This paper contributes to the growing literature studying the mental health outcomes during the COVID-19 pandemic. This paper offers further empirical evidence of the negative mental health impact of citywide lock-downs by studying the lock-down happened in Shanghai, People's Republic of China during April, and May 2022. Using two measures of lock-down, binary and strictness, both my baseline Ordinary Least Square (OLS) and Double Machine Learning (DML) estimation shows consistently that online searches of keywords including "depression" and "anxiety" statistically significantly increased during the citywide lock-down, which indicates a deterioration in mental health. Searches on "suicide" shows heterogeneous response to binary lock-down and the strictness of lockdown. I provide the first evidence that mental health in lock-down residents could be affected by citywide lock-down differently when using different indicators for lock-down.

Keywords: COVID-19; lock-down; mental health; online search

JEL Codes: I10; I18

1 Introduction

As the largest city and the most economically important region in China, Shanghai has been the largest port for international flights both for passengers and air cargo services during the pandemic. Nearly 40% of the international flights of China during the pandemic in 2021 are departing or arriving from/at Shanghai Pudong International Airport[1]. Since the implementation of the zero-COVID policy, confirmed COVID-19 cases in China are primarily originated from overseas. Therefore, Shanghai has been faced with huge challenges to control the virus aiming to completely eliminate infections.

The largest wave of infection in Shanghai since 2020 started on March 1st, 2022, which later been confirmed that it was initially leaked from a quarantine hotel for passengers on international flights[2]. Skyrocketing infection numbers later resulted in the first city-wide lock-down of Shanghai. The lock-down persisted for over two months, and the policy eventually ”eliminated all infectious chains” and achieved its zero COVID goal.

The COVID-19 pandemic is possible to have negative effect on people’s mental health as natural disasters and economic downturn (Chaves et al., 2018; Beaglehole et al., 2018), partly due to the largely utilized quarantine policy, which Hossain et al. (2020) believes could result in severe mental health issues for population undergone isolation in various contexts (patients, caregivers, and healthcare providers).

Due to the huge challenge of data availability, direct measurement of Shanghai residents’ mental health status barely exists, which makes my study on the mental health effects not as explicit as one may expect. Nevertheless, Internet and especially online search engine data makes it possible for me to get a peek of how Shanghainese were doing during the difficult time. As the largest and the dominant search engine in the Mainland China, Baidu provides a keyword search index similar to Google Index, which implicitly reflects people’s mental health. Weaver III et al. (2010) found that people who search information online about illnesses tend to be those with illness. This is the psychological

[1] Ministry of Transport of the People’s Republic of China

[2] See https://www.thatsmags.com/shanghai/post/34243/all-of-shanghai-to-go-into-lockdown-amid-covid-19-epidemic.

foundation of the paper, using Baidu search behavior of the Shanghai residents as the proxies for their mental health.

Tefft (2011) uses the same type of proxy (Google Index, GI) for mental health status, studying the relationship between business cycle (especially unemployment and unemployment insurance) and mental health. Similar studies include Parker et al. (2017), which uses GI as explanatory variable to predict premature mortality.

Farkhad & Albarracín (2021) studies the mental health effects of mitigation policies in 50 states of the US during COVID, including stay-at-home orders, restaurant limit, and non-essential business closure. Their staggered Difference-in-Differences model found that the Google Index for keywords like "isolation", "worry", and "depression" etc. did increase significantly immediately after stay-at-home orders and restaurant/bar limits. Also, searches for "antidepressant" and "suicide" reduced during those mitigation policies, indication no negative effects of such policy on severe psychotic symptomatology.

The main contribution of this study can be summarized into three aspects. Firstly, the scale and magnitude of the lock-down in Shanghai 2022 is incomparable to any such lock-downs, considering the population affected and the economic importance of the city globally. Equally importantly, unlike similar policy elsewhere, essential services were not permitted under the lockdown rule at the time, and most residents were strictly confined in their apartment during the city-wide lockdown. Secondly, the use of Baidu Index as proxy for residents' mental health addresses an essential data availability issue, since it is usually infeasible to gather enough survey/test information regarding the mental status of a major city's residents, especially on a daily basis. Such availability issue becomes even more severe during extreme times, such as citywide shutdown. Thirdly, the Double Machine Learning estimated utilized in the paper generates an alternative evaluation for the causal relationship between the citywide shutdown and mental health.

This paper tries to evaluate the mental health impact of the citywide lock-down in Shanghai. The study is organized as follows. The second section summarizes the timeline of the lock-down in early 2022, introducing the various stages of the lock-down as well as details that helps explain the empirical design of the paper. In the third part of the paper, the data and variables are introduced in detail. The fourth section explains the baseline Ordinary Least Square (OLS) model employed in the paper as well as the Double Machine Learning (DML) model as a robustness check of the causality. Results reporting and discussion are included in the fifth and sixth section of the paper. Lastly, I summarize the conclusions in section seven.

2 Background

2.1 Start of Lock-down

On March 27th at 8 pm, the Shanghai Municipal government announced that the eastern part of Shanghai will be firstly locked down (orange area on Figure 1) from March 28th 5 am to April 1st 5 am. From April 1st 3 am, the western part of Shanghai (yellow area on Figure 1) will be locked down till April 5th 3 am.

2.2 "Static Management" and The Three Zones Policy

From 5 am on April 1st, nearly the whole city was under the Citywide Static Management and the initial lock-down plan was de facto abolished. The government announced the new city grid management policy, which labels residential areas into three types (lock-down Zone, Controlled Zone, and Precautionary Zone). Population under three zones are summarized in Appendix Table A1.

lock-down Zones refer to neighborhoods that have reported new infections in the previous seven days, and residents are required to stay at home for a week under closed-loop management.

