

# Modeling COVID-19 Effects on Mental Health Outcomes in China

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## Introduction

China's Zero-COVID strategy relied on aggressive non-pharmaceutical interventions, including lockdowns, mass testing, mobility restrictions, and community-level quarantines that varied in intensity across provinces and over time. The policies imposed substantial and uneven constraints on daily activity, social interaction, and employment providing a natural setting to study how large-scale and persistent containment measures may have affected mental health.

Assessing the psychological consequences of Zero-COVID is complicated by the simultaneous presence of COVID-19 morbidity and mortality, which may independently influence mental health. In addition, individuals differ in baseline levels of depression and vulnerability to stress, making cross-sectional comparisons difficult to interpret. Longitudinal data are therefore critical for isolating changes in mental health associated with evolving local conditions rather than stable individual differences.

We study this question using multilevel longitudinal models that exploit within-individual and across-province variation over time while accounting for the hierarchical structure of the CFPS sample. **This approach allows us to estimate how changes in province policy stringency and pandemic intensity relate to changes in depression, net of persistent individual characteristics and common time trends.**

## Data

**China Family Panel Studies (CFPS)**

# Top 10 Provinces by Number of People

ID	Name	Communities	Families	People	Post-COVID		
					CESD	Stringency	Cases per 100k
41	Henan	214	646	995	12.862	62.164	0.148
62	Gansu	202	689	980	15.362	55.751	0.164
21	Liaoning	219	573	808	12.319	55.634	0.215
13	Hebei	134	468	693	13.892	44.647	0.029
37	Shandong	129	376	554	11.343	56.537	0.072
44	Guangdong	222	432	531	13.255	62.348	2.837
14	Shanxi	90	292	428	14.168	60.582	0.309
31	Shanghai	164	301	426	11.066	56.556	1.284
23	Heilongjiang	103	224	316	13.059	52.253	0.124
51	Sichuan	107	231	299	13.699	50.084	0.423

Individual-level mental health and demographic data come from the China Family Panel Studies (CFPS), a nationally representative, biennial longitudinal survey administered by the Institute of Social Science Survey at Peking University. The CFPS tracks individuals, families, and communities across China and collects detailed information on health, economic conditions, education, and family structure. We use four survey waves as our unit of time: 2016, 2018, 2020, and 2022. After cleaning and merging with province-level pandemic data, the final analytical sample consists of 51,224 person-wave observations covering 12,806 individuals, 7,770 families, and 3,318 communities across 33 provinces. Depression is measured using the CESD-20 scale, which captures the frequency of depressive symptoms over the past week.

