Factors associated to the duration of localized lockdowns during the COVID-19 pandemic in Chile

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Abstract

Since the COVID-19 pandemic began, several countries have implemented consistent containment measures, primarily lockdown and social distancing. These approaches varied widely, prompting many scientists to study their efficacy. This study explored epidemiological, demographic and socioeconomic factors associated with the duration of lockdown in Chile between March 25th and December 25th, 2020. Our findings showed that population, overcrowding, number of occupied ICU beds, number of active cases, and number of deaths were significantly associated with the duration of the lockdown, being identified as risk factors for longer lockdown. The lockdown indicator (i.e., if the commune was in lockdown for the first or second time) was indicated as a protection factor, which implies a 34.4 % reduction in the duration of the second lockdown compared to the first.

1 Introduction

At the beginning of 2020, when the World Health Organization (WHO) declared COVID-19 a pandemic, countries started to implement containment measures to reduce viral transmission, mainly lockdown and social distancing. Rapidly, more than half of the global population was under strict forms of movement restrictions and social distancing. The approaches taken by national governments varied widely. In Chile, the first measures were kindergartens and school closing, followed by country borders closure. A few days later, on March 25th, the government started to implement localized lockdown at the commune level, which is the smallest administrative division in Chile.

The lockdown was decreed by the Chilean government based on some criteria defined by the Chilean Ministry of Health. Basically, four indicators were considered: the number of active cases, the increase in the incidence of active cases, the total number of active cases per km^2, and the availability of ICU beds. These indicators were analyzed individually for each commune. The government also established criteria to end lockdown. Regionally, the ICU occupancy should be $\leq 85\%$ and the percentage of positivity of the PCR exams $< 10\%$ in the previous seven days. At the communal level, a constant decrease in new cases was required during the previous 21 days, which means a reproductive number ≤ 1. Besides, there should be a capacity to trace and isolate 90% of the new confirmed cases in less than 48 hours, and identify and trace 75% of the contacts of those cases during 14 days. While the Chilean government clearly established the criteria for starting and ending a quarantine, there was no solid scientific evidence yet to support them, therefore they could be questionable.

2 Goals

The main goal of this study was to explore epidemiological, demographic and socioeconomic factors related to the duration of lockdown in Chile. For this purpose, it was considered the lockdown carried out between March 25th and December 25th, 2020. More details about the dataset used in this study can be found in Ortiz et al. (2021).

3 Methods

Survival models were used to explore the factors associated with the duration of lockdown, where the event of interest is leaving the lockdown. Survival models are also capable of handling time-varying predictors, which are very common in clinical research. A simple approach to include time-dependent predictors is to extend the proportional hazard model (Cox, 1972; Therneau, 2000). Thus, the risk function is formulated as:

$$h(t \mid x, z(t), \beta, \alpha) = h_0(t) \exp\{x^\top \beta + \alpha\, z(t)\},$$

where β and α are regression coefficients associated to the fixed and time-dependent predictors, respectively. x denotes the fixed predictors and $z(t)$ denotes the predictors that vary over time. In these cases, since the predictors are time-dependent, the relative risk is also time-dependent, which means that the risk of the event occurring at time t is no longer proportional to the reference risk and the model is no longer a proportional hazards model. Besides, $h_0(t)$ can be defined as a parametric or nonparametric function.

Particularly, in this study we consider the following information as fixed predictors over time: population (in 100,000 inhabitants), population density (inhabitants per km^2), number of immigrants (per 100,000 inhabitants), overcrowding (number of people over the number of households), socioeconomic development index (IDSE, between 0 and 1), and rurality index of the communes (from 0 to 100). In addition, it was considered whether the commune held the regional or province city and whether a commercial airport or harbor is present in it. Other information incorporated into the model was a lockdown indicator, which indicated whether the commune was in lockdown for the first or second time within the follow-up period.

Throughout the follow-up period, the Ministry of Health periodically reported epidemiological information related to the pandemic situation in the country. Data such as the total number of active cases (per 100,000 inhabitants), the number of deaths (per 100,000 inhabitants), the number of occupied ICU beds (per 100,000 inhabitants), and the positivity of PCR exams (between 0 and 1) were incorporated into the model as time-dependent predictors. This temporal information was considered per week. Positivity was calculated as:

$$\text{positivity} = \frac{\text{asymptomatic cases} + \text{symptomatic cases}}{\text{PCR exams}}.$$

4 Results

The first step of the analysis was a variable selection, where only predictors with p-value below the significance threshold of 5% were kept (population, overcrowding, lockdown indicator, ICU beds, active cases, and deaths). Thus, the final model is written as:

$$\begin{aligned} h(t \mid \cdot) = h_0(t) \exp\big\{&\beta_1 * \text{population} + \beta_2 * \text{overcrowding} + \beta_3 * \text{lockdown\_id} + \\ &\alpha_1 * \text{ICU}_i + \alpha_2 * \text{active\_cases}_i + \alpha_3 * \text{deaths}_i\big\}, \end{aligned} \tag{1}$$

where $h_0(t)$ follows a Weibull distribution with shape (a) and scale (b) parameters. The estimated coefficients, hazard ratios as well as their respective confidence intervals are presented in Table 1.

Table 1: Estimated coefficients and hazard ratios related to the predictors of survival model and their respective 95% confidence interval.

Predictor	Estimate	$CI_{95\%}$	Hazard ratio	$CI_{95\%}$
Population	-0.188	(-0.127, -0.249)	0.828	(0.880, 0.780)
Overcrowding	-0.261	(-0.105, -0.417)	0.770	(0.901, 0.659)
Lockdown indicator	0.296	(0.519, 0.072)	1.344	(1.681, 1.075)
ICU	-0.062	(-0.036, -0.089)	0.940	(0.965, 0.915)
Active cases	-0.010	(-0.008, -0.012)	0.990	(0.992, 0.988)
Deaths	-0.004	(-0.003, -0.006)	0.996	(0.997, 0.995)

In addition, $a = 0.95\ (0.79, 1.10)$ and $b = 1.60\ (1.08, 2.13)$ are estimated values for the parameters of $h_0(t)$ distribution and their respective 95% confidence intervals. The model was fitted in R using the `flexsurv` (Jackson et al., 2021).

The results presented in Table 1 indicate that population, overcrowding, ICU beds, active cases, and deaths were significantly associated with the duration of lockdown, being identified as risk factors for longer lockdown. However, the lockdown indicator is a protection factor, indicating a 34.4% reduction in the duration of the second lockdown when compared to the first, i.e., the second time a commune goes into lockdown is shorter, on average.

5 Preliminary conclusions

A part from epidemiological data such as the number of active cases, the number of occupied ICU beds, and the number of deaths, our findings indicate that demographic and socioeconomic factors such as the population and overcrowding of the commune are also significantly associated with the duration of lockdown. In addition, the information on whether the commune was under lockdown for the first or second time is also related to. We use a survival model to explain these associations, providing useful and practical information to support government decisions regarding local lockdown in Chile.

References

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