Controlled Zones refer to neighborhoods where no infections were reported in the previous week. Residents are allowed to retrieve food deliveries or take a walk at designated spots at staggered hours within the compound.

Precautionary Zones are communities that have not reported infections over the past 14 days. Residents can leave their neighborhood but must stay within their sub-district, and they are encouraged to limit their movement. Those living in Precautionary zones can now move around their neighborhoods but must observe social distancing and could be sealed off again if there are new infections.

2.3 End of Lock-down

Starting from 12 am of June 1st, lock-down was lifted for residents and businesses in the Precautionary Zones, and public transportation as well as roads resumed[3]. This was the end of the citywide lock-down/static management. Figure 2 below illustrated the entire timeline of the citywide lock-down.

3 Data

3.1 Lock-down Strictness Indicator

I use the proportion of population in Shanghai under lock-down as the proxy for the strictness of the citywide lock-down. In the initial stage (March 28th to April 1st), only the eastern part of the city was under lock-down, which according to the Press Conferences of Shanghai People's Government on COVID-19 Pandemic Prevention No.139, there were around 9 million residents out of 25 million population locked down first (about 36%). From April 1st to April 11th, the whole city was practically under lock-down therefore my indicator is 100%.

After the abandonment of the initial plan, the three zones policy started. Based on new cases data from April 5th to April 11th (exactly 7 days, which corresponds to the definition of the three zones), from April 12th, some parts of the city were deemed as Controlled Zones and Precautionary Zones. From this point onwards, the definition of strictness becomes the proportion of population outside of the Precautionary Zones[4]. The strictness index in 2022 is shown in Figure 3 below.

An alternative proxy is a binary variable indicating citywide lock-down, which could also be convincing since during the period of March 28th to June 1st, nearly all residents

[3]Designated high-risk and medium-risk areas were still under lockdown, which was same as rest of the country. The lock-down in this paper is confined to the citywide lock-down.

[4]There are three approximation I made to address the missing values here. First, from April 12th to April 19th, there was no mention of changes in the zones, which I suspect was because the administration needed seven days based on their definition of the zones to "downgrade" a zone. Therefore, I assume the strictness to be stable in this period. Second, April 20th was the earliest date that the government started to "downgrade" zones, but it was until April 28th when the press conference began reporting changes in the zones daily. The strictness indicators from April 21st to April 27th are consequently extrapolated in the second-order polynomial form from the numbers starting April 28th and onwards. Third, before March 28th and after May 30th, strictness data are no longer available. During these periods, there were only lock-down of a few residential compounds in small scale, so I assume a strictness indicator of zero for those dates.

were affected by the policy and their response could be insensitive to exactly what percentage of the population was put under lock-down and Controlled Zones.

3.2 Mental Health Indicators and Control Variables

Due to the very nature of the topic, it is in practical impossible to obtain any survey data during the citywide lock-down. Thus, I used the Baidu index as a proxy for the residents' mental health status. The date range is from Jan 1st, 2020, to Sep 30th, 2022. See Table 1 for the keywords I used.

Baidu is the number 1 search engine in mainland China measured by market share (over 75% nationwide in 2022[5]), and Baidu Index is calculated by summing up and weighting the times users search the keyword on all Baidu-developed platforms. It has been shown to be an important indicator in various fields, including epidemiology.

The Baidu Index keywords I intend to use come from four categories, including COVID related, symptom related, policy related, and mental health related words. In order to control for seasonality of the search index, I include the daily index data from Sep 2018 to Sep 2022 in all provincial administrative regions of China, excluding Macau, Hong Kong and Taiwan (31 regions in total)[6]. The index data also distinguish users by the platform their using when doing the searches (PCs and mobile devices)[7].

Trend of the normalized Baidu Index variables are shown below in Figure 4. The red dotted lines denote the start and end of the citywide lock-down in Shanghai. Seasonality for all three indexes is profound, and we can notice significant spike of depression and anxiety searches during the citywide lock-down in April and May 2022.

3.3 COVID-19 Cases

To control for the progression of the pandemic in Shanghai, I obtained data from China CDC for daily new cases, new death and new recovered numbers in Shanghai from the start of the pandemic on Jan 20th, 2020.

[5]Market share of search engines in China 2022, by pageview. (2022, July 26). Statista. https://www.statista.com/statistics/253340/market-share-of-search-engines-in-china-pageviews/

[6]The exclusion is due to the low market share of Baidu Search Engine in those regions (less than 1%).

[7]I separately estimated the model using only the PC index and the mobile index respectively for the mental health variables and found no differences in statistical significance whatsoever.

3.4 Other controls

Other control variable includes number of weeks since the start of the pandemic (controlling for general time trend), month of the year variable (controlling for seasonality), and weeks since the lock-down (controlling for lagged effects).

The summary statistics of my sample are shown in Table 2.

4 Empirical Design

4.1 Baseline Model

The baseline model follows Tefft (2011), a canonical Interrupted Time Series (ITS) model:

$$Y_{wt} = \alpha + \beta \ lockdown_{wt} + X_{wt}\phi + \lambda_w + \delta_m + \epsilon_t \tag{1}$$

where Y_{wt} is the outcome variable measuring residents' mental status in week w and date t; $lockdown_{wt}$ is the lock-down indicator in week w and date t, measured by either strictness or a lock-down binary variable; X_{wt} is other control variables in week w and date t. Lastly, λ_w and δ_m is the week and month of the year dummy variables. The standard error is robust to hetero-skedasticity and serial correlation.