## COVID-19 Mortality Data

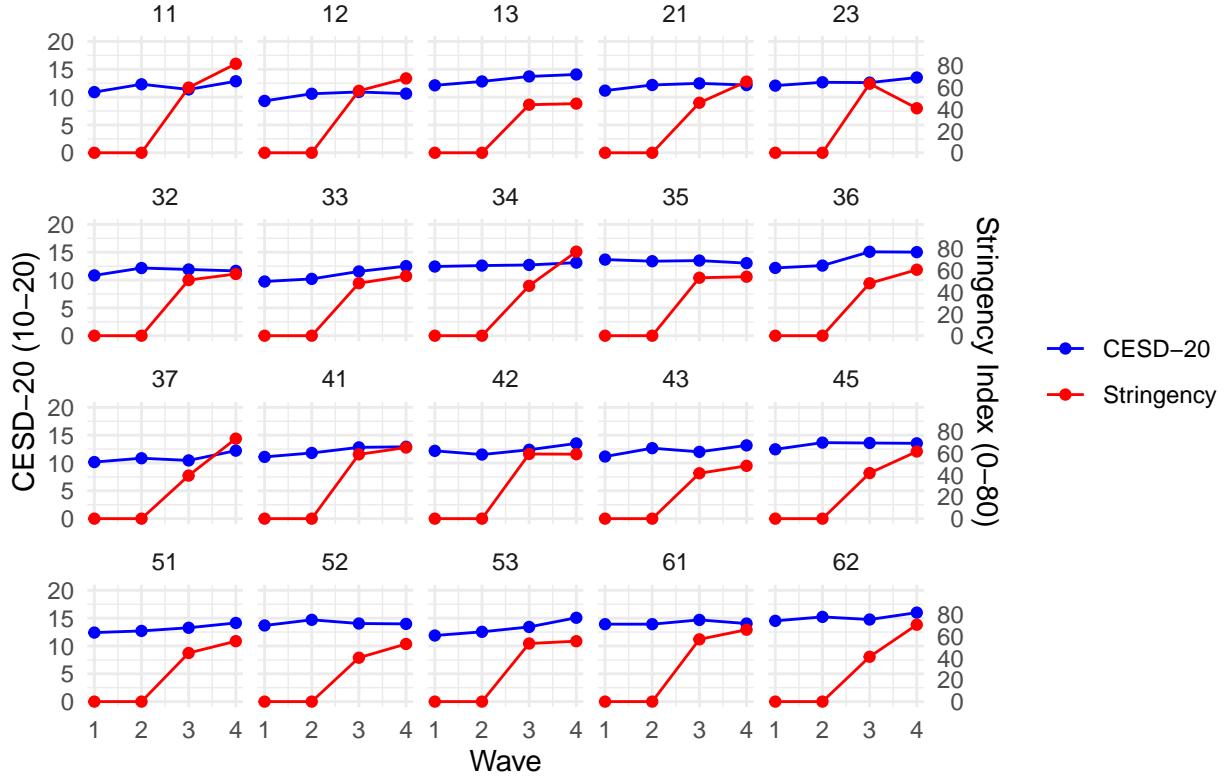
Data on COVID-19 cases and deaths come from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, sourced from official Chinese reporting channels including the National Health Commission of China and the China CDC. We aggregate these data to the monthly and province level to match the temporal resolution of the survey data.

## Policy Stringency Data

Measures of COVID-19 containment policy severity are drawn from the Oxford COVID-19 Government Response Tracker (OxCGRT). We use the Oxford Stringency Index, which summarizes the intensity of these policies on a standardized scale (Hale et al., 2021). Monthly averages of the

stringency index are constructed to align with the CFPS survey timing.

### Depression & Stringency Over Time (20 Sampled Provinces)



The figure above maps stringency over wave onto depression.

## Methods

We use multilevel longitudinal models that leverage repeated observations of the same individuals over time. This approach allows us to focus on within-person changes in mental health as local pandemic conditions evolve, rather than relying on cross-sectional comparisons that may be confounded by stable individual differences.

The CFPS data have a hierarchical structure, with individuals nested within families, communities, and provinces. Observations within these units are likely correlated due to shared environments, social conditions, and institutional factors. Multilevel modeling provides a principled way to account for this dependence by including random effects at each relevant level, avoiding underestimated uncertainty and biased inference.

We include random intercepts for individuals to account for correlation across waves within the same person. In addition, we cluster at the family and community levels to capture shared household conditions and local-level contextual factors that may shape mental health outcomes. We include province-level random intercepts to absorb persistent differences across provinces, such as baseline mental health environments, health system capacity, and reporting practices. We prefer community-level clustering to county-level clustering because communities are smaller and more socially cohesive units, where correlated mental health outcomes are more plausible, while counties are comparatively large and heterogeneous.

Survey wave fixed effects are included to control for common time shocks affecting all respondents, such as nationwide changes in economic conditions, information environments, the effect of COVID overall, and changing mental health resources over time. This ensures that identification comes from variation in local pandemic conditions relative to broader national trends. Also, we include a small set of individual-level controls—age, self rated health, gender, education, marital status, and urban residence. These controls were chosen because they are well-established correlates of depression.

Our key treatment variables—policy stringency and COVID-19 deaths—are measured as three-month moving averages. We use moving averages for two reasons. First we denoies our estimates. Second, rolling and cumulative COVID impacts are more realistic than point estimates of impacts at the start of the month—this better speaks to the mechanism we interrogate.

