Inequality and the Marginal Well-Being Costs of Lockdowns: The case of Chile´s Local Lockdowns Design

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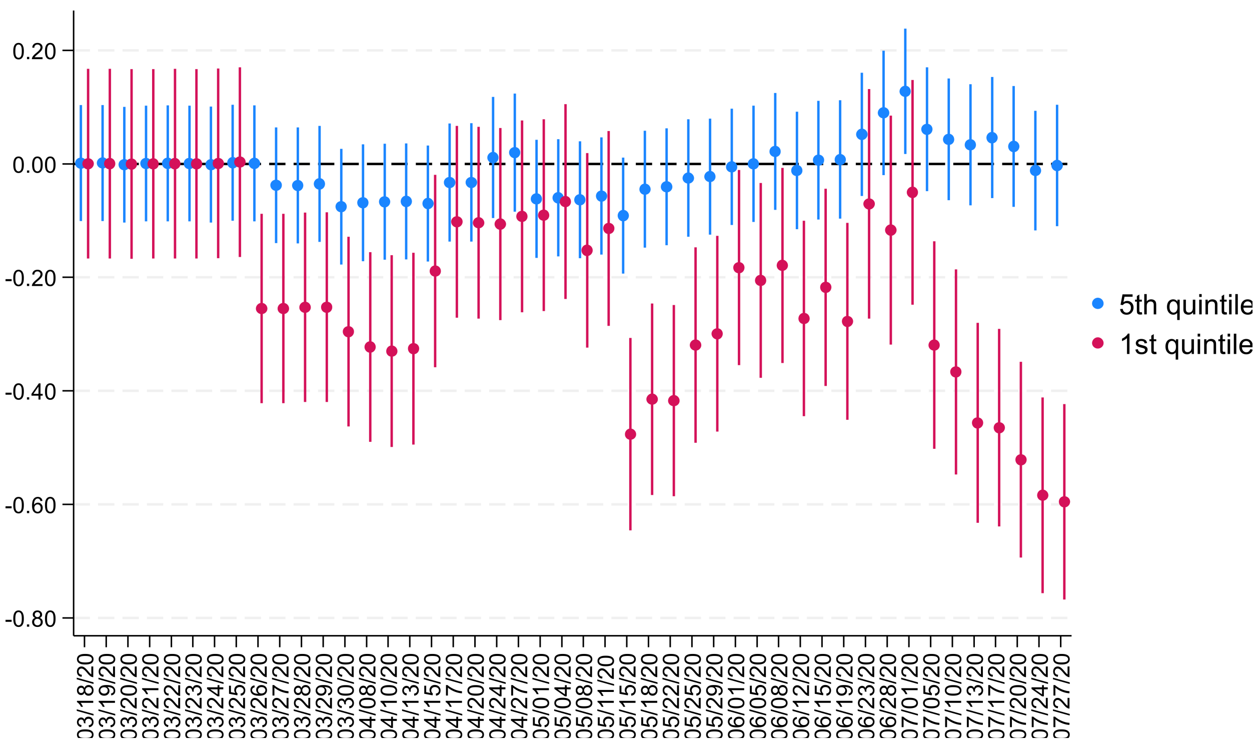
Appendix: FE Estimations Robustness Checks