4.2 Double Machine Learning (DML) Model

Proposed by Chernozhukov et al. (2018), the DML model obtains the causal parameter of interest in the presence of a high-dimensional nuisance parameter which is estimated using various machine learning (ML) techniques, including LASSO, random forests, decision trees, and boosted regression trees.

We start with a data generating process as the Partially Linear Regression model (PLR) in Robinson (1988):

$$Y = \theta_0 D + g_0(X) + u_i \tag{2}$$

$$D = m_0(X) + v_i \tag{3}$$

where $E[u_i|X, D] = E[v_i|X] = 0$.

Here, Y is the outcome, D is the treatment, and $X = (x_1, x_2, \ldots, x_p)$ is the vector of controls, which affects the treatment assignment D via the nuisance function $m_0(X)$, and the outcome Y via another nuisance function $g_0(X)$. With the above setup (causal relationship shown in Figure **??**), directly estimate the θ_0 using ML method will generate biased and invalid estimates due to regularization. A simple ML method will split the sample into a training set $i \in I^C$ and a test set $i \in I$.

Another source of the bias is over-fitting, which can be overcome by cross-fitting, a common method in ML. Cross-fitting switches the training and test sample, so that the entire sample can be used for estimation.

5 Results

5.1 Baseline Model

First sets of estimation use the binary indicator of lockdown as the treatment variable, normalized Baidu Index of "depression", "anxiety", and "suicide" as the outcome variable. To control for the progression of infections in Shanghai, I use the daily new cases, daily new deaths, daily number of the recovered, as well as Baidu Index of "COVID-19", "pandemic", "fever", and "cough". Weekly time trend, month of the year, and weeks since the initial lockdown are serving as additional controls.

From Table 3, it is noted that for both depression and anxiety, the citywide lockdown significantly increased Baidu searches of those two keywords, regardless of the indicators of lockdown. Searches in "suicide" exhibit mixed results, where stricter lockdown decreased the number of searches, but the binary lockdown indicator is positively correlated with such searches.

An interesting finding here is that although residents' mental health was generally worse off during the lockdown, with time going by since the start of the lockdown they were searching less and less mental illness-related keywords. Note that the magnitude of such "recovery" is a lot slower than the general deterioration caused by the lockdown.

5.2 Double ML

Using normalized search index on "depression", "anxiety", and "suicide" as proxies for mental health, and under the Partially Linear Regression model (PLR), the DML results are summarized in Table 4. The learners in the ML part includes LASSO, Random Forest, Decision Tree, and Boosted Tree.

The results show that the lockdown significantly increased depression in Panel (a) of Figure 5. Furthermore, in Panel (b), both continuous and binary measure of the lockdown statistically significantly lead to more serious anxiety issue for residents in Shanghai.

As for tendency to suicide shown in Panel (c) of Figure 5, LASSO and Random Forest learner with the strictness as treatment variable detects a deterrence effect to suicide searches, whereas the binary lockdown indicator does not show enough significance. Similar to the suicide "benefit" of lock-downs found here, Calderon-Anyosa & Kaufman (2021) found that suicide rate immediately decreased following COVID-19 lockdown in Peru and climbed back up after the lockdown. When using binary treatment variable for lockdown, the estimated coefficients become positive in spite of the statistical insignificance.

5.3 Baseline: Counterfactual Analysis

With the above ITS setup, I generated the counter-factual of mental health outcomes when there is no lockdown happening. In general, the counter-factual appear to be aligned with the parameter estimation in Table 3. The results are shown in Figure 6 - 11, where both binary and continuous treatment variables are used.

6 Conclusion and Discussion

Generally speaking, both the strictness and the binary lockdown indicator exhibit negative impact on Shanghai residents' mental health in terms of depression and anxiety. Suicide effect is more complicated, since using binary and continuous treatment result in coefficients with opposite signs.

To conclude, this study confirms the negative effect of the citywide lockdown on residents' mental health. The deterioration of the mental health will lead to worse labor market outcomes[8], which needs to be investigated with more data. Also, the changes in mental health this paper studies are merely short-term. More efforts are worthy to be put into this area, evaluating the effects in longer term.

[8]See Andersen (2015), Banerjee et al. (2017), Charles et al. (2008), Ettner et al. (1997).

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7 Tables

Table 1: Baidu Index and Keywords

Category	Keyword	Translation
COVID-19	新冠	COVID, COVID-19, Coronavirus
	新冠病毒	COVID-19 Virus, Coronavirus
	疫情	Pandemic
Symptoms	发热	Fever
	咳嗽	Cough
Health Policy	封城	City-wide Lock-down
	静默	Silencing
Mental Health	抑郁	Depression
	焦虑	Anxiety
	自杀	Suicide

This table lists all the Baidu indexes used in my study. The first three categories are the control variables to account for COVID and lockdown related sentiments, and the last category ”Mental Health” is the main outcomes of interest. ”Lock-down” was the term used by both officials and media, referring to the city-wide lock-down since the initial lock-downs in Wuhan 2020 when the pandemic firstly broke out. From around 2021, the word “lock-down” was rarely used in official news and documents to avoid “inciting social panic”. Instead, words like “静默” (silencing) are starting to be used often, which are considered more implicit.