## Model

Our data have survey wave  $w$  nested within person  $i$ , who belongs to family  $f$  in community  $c$  in province  $p$ . Let  $y_{wifcp}$  denote the CESD-20 depression score for individual  $i$  in family  $f$ , community  $c$ , province  $p$  at wave  $w$ . Our main province-by-time treatments are the three-month moving averages of the Oxford policy stringency index and COVID-19 deaths per capita, denoted  $\text{Stringency}_{pw}$  and  $\text{Deaths}_{pw}$ , respectively.

We specify the following five-level random-intercept model:

$$\begin{aligned}
\text{Level 1 (wave within person): } \quad & y_{wifcp} = \pi_{ifcp} + \beta_1 \text{Stringency}_{pw} + \beta_2 \text{Deaths}_{pw} \\
& + \boldsymbol{\beta}_Z^\top \mathbf{Z}_{wifcp} + \boldsymbol{\lambda}^\top \mathbf{W}_w + \varepsilon_{wifcp}, \\
& \varepsilon_{wifcp} \sim \mathcal{N}(0, \sigma_\varepsilon^2) \\
\text{Level 2 (person): } \quad & \pi_{ifcp} = \beta_{fcp} + \boldsymbol{\beta}_X^\top \mathbf{X}_{ifcp} + u_i, \\
& u_i \sim \mathcal{N}(0, \sigma_i^2) \\
\text{Level 3 (family): } \quad & \beta_{fcp} = \gamma_{cp} + u_f, \\
& u_f \sim \mathcal{N}(0, \sigma_f^2) \\
\text{Level 4 (community): } \quad & \gamma_{cp} = \alpha_p + u_c, \\
& u_c \sim \mathcal{N}(0, \sigma_c^2) \\
\text{Level 5 (province): } \quad & \alpha_p = \nu + u_p, \\
& u_p \sim \mathcal{N}(0, \sigma_p^2),
\end{aligned}$$

where  $\nu$  is the grand mean depression level.

At Level 1,  $\mathbf{Z}_{wifcp}$  collects time-varying individual covariates (centered age and self-rated health), and  $\mathbf{W}_w$  is a vector of survey-wave indicators (2016, 2018, 2020, 2022) that flexibly absorbs common shocks over time. The coefficients  $\beta_1$  and  $\beta_2$  capture the average associations between province-level policy stringency, COVID-19 deaths, and depression, conditional on covariates and random intercepts.

At Level 2,  $\mathbf{X}_{ifcp}$  contains time-invariant or slow-moving individual characteristics (gender, education, marital status, and urban residence), and  $u_i$  is a person-specific random intercept. The terms  $u_f$ ,  $u_c$ , and  $u_p$  are random intercepts for families, communities, and provinces, respectively, allowing for clustering of depression outcomes within each higher level.

## Results

Table 1 reports estimates from our baseline multilevel model relating province-level COVID-19 policy stringency and COVID-19 deaths per capita to individual depressive symptoms. After adjusting for survey wave fixed effects, individual-level controls, and random intercepts at the person, family, community, and province levels, neither policy stringency nor COVID-19 mortality is significantly associated with CESD-20 scores. The estimated coefficients on both treatment variables are small in magnitude and statistically indistinguishable from zero. (See Appendix Item A.)

Table 1: Full Model

Term	Estimate	Std. Error	df	t-value	p-value
(Intercept)	14.01	0.33	265.8	43.09	<0.001
X3month_avg_StringencyIndex_Average	-0.00003	0.01	22080.0	-0.01	0.996
X3month_avg_new_deceased_per_capita	-2.10	1.34	24340.0	-1.56	0.119
wave2	0.73	0.09	23180.0	7.88	<0.001
wave3	1.13	0.32	22310.0	3.59	<0.001
wave4	1.81	0.37	22540.0	4.87	<0.001
age_c	-0.04	0.01	9762.0	-6.66	<0.001
health_c	1.46	0.04	30280.0	38.83	<0.001
urban1	-0.53	0.15	1624.5	-3.49	<0.001
gender1	-1.16	0.12	5396.8	-9.93	<0.001
education3	-1.07	0.21	10100.0	-5.21	<0.001
education4	-1.85	0.20	9737.0	-9.04	<0.001
education5	-2.21	0.23	10847.0	-9.69	<0.001
education6	-2.35	0.28	13363.0	-8.29	<0.001
education7	-2.60	0.33	14715.0	-7.99	<0.001
education8	-2.90	0.98	21296.0	-2.97	0.003
education9	-0.38	2.96	28693.0	-0.13	0.898
education10	0.24	0.36	28889.0	0.66	0.512
marital2	0.13	0.22	13854.0	0.61	0.542
marital3	0.92	0.74	29426.0	1.24	0.214
marital4	2.85	0.39	20547.0	7.26	<0.001
marital5	3.69	0.35	16864.0	10.53	<0.001