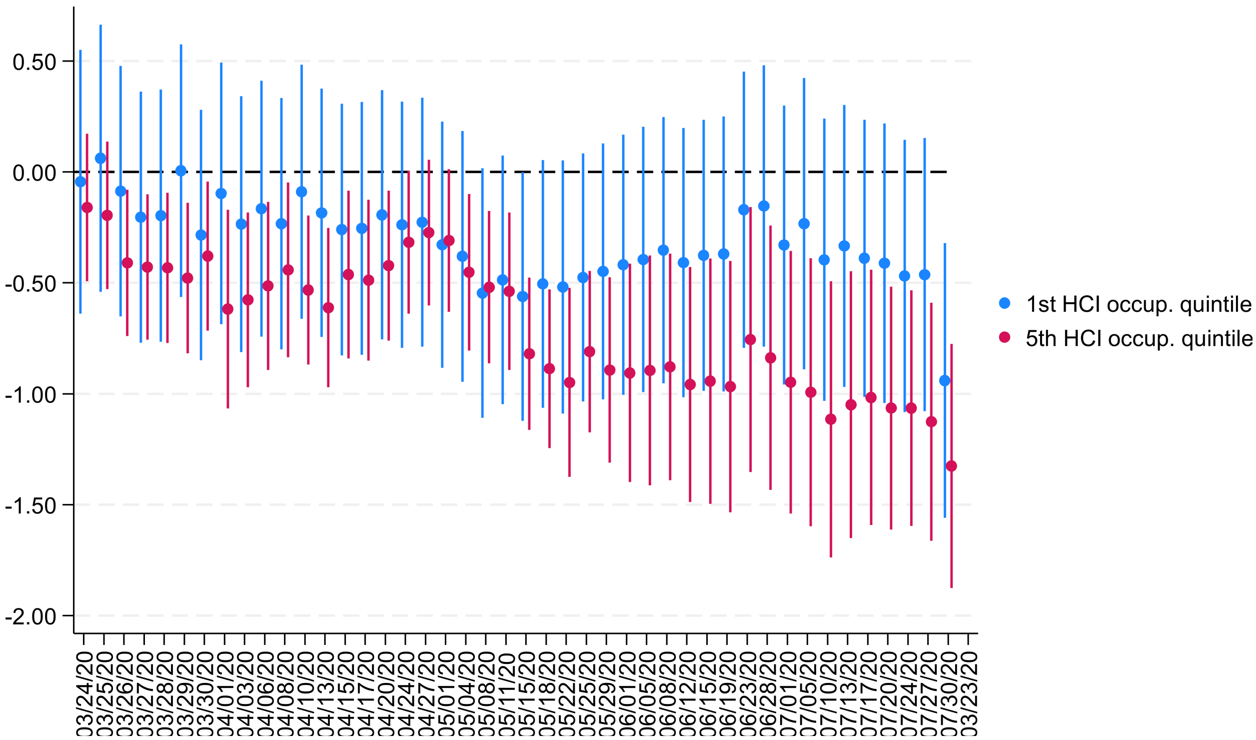
A. Excess probability of Lockdown by Contact-Intensive Occupation Quintile, Conditional on All Statistically Significant Epidemiological Controls

Figure A1. **Lockdown Probability and Per Capita Income:** Coefficient's interaction between residual probability of lockdown and date, by municipalities pre-pandemic average per capita income quintile.



Source: Own estimations using Ministry of Sciences epidemiological data, 2017 CASEN Household Survey, and 2019 Census.Note: HCI refers to the High Contact Intensity Index.

Figure A2. **Lockdown Probability and Contact Intensity:** Coefficient's interaction between residual probability of lockdown and date, by municipalities contact intensity occupation index quintiles.



Source: Own estimations using Ministry of Sciences epidemiological data,2017 CASEN Household Survey, and 2019 Census. Note: HCI refers to the High Contact Intensity Index.

B. Different FE Specifications of a Municipality's Probability of Being or Staying under Quarantine.

Table B1. **Robustness Check:** Alternative Fixed Effects estimation specifications of Equation 3. Y_{it} is an indicator variable for municipality i's lockdown status at time t; α_i is a municipality fixed effect; $lag_\tau \Delta rate_{it}$ corresponds to lagged growth rates, where τ indicates the number of periods that separates period t and the period in which $lag_\tau \Delta rate_{i,\tau}$ is calculated;$lag_\tau rate_{i,t}$ and $lag_\tau IC\ beds\ rate_{i,t}$ are defines analogously, where the former is the rate of cases and the later the rate of intensive care beds.

	Dependent variable: Pr(confinement)=1						
	(1A)	(1B)	(1C)	(2)	(3A)	(3B)	(3C)
$lag_1 \Delta rate_{i,t}$	0.015 ***	0.013 ***	0.013 ***		0.117 ***	0.117 ***	0.082 ***
	(0.00)	(0.00)	(0.00)		(0.04)	(0.04)	(0.03)
$lag_2 \Delta rate_{i,t}$	0.008 *	0.011 ***	0.010 ***		0.063 ***	0.063 ***	0.044 ***
	(0.00)	(0.00)	(0.00)		(0.02)	(0.02)	(0.01)
$lag_3 \Delta rate_{i,t}$	-0.006 *	0.000					
	(0.00)	(0.00)					
$lag_4 \Delta rate_{i,t}$	-0.009						
	(0.01)						
$lag_5 \Delta rate_{i,t}$s	-0.023 ***						
	(0.01)						
$lag_6 \Delta rate_{i,t}$	-0.025 ***						
	(0.00)						
$lag_1 rate_{i,t}$				-0.042 **	-0.161 ***	-0.160 ***	-0.114 **
				(0.02)	(0.05)	(0.05)	(0.04)
$lag_2 rate_{i,t}$				-0.054 **			
				(0.02)			
$lag_3 rate_{i,t}$				-0.062 ***			
				(0.02)			
$lag_1 ex\ death\ rate_{i,t}$						-0.043	
						(0.08)	
$lag_1 IC\ beds\ rate_{i,t}$							-0.023 ***
							(0.01)
N	4388	5203	5480	5240	5480	5480	5480
R2-Adjusted	0.38	0.32	0.31	0.49	0.48	0.48	0.53

Note: Standard errors are presented in parentheses, *p<0.1; **p<0.05; ***p<0.01.