Table 2: Descriptive Statistics

Variable	Mean	S.D.	Min	Max	N
Lockdown strictness	0.03	0.14	0	1	985
Lockdown dummy	0.07	0.25	0	1	985
Number of new case	666.92	3385.12	0	27719	985
Recovered	64.43	336.26	0	4242	985
Death	0.60	4.54	0	52	985
Fever search index	236.17	59.16	59	713	985
Cough search index	317.50	90.53	112	820	985
Lockdown search index	146.26	138.47	0	1930	985
Silence search index	175.93	437.35	0	7499	985
COVID search index	885.66	457.29	0	3179	985
Pandemic search index	721.41	380.42	0	1802	985
Depression search index	208.98	24.73	99	313	985
Anxiety search index	222.95	34.68	78	397	985
Suicide search index	377.79	61.95	147	807	985

This table exhibits the descriptive statistics. The first two rows are the two treatment variables that are separately used in the empirical study, a strictness indicator that is between zero and one as well as a binary indicator of citywide lock-down. The control variables include COVID infection data and COVID/lock-down related Baidu Index. Last three rows summarize the main outcomes of interest, my proxies for mental health.

Table 3: Baseline Estimation Results

	Depression		Anxiety		Suicide	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Strictness	0.781		2.414***		-1.299***	
	(0.606)		(0.683)		(0.473)	
Lockdown		0.997***		1.681***		0.189
		(0.147)		(0.159)		(0.150)
Weeks since Lockdown	-0.016***	-0.019***	0.025***	0.020***	-0.034***	-0.035***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
COVID Infection Controls	✓	✓	✓	✓	✓	✓
Control Baidu Index	✓	✓	✓	✓	✓	✓
Weekly Trend	✓	✓	✓	✓	✓	✓
Week of Year	✓	✓	✓	✓	✓	✓
Month of Year	✓	✓	✓	✓	✓	✓
R-Squared	0.281	0.302	0.400	0.450	0.239	0.236
N	1004	1004	1004	1004	1004	1004

Dependent variables: Baidu Index (online searches) on keywords "depression", "anxiety", and "suicide". Column (1), (3), and (5) use the strictness of lock-down as the treatment variable, taking into account the daily aggregated level of lock-down in Shanghai. Column (2), (4), and (6) use a binary lock-down indicator. COVID infection controls: number of new cases, number of COVID recovery, number of COVID death. Control Baidu Index: search trends in COVID-19, coronavirus, pandemic, fever, cough, city-wide lock-down, and silencing. All specifications include weekly trend, week of the year effect, and month of the year effect. Hetero-skedasticity and serial correlation-robust standard errors are adopted. $*p < 0.10, **p < 0.05, ***p < 0.01$.

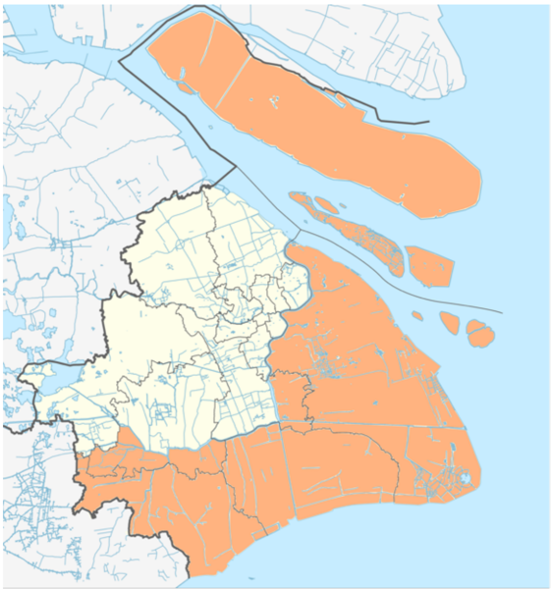
Table 4: DML Estimation Results

Outcome	ML Learner	Treatment	Coef.	S. E.
Depression	LASSO	Strictness	0.54	0.50
	Random Forest		-0.40	0.49
	Decision Tree	Binary Lockdown	0.67***	0.24
	Boosted Tree		0.60***	0.18
Anxiety	LASSO	Strictness	1.52***	0.50
	Random Forest		0.48	0.45
	Decision Tree	Binary Lockdown	0.86***	0.24
	Boosted Tree		0.30	0.20
Suicide	LASSO	Strictness	-1.30***	0.43
	Random Forest		-1.15**	0.57
	Decision Tree	Binary Lockdown	0.48	0.45
	Boosted Tree		0.27**	0.14

Dependent variables: Baidu Index (online searches) on keywords ″depression,″ ″anxiety,″ and ″suicide″. The same control variables as in Table 3 are used. The table presents results using different machine learning algorithms including LASSO, Random Forest, Decision Tree, and Boosted Tree as part of a Double Machine Learning (DML) framework. Treatment variables include ′Strictness′ of lockdown, accounting for the daily aggregated level of lockdown enforcement, and a binary ′Lockdown′ indicator. Specifications utilize a 2-folds cross-fitting repeated for 10 iterations to ensure robustness. All variables used in the estimations are standardized. The models aim to isolate the effect of lockdown stringency and presence on mental health indicators derived from online search behaviors. $*p < 0.10, **p < 0.05, ***p < 0.01$.