By contrast, survey wave indicators are strongly associated with depressive symptoms. Relative to the pre-pandemic 2016 baseline wave, depression scores significantly increase monotonically across subsequent waves, with particularly large increases observed in the 2020 and 2022 survey waves. These patterns are consistent across all model specifications we consider.

To assess the robustness of the baseline results, we estimate several extensions of the model. First,

we allow the effect of policy stringency to differ in the final survey wave by interacting stringency with a wave-4 indicator. This interaction term is not statistically significant, and the main effect of stringency remains close to zero. Second, we remove survey wave fixed effects; while the stringency coefficient becomes statistically significant in this specification, the estimate is no longer robust once wave indicators are reintroduced, indicating that this relationship is driven by aggregate time trends rather than within-wave variation. Third, we restrict identification to within-province variation in stringency after 2020 by demeaning stringency at the province level; the resulting estimate remains statistically insignificant. Finally, we allow the effect of stringency to vary across provinces by including a random slope for stringency at the province level. The average stringency effect remains statistically insignificant, and estimated cross-province heterogeneity in the stringency slope is limited. (See Appendix Item B.)

Figure 1 illustrates mean CESD-20 scores by survey wave. Depression levels increase sharply between the pre-pandemic and post-pandemic waves, highlighting a substantial rise in reported depressive symptoms over time. Consistent with the regression results, this figure underscores that observed changes in depression are primarily associated with broad temporal shifts rather than differential exposure to local pandemic policies or mortality intensity.