C. Instrumental Variable Estimates

In this section, we analyze to which degree central planner's lockdown decisions (Y_{it}) were conditioned on municipalities' baseline socioeconomic non-varying conditions (Z_i), controlling by the expected probability of lockdown based on municipalities time-varying infections trends.

We propose a two stages alternative identification method to attempt to distinguish the relative importance of the different municipality characteristics highly correlated to our measure of immediate epidemiological risk -infection rates of growth- on the likelihood of being locked down. We instrument the estimated coefficients on contagion growth from Equation 3. Our instrument measures the unobserved municipality variation in the probability of lockdown that can be purely attributed to lagged case growth, computed as:

$$\hat{Y}_{it} = \sum_{\tau=1}^{\tau=J} \hat{\delta}_\tau lag_\tau \Delta rate_{it}\,, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T\,, \tag{1}$$

where $\hat{Y}_{it}$ is the estimated probability of municipality i facing a lockdown at time t, only given by recent cases growth ($lag_\tau \Delta rate_{it}$), which is calculated using $\hat{\delta}_\tau$, the estimated slope coefficients of the fixed effect regression from Equation 3.

In our second stage, we estimate the conditional marginal effect on municipalities' probability of lockdown at different levels of our SES factors of interest, controlling for the unobserved municipality-level time-varying epidemiological risk ($\hat{Y}_{it}$). Accordingly, the objective of our proposed specification is to ascertain the extent to which the central planner's decisions regarding lockdowns (Y_{it}) are influenced by municipalities' baseline socioeconomic conditions that remain constant over time (Z_i), beyond what can be attributed to time-varying epidemiological risks.

$$Y_{it} = \beta_0 + \beta_{\mathrm{Z}_i} Z_i + \beta_1 \hat{Y}_{it} + \epsilon_{it} \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T\,, \tag{2}$$

Our attention is focused on the estimates of the parameters β_{Z_i}, which measures how variations in socioeonomic outcomes levels, determined before the pandemic started, affect municipalities' probability of lockdown differently at different ranges of Z_i.

In Panel A of Table C1, we report OLS estimates of Equation (2) excluding our measure of epidemiological risk $\hat{Y}_{it}$ as a control. These results suggest that municipalities with lower probabilities of lockdown have better self-reported health, higher income, and low-contact occupations. The opposite is true for the poverty index, age, and the fraction of the population at risk. In Panel B, we re-estimate Equation (2) now controlling for epidemiological risk. Interestingly, effects associated with SES factors are similar in magnitude, as well as in terms of statistical significance, when they are compared with results documented in Panel A. These findings are consistent with the hypothesis that municipalities' socioeconomic characteristics and their degree of contact intensity may have influenced government decisions beyond the immediate epidemiological context of the pandemic.

As a final robustness check, we include a proxy for mobility in the estimation of municipality-level time-varying epidemiological risk ($\hat{Y}_{it}$). The literature suggests that mobility plays a central role in the analysis of the spread of the COVID-19 pandemic. In the case of Chile, Bennett (2021) shows that mobility patterns can determine the public health effectiveness of lockdowns and, at the same time, is linked to contact-intensive occupations.

Accordingly, we modify our instrumental variable approach to account for time-varying mobility lags, building on established literature correlations between occupation types and pandemic mobility (Tokey, 2021). The adjustment to our instrumental variable factors in mobility through a municipality-level index, m_{it}. This index uses cellphone data to compute a proxy for each municipality's daily mobility level. In the following equation, we re-estimate Equation 3, now including lagged observed mobility ($lag_\tau \Delta m_{it}$):

$$Y_{it} = \alpha_i + \sum_{\tau=1}^{\tau=J} \delta_\tau lag_\tau \Delta rate_{it} + \phi_\tau lag_\tau m_{it} + \varepsilon_{it} \,, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \,, \tag{3}$$