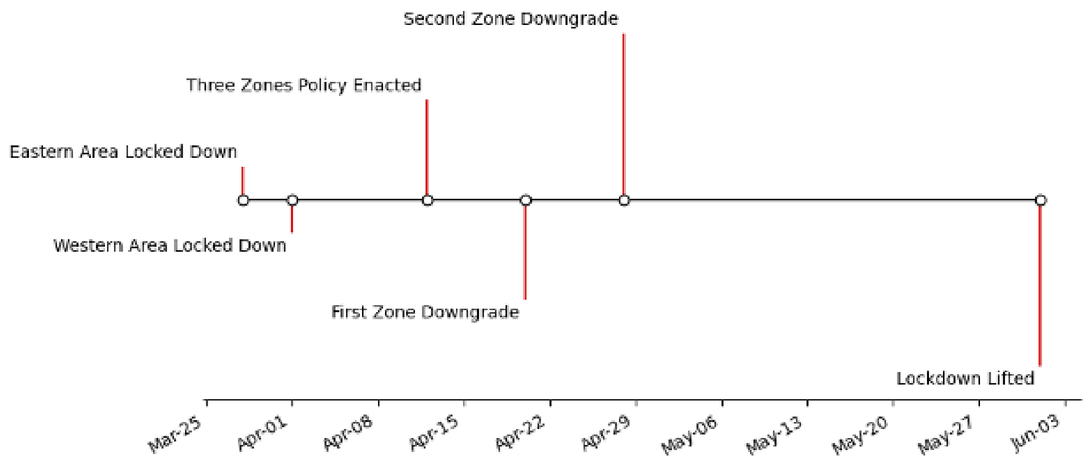
8 Figures

Figure 1: Initial Shanghai Lock-down Plan, March 2022



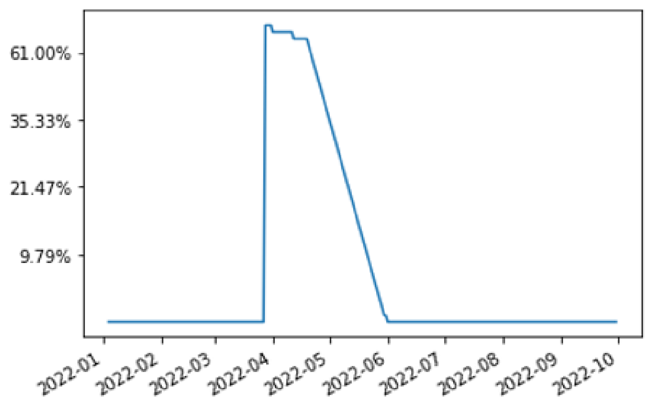
This map from Wikipedia on Shanghai Lock-down 2022 illustrates the geographical areas of Shanghai affected by the initial lockdown plan in response to the COVID-19 outbreak in March 2022. Areas marked in orange indicate the zones under strict lockdown measures.

Figure 2: Timeline



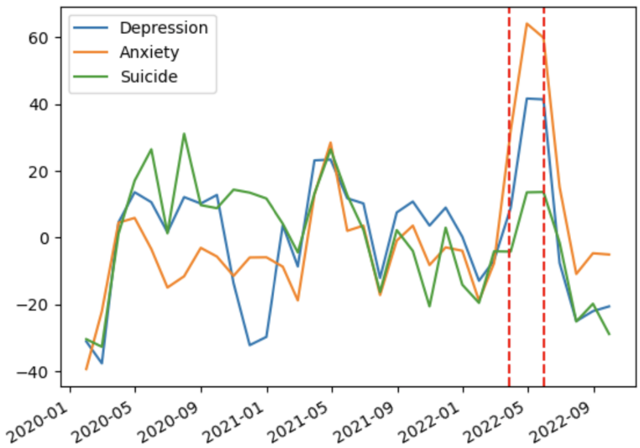
This timeline delineates the key phases of the lockdown strategy implemented in Shanghai during the COVID-19 pandemic in 2022. It marks significant events such as the initiation of lockdowns in the Eastern and Western areas, the enactment of the Three Zones policy, strategic downgrades of lockdown zones, and the eventual lifting of the lockdown.

Figure 3: Trend of Lock-down Strictness



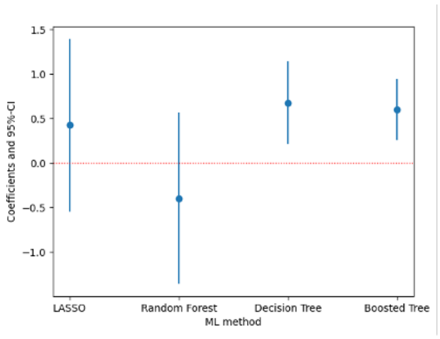
This figure displays the proportion of Shanghai's population under lockdown as a measure of lockdown strictness from January to October 2022. The initial peak represents the complete lockdown of the city, followed by a rapid decrease as restrictions eased. The percentage values indicate the strictness level, with 100% corresponding to a full citywide lockdown.

Figure 4: Trend of Baidu Index on Mental Health Keywords

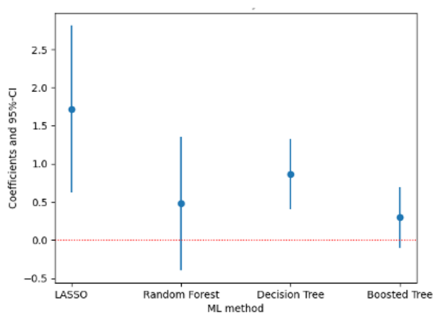


This graph shows the trend of Baidu search index values in Shanghai for the keywords ”Depression,” ”Anxiety,” and ”Suicide” from January 2020 to September 2022. The lines represent monthly fluctuations in search interest, with spikes indicating increased public interest or concern related to these mental health issues. The two vertical dashed red lines mark the start and end of the citywide lock-down in Shanghai.