## Mean Depressive Symptoms by Survey Wave After Controls

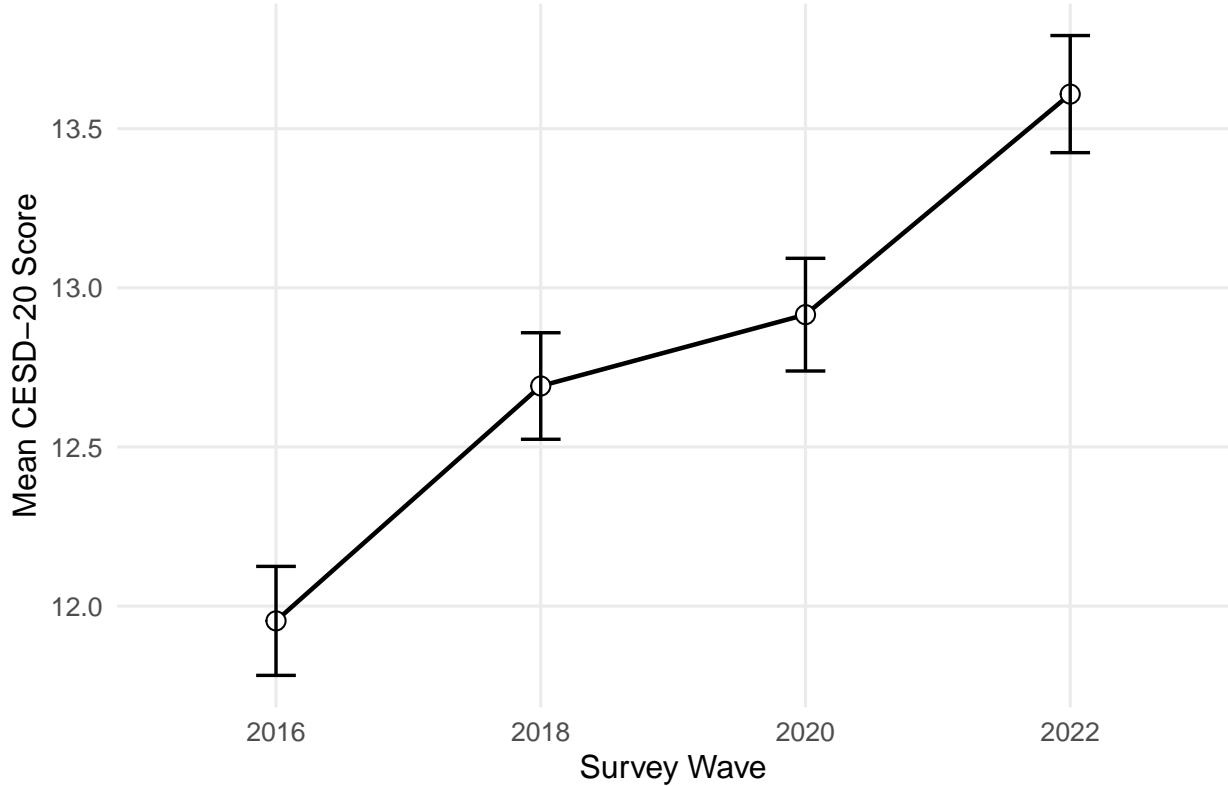


Figure 1: Mean CESD-20 depression scores by survey wave

Figure 2 compares observed and model-predicted CESD-20 trajectories for a random sample of individuals, showing that predictions primarily reflect overall time trends rather than individual-specific responses to local pandemic conditions.

Taken together, the results indicate that, conditional on controls and fixed effects, we do not find evidence of a statistically significant association between province-level COVID-19 policy stringency or COVID-19 mortality and individual depressive symptoms. We defer discussion of potential explanations and implications of these findings to the conclusion.