The instrument for lockdown risk driven by epidemiology factors that controls for mobility, is calculated for each municipality i at time t as follows:

$$\hat{Y}^m_{it} = \sum_{\tau=1}^{\tau=J} \hat{\delta}_\tau lag_\tau \Delta rate_{it} + \hat{\phi}_\tau lag_\tau m_{it} \,, \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \,, \tag{4}$$

where $\hat{Y}^m_{it}$ is the estimated probability of municipality i facing a lockdown at time t, and $\hat{\delta}_\tau$ and $\hat{\phi}_\tau$ are the estimated slope coefficients of the fixed effect regression from Equation (3). We then re-estimate Equation (2) as follows:

$$Y_{it} = \beta_0 + \beta_{\mathrm{Z_i}} Z_i + \beta_1 \hat{Y}^m_{it} + \epsilon_{it} \quad i = 1, 2, \ldots, n; \quad t = 1, 2, \ldots, T \,, \tag{5}$$

The estimation of Equation (5) is presented in Table C2. As can be seen, the observed effects of SES variables are comparable in magnitude and statistical significance to those reported in Table C1.

Table C1. **Instrumental Variable Estimates.** Estimation results of Equation (2). The table reports the marginal change in municipalities' probability of lockdown with respect to epidemiological risk ($\hat{Y}$) and municipalities' SES factors (Z). Panel A reports OLS estimates; panel B reports OLS estimates controlling by our baseline measure of epidemiological risk that is only based on COVID cases growth.

Panel A	Pov.Index	Low.Contact.Occup.	Perc.Income	Good Health	Age	Pop.at.Risk
Z	2.345***	-1.776***	-0.289***	-0.409***	0.033***	2.152***
	(0.346)	(0.235)	(0.036)	(0.083)	(0.007)	(0.435)
Observations	6240	6240	6240	6240	6240	6240
R-squared	0.073	0.061	0.067	0.044	0.042	0.044

Panel B	Pov.Index	Low.Contact.Occup.	Perc.Income	Good Health	Age	Pop.at.Risk
Z	2.666***	-1.874***	-0.307***	-0.451***	0.038***	2.452***
	(0.368)	(0.266)	(0.040)	(0.091)	(0.007)	(0.477)
$\hat{Y}$	0.928***	0.853***	0.848***	0.893***	0.937***	0.937***
	(0.260)	(0.260)	(0.259)	(0.263)	(0.254)	(0.255)
Observations	5399	5399	5399	5399	5399	5399
R-squared	0.087	0.063	0.070	0.050	0.053	0.053

Note: Note: *Pov.Index* is an index that measures income-based poverty of households; *Perc.Income* corresponds to the average per capita income in CLP$; *Low.Contact.Occup.* is a proxy for the level of contact occupation intensity of the population; *Health* is a self reported health assessment index, ranging from 1 (very bad) - to 7 (excellent); *Age* is the average age of the population; *Pop.at.Risk* is the percentage of the population over 50 years old. Standard errors are presented in parentheses, *p<0.1; **p<0.05; ***p<0.01.

Table C2. **Instrumental Variable Estimates with Mobility.** Estimation results of Equation (5). The table reports the marginal change in municipalities' probability of lockdown with respect to epidemiological risk ($\hat{Y}_{it}^{m}$) and municipalities' SES factors (Z): *Pov.Index* is an index that measures income-based poverty of households; *Perc.Income* corresponds to the average per capita income in CLP$; *Low.Contact.Occup.* is a proxy for the level of contact occupation intensity of the population; *Health* is a self reported health assessment index, ranging from 1 (very bad) - to 7 (excellent); *Age* is the average age of the population; *Pop.at.Risk* is the percentage of the population over 50 years old.

	Pov.Index	Low.Contact.Occup.	Perc.Income	Good Health	Age	Pop.at.Risk
Z	2.280***	-1.466***	-0.247***	-0.360***	0.035***	2.484***
	(0.390)	(0.334)	(0.050)	(0.091)	(0.007)	(0.417)
$\hat{Y}^m$	-0.394**	-0.539***	-0.505**	-0.707***	-0.843***	-0.941***
	(0.183)	(0.202)	(0.200)	(0.175)	(0.179)	(0.157)
Observations	5399	5399	5399	5399	5399	5399
R-squared	0.093	0.074	0.080	0.073	0.089	0.098

Note: Standard errors are presented in parentheses, *p<0.1; **p<0.05; ***p<0.01.

References

Bennett, M. (2021). All things equal? Heterogeneity in policy effectiveness against COVID-19 spread in chile. *World Development*, 137:105208.

Tokey, A. I. (2021). Spatial association of mobility and COVID-19 infection rate in the USA: A county-level study using mobile phone location data. *Journal of Transport & Health*, 22:101135.