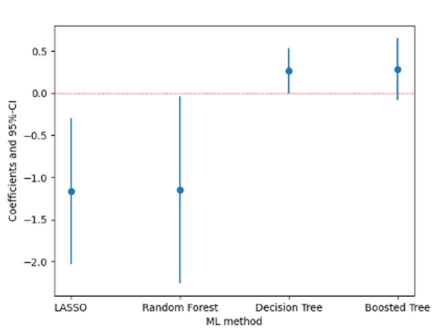
Figure 5: Double Machine Learning Estimation



(a) Depression



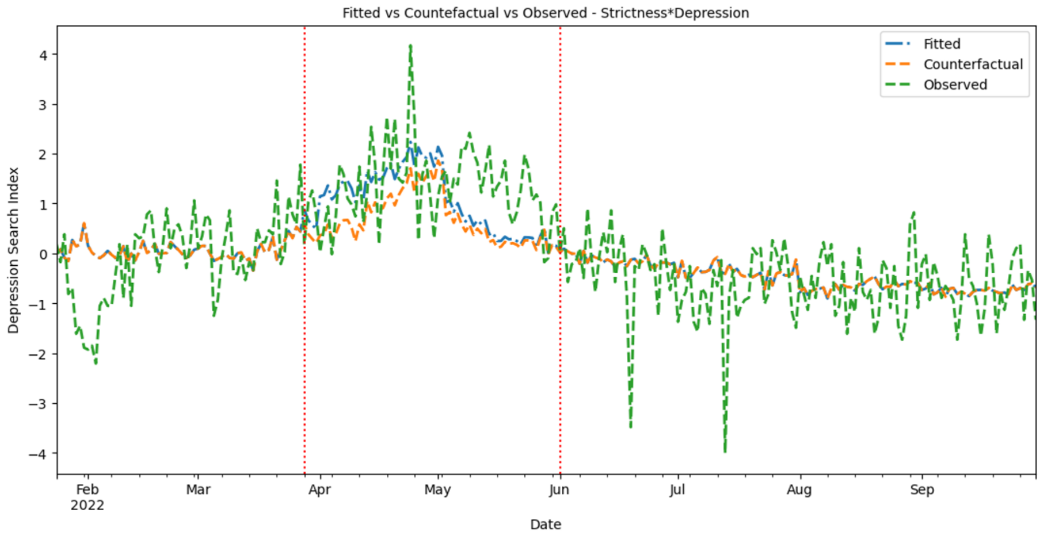
(b) Anxiety



(c) Suicide

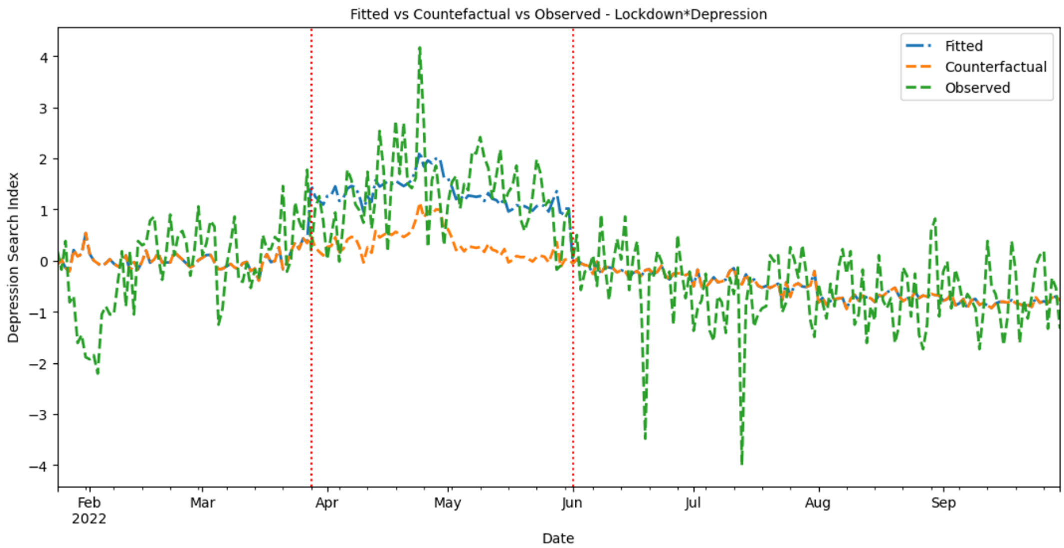
This figure shows the estimation results from four different machine learning methods: LASSO, Random Forest, Decision Tree, and Boosted Tree. Each sub-figure represents the coefficient estimates on different mental health outcomes: (a) Depression, (b) Anxiety, and (c) Suicide. The coefficients are presented along with their 95% confidence intervals, depicted as vertical bars. The dotted red line at y = 0 represents no effect.

Figure 6: Counterfactual of Depression Search with Strictness as Treatment



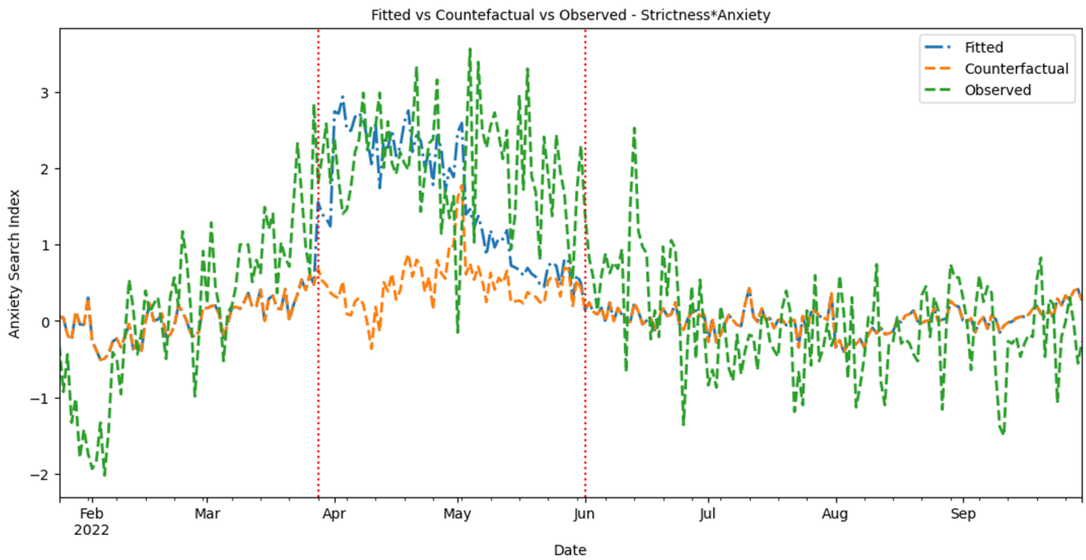
This graph presents the trend in Baidu search index values of Shanghai residents for ”depression” throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of varying lockdown strictness. The two vertical dashed red lines mark the start and end of lockdown policy.