## Actual vs. Predicted Depression Trajectories

Random sample of 20 individuals

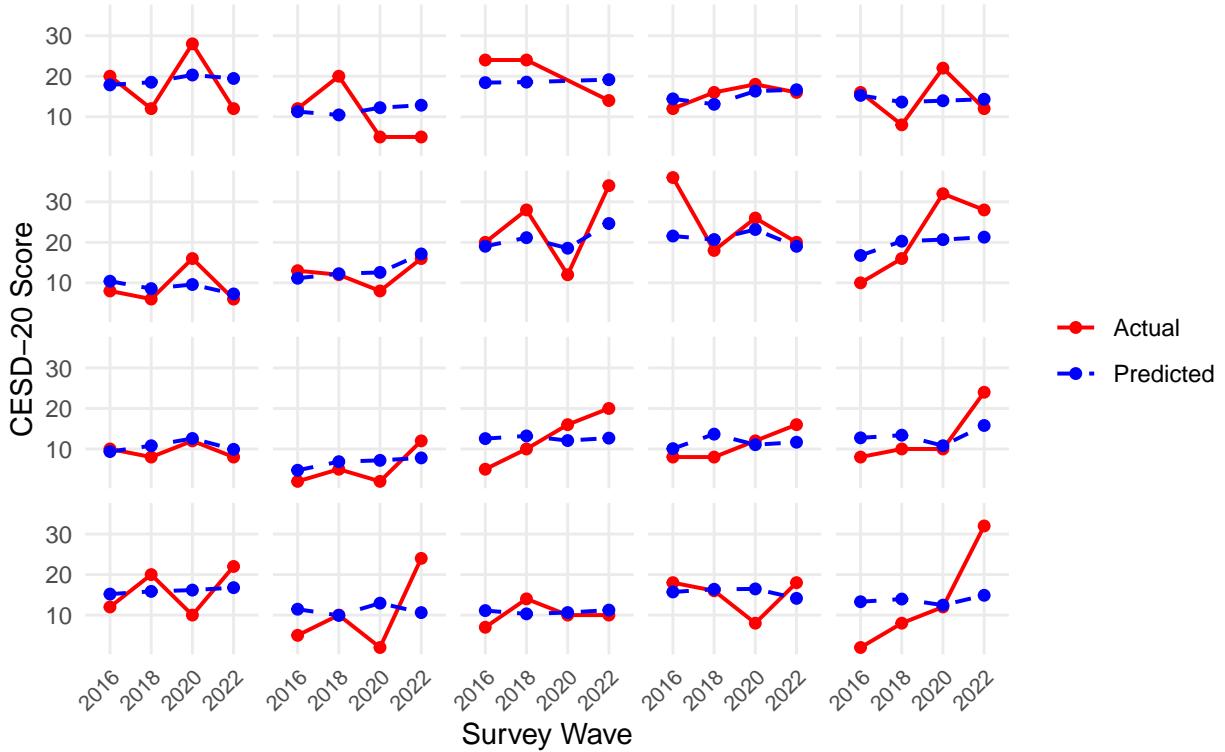


Figure 2: Actual and predicted CESD-20 trajectories for a random sample of individuals

## Conclusion

Across all specifications, we do not find a statistically significant association between COVID-19 policy stringency or COVID-19 mortality and depressive symptoms after accounting for individual characteristics and the hierarchical structure of the data. These null results persist across model extensions, including interactions, within-province variation, and random slopes, suggesting that the findings are not driven by a particular modeling choice.

These results should be interpreted with caution given several limitations. Although the CFPS is longitudinal, survey observations are clustered in a small number of months within each wave. Major changes in China's COVID-19 policies did not necessarily occur during these survey periods, limiting our ability to detect mental health responses to evolving policy conditions. As a result, meaningful variation in exposure may be poorly aligned with measurement of depressive symptoms.

In addition, the analytic sample is subject to selection and attrition concerns. Individuals who die—whether from COVID-19, suicide, or other causes—are necessarily excluded from later waves, and survey attrition may be correlated with worsening mental health. Both mechanisms could bias estimated effects toward zero.

An additional limitation is the potential unreliability of official COVID-19 data in China, as government involvement in data collection and reporting may create incentives to systematically underreport cases or deaths, introducing measurement error in key treatment variables.

Future work would benefit from more temporally granular mental health data that span the full calendar year. Finer measurement would allow for tighter alignment between policy changes and psychological outcomes. We could also include economic impact data to control for confoundingness.

## Appendix A: Model Results (Required)

### Model Call

```
model_full <- lmer(  
  cesd20 ~  
    X3month_avg_StringencyIndex_Average +  
    X3month_avg_new_deceased_per_capita +  
    wave +  
    age_c +  
    health_c +  
    urban +  
    gender +  
    education +  
    marital +  
    (1 | provcd) +      # province  
    (1 | cid) +        # community  
    (1 | fid) +        # family  
    (1 | pid),          # person  
  data = cfps_model,  
  REML = TRUE  
)
```

### Model Output

```
library(arm)  
display(model_full)  
  
## lmer(formula = cesd20 ~ X3month_avg_StringencyIndex_Average +  
##       X3month_avg_new_deceased_per_capita + wave + age_c + health_c +  
##       urban + gender + education + marital + (1 | provcd) + (1 |  
##       cid) + (1 | fid) + (1 | pid), data = cfps_model, REML = TRUE)  
##           coef.est  coef.se  
## (Intercept)     14.01    0.33  
## X3month_avg_StringencyIndex_Average   0.00    0.01  
## X3month_avg_new_deceased_per_capita -2.10    1.34  
## wave2            0.73    0.09  
## wave3            1.13    0.31  
## wave4            1.81    0.37  
## age_c            -0.04    0.01  
## health_c          1.46    0.04  
## urban1           -0.53    0.15  
## gender1          -1.16    0.12  
## education3       -1.07    0.21  
## education4       -1.85    0.20  
## education5       -2.21    0.23  
## education6       -2.35    0.28  
## education7       -2.60    0.33
```

```

## education8           -2.90    0.98
## education9          -0.38    2.96
## education10         0.24    0.36
## marital2            0.13    0.22
## marital3            0.92    0.74
## marital4            2.85    0.39
## marital5            3.69    0.35
##
## Error terms:
## Groups   Name      Std.Dev.
## pid      (Intercept) 3.68
## fid      (Intercept) 2.66
## cid      (Intercept) 1.27
## provcd   (Intercept) 0.78
## Residual             5.63
## ---
## number of obs: 30775, groups: pid, 7879; fid, 5648; cid, 2326; provcd, 31
## AIC = 204048, DIC = 203917.1
## deviance = 203955.7