Figure 7: Counterfactual of Depression Search with Lock-down as Treatment



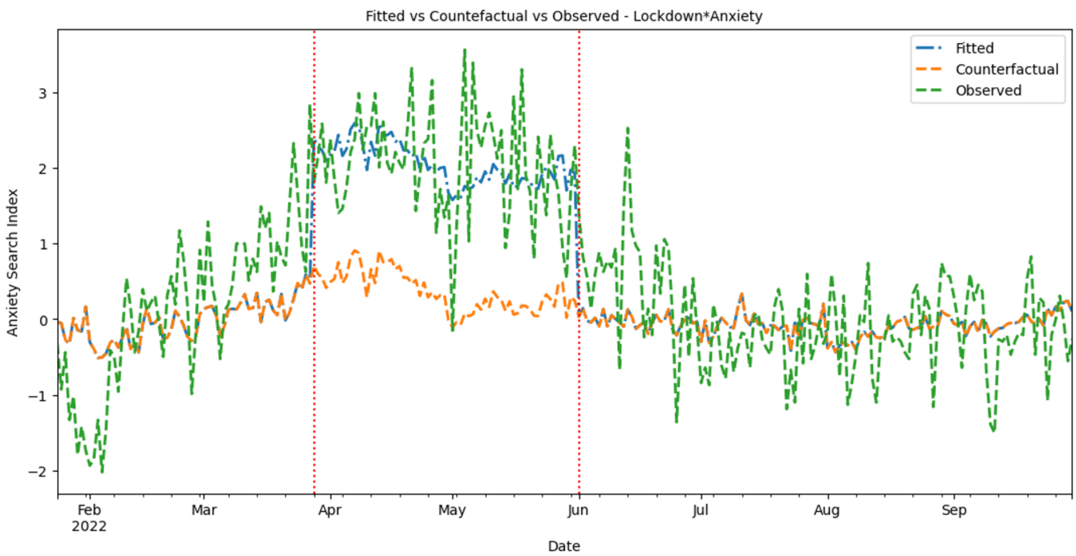
This graph presents the trend in Baidu search index values of Shanghai residents for ”depression” throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of the city-wide lockdown. The two vertical dashed red lines mark the start and end of lockdown policy.

Figure 8: Counterfactual of Anxiety Search with Strictness as Treatment



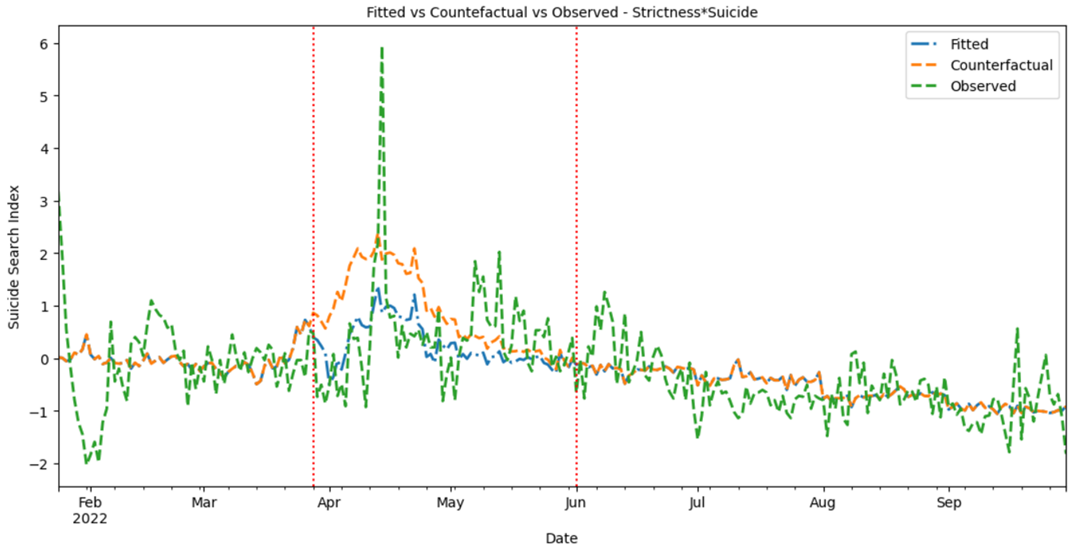
This graph presents the trend in Baidu search index values of Shanghai residents for ”anxiety” throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of varying lockdown strictness. The two vertical dashed red lines mark the start and end of lockdown policy.