```

## Appendix B: Extension Models Code

```

## -----
## 2. interacting stringency with wave 4
## -----

cfps_model <- cfps_model %>%
  mutate(
    wave4 = ifelse(wave == 4, 1, 0)
  )

model_int_wave4 <- lmer(
  cesd20 ~
    X3month_avg_StringencyIndex_Average +
    X3month_avg_new_deceased_per_capita +
    wave + # still have wave FE
    X3month_avg_StringencyIndex_Average:wave4 +
    age_c +
    health_c +
    urban +
    gender +
    education +
    marital +
    (1 | provcd) +
    (1 | cid) +
    (1 | fid) +
    (1 | pid),

```

```

  data = cfps_model,
  REML = TRUE
)

summary(model_int_wave4)

## -----
## 3. removing wave fixed effects from baseline
## -----

model_no_wave <- lmer(
  cesd20 ~
    X3month_avg_StringencyIndex_Average +
    X3month_avg_new_deceased_per_capita +
    age_c +
    health_c +
    urban +
    gender +
    education +
    marital +
    (1 | provcd) +
    (1 | cid) +
    (1 | fid) +
    (1 | pid),
  data = cfps_model,
  REML = TRUE
)

summary(model_no_wave)

## -----
## 4. within province stringency
## -----

model_within_prov_post2020 <- lmer(
  cesd20 ~
    stringency_wp_post2020 +
    X3month_avg_new_deceased_per_capita +
    wave +           # you can drop this if you want
    age_c +
    health_c +
    urban +
    gender +
    education +
    marital +
    (1 | provcd) +
    (1 | cid) +

```

```

(1 | fid) +
(1 | pid),
data = cfps_model,
REML = TRUE
)

summary(model_within_prov_post2020)

## -----
## 5. Random slope for stringency by province
## -----
```

model\_random\_slope <- lmer(
cesd20 ~
X3month\_avg\_StringencyIndex\_Average +
X3month\_avg\_new\_deceased\_per\_capita +
wave +
age\_c +
health\_c +
urban +
gender +
education +
marital +
(1 + X3month\_avg\_StringencyIndex\_Average | provcd) + # random slope
(1 | cid) +
(1 | fid) +
(1 | pid),
data = cfps\_model,
REML = TRUE
)

## Bibliography

Murong Xuecun. (2023, April 18). China's 'zero Covid' policy was a mass imprisonment campaign. The Guardian. <https://www.theguardian.com/commentisfree/2023/apr/18/china-zero-covid-policy-xi-jinping>

Yan, K., Jiang, S., Xia, L., Jin, T., Dai, A., Gu, C., & Li, A. (2025). China's zero-COVID policy and psychological distress: a spatial quasi-experimental design. Journal of Social Policy, 54(3), 1029–1046. doi:10.1017/S0047279423000430

Schifrin, N., & Cebrián Aranda, T. (2022, November 28). Thousands in China protest zero-COVID policy in largest demonstrations in decades. PBS NewsHour. <https://www.pbs.org/newshour/show/thousands-in-china-protest-zero-covid-policy-in-largest-demonstrations-in-decades>

## References

- [1] Institute of Social Science Survey, Peking University. *China Family Panel Studies (CFPS)*. 2010–2022. <https://www.isss.pku.edu.cn/cfps/>.
- [2] Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., and Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, 5, 529–538. doi:10.1038/s41562-021-01079-8
- [3] Dong, E., Du, H., and Gardner, L. (2020). An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases*. Data available from <https://github.com/CSSEG-ISandData/COVID-19>.
- [4] Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement*, 1(3), 385–401.