Figure 9: Counterfactual of Anxiety Search with Lock-down as Treatment



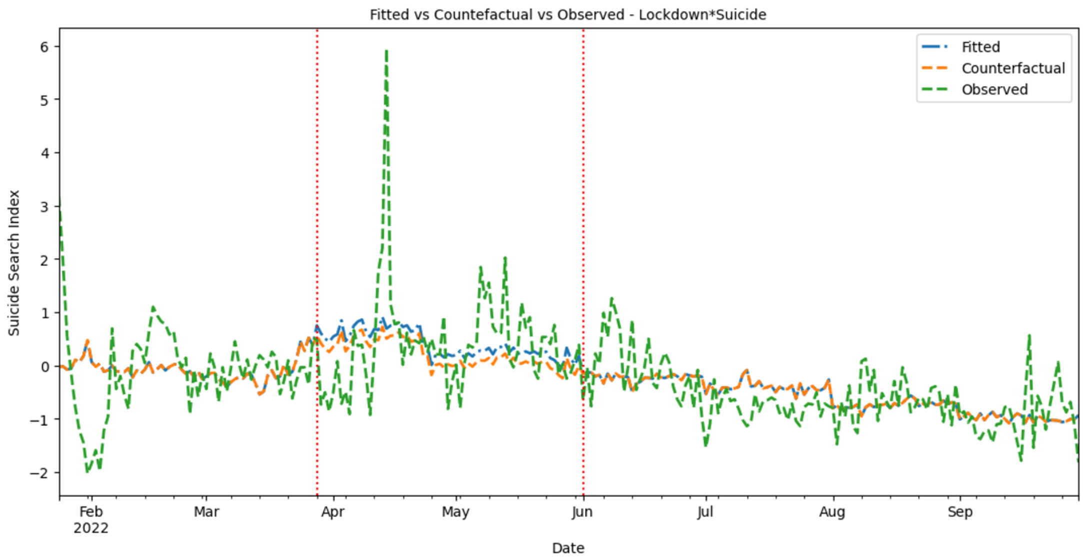
This graph presents the trend in Baidu search index values of Shanghai residents for ”anxiety” throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of the city-wide lockdown. The two vertical dashed red lines mark the start and end of lockdown policy.

Figure 10: Counterfactual of Suicide Search with Strictness as Treatment



This graph presents the trend in Baidu search index values of Shanghai residents for "suicide" throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of varying lockdown strictness. The two vertical dashed red lines mark the start and end of lockdown policy.

Figure 11: Counterfactual of Suicide Search with Lock-down as Treatment



This graph presents the trend in Baidu search index values of Shanghai residents for "Suicide" throughout 2022. It compares observed data (green dashed line) against both a fitted model under the baseline empirical design (orange line) and a counterfactual scenario (blue dashed line) that estimates what search trends might have looked like without the influence of the city-wide lockdown. The two vertical dashed red lines mark the start and end of lockdown policy.

9 Appendix

Table A1: Population Under the Three Zones Policy (in thousands)

Date	Lockdown Zone	LZ Percentage	Controlled Zone	CZ Percentage	Precautionary Zone	PZ Percentage
Apr 12th	15010	69.52%	1780	8.24%	4800	22.23%
Apr 20th	11878	49.05%	4480	18.50%	7856	32.44%
Apr 28th	5270	22.35%	5930	25.15%	12380	52.50%
Apr 29th	4440	18.81%	5390	22.83%	13780	58.37%
Apr 30th	3000	12.50%	6000	25.00%	15000	62.50%
May 1st	2760	11.79%	5510	23.54%	15140	64.67%
May 2nd	2540	10.86%	5380	23.00%	15470	66.14%
May 3rd	2390	10.23%	5190	22.22%	15780	67.51%
May 4th	2340	10.03%	4510	19.34%	16470	70.63%
May 5th	2350	10.08%	4300	18.44%	16670	71.48%
May 6th	2350	10.11%	4030	17.34%	16860	72.55%
May 7th	2450	10.52%	3820	16.40%	17020	73.08%
May 8th	2300	9.88%	3620	15.54%	17370	74.58%
May 9th	2110	9.06%	3270	14.03%	17920	76.91%
May 10th	2080	8.93%	3240	13.91%	17970	77.16%
May 11th	1970	8.46%	3030	13.01%	18290	78.53%
May 12th	2150	9.25%	3350	14.41%	17740	76.33%
May 13th	1820	7.87%	3250	14.04%	18070	78.09%
May 14th	1150	4.94%	3480	14.95%	18640	80.10%
May 15th	980	4.21%	3280	14.10%	19000	81.69%
May 16th	860	3.69%	3000	12.88%	19440	83.43%
May 17th	790	3.39%	2710	11.63%	19800	84.98%
May 18th	710	3.05%	2360	10.13%	20220	86.82%
May 19th	630	2.71%	2110	9.07%	20530	88.23%
May 20th	560	2.41%	1970	8.46%	20750	89.13%
May 21st	510	2.19%	1770	7.60%	21000	90.21%
May 22nd	480	2.06%	1590	6.83%	21200	91.10%
May 23rd	420	1.81%	1470	6.33%	21350	91.87%
May 24th	390	1.68%	1380	5.94%	21460	92.38%
May 25th	350	1.51%	1310	5.64%	21560	92.85%
May 26th	320	1.38%	1120	4.83%	21770	93.80%
May 27th	260	1.12%	890	3.84%	22040	95.04%
May 28th	250	1.08%	780	3.37%	22140	95.55%
May 29th	220	0.95%	670	2.89%	22280	96.16%
May 30th	190	0.82%	450	1.94%	22500	97.23%

This table summarizes the number and proportion of Shanghai population under each type of lockdown zones since the three-zone policy from April 12th, 2022 to May 30th, 2022. Data source: Press Conferences of Shanghai People's Government on COVID-19 Pandemic Prevention No.150-202