The unequal impact of the COVID-19 pandemic on life expectancy across Chile: Supplementary materials

1 Municipality classification

Chile is composed by a total of 16 regions. Each region is divided into smaller units, called municipalities. There are a total of 366 municipalities. We classified them as urban or nonurban based on the same criterion as in (I) , that is, if the following two conditions hold: i) population density greater than 70 people per square kilometer, and ii) the proportion of people living in a urban environment is greater than 88%. We excluded all municipalities having fewer than 16,000 people according to census. In Tables [1](#page-4-0) and [2](#page-5-0) we show the total number of municipalities and people on urban, non-urban and excluded municipalities. The names of all municipalities and their urbanity status is shown in Table [3.](#page-6-0) We note that although 147 out of 339 municipalities where excluded, this only signifies a 7% of the population.

To study whether excluding small municipalities would bias our results, we created a supermunicipality made by all the excluded. Notably, only two (out of 147) municipalities in this group would have been otherwise categorized as urban (El Quisco, Algarrobo), so it is safe to assume that this super-municipality is a non-urban one. In Fig. [1](#page-7-0) we compare time evolution of life expectancy at birth and probability of dying before reaching age 65 (Figures 1 and 2 of the main text) for the non-urban municipalities, along with the values for the excluded (mostly non-urban) super-municipality. These are in close agreement.

2 Estimation of mortality rates

We implemented method of (*2*), which consists on a hierarchical Bayesian model for the estimation of age-specific mortality rates on small area setups. The main idea is that by modeling a joint structure for these rates as a function of time and space, it would be possible to smooth out the effect of poor empirical estimates for years/locations where only a few population counts were available. In practice, we found that estimates were reasonable as long as the population of municipalities was reasonably large. We applied the algorithm to all municipalities for each region, and each year between 2002 and 2020, separating by gender (male, female, all). This gave a total of 16×3 algorithm runs. For each a run, we obtained a total of 3,000 Monte Carlo samples that we used for computing credible intervals. Additionally, we ran the algorithm to compute mortality rates for each region, and for the totality of urban and non-urban municipalities, as necessary. In all cases, we estimated mortality rates based on 5 years intervals, up to age 80+ (see below for a discussion of the cutoff age).

We excluded from our analyses some municipalities/years based on the visual inspection of total deaths per year. A cluster of 6 municipalities appeared to have corrupted data in the years surrounding 2004. Those are shown in Fig. [2.](#page-8-0)

3 Regressions

4 Sensitivity analyses

Since deaths are revealed to us in full detail, and because Chilean death recording system is reliable (*3*), the main source of corruption in mortality rates should stem from possible biases in population estimates. We explored what was the impact of different ways using population estimates in constructing the life tables, and used a number of several alternative estimates to re-create the results shown in the main text. These are explained below.

2

Improving official projections

For year specific population counts between 2002 and 2020, we used the official population projections provided by the national institute of statistics, available at the municipality level and with resolution of years. These are made with simple interpolation and extrapolation methods as described in (*4*). However, we found that these projections were often inconsistent, mostly from 2017 on. Therefore, we considered two alternative estimates in addition to official projections, that only differed from official estimates starting 2017. For one estimate we used the official census counts at 2017 for years 2018, 2019 and 2020. The second estimate corresponds to the cohort component projection method, where we used births in 2017 (the only available) and deaths in 2018, 2019, 2020 to infer municipality and age specific population counts after 2017. In Fig. [5](#page-8-0) we show comparisons between resulting estimates. We observe that indeed they produce different estimates, and differences between methods increase for later years. Notably, estimates based on official projections deviate wildly from other in some municipalities, indicating a possible lack of accuracy. In particular, we should expect that estimations based on projections at census year 2017 should be similar to the ones provided by our alternative estimates.

Maximum age

Another source of bias is given by cutoff age used when turning age-specific mortality rates into life expectancy estimates. Official census information (2002,2017) contains age-specific population counts for each municipality and gender, up to age 90. However, official census projections collapses all ages above 80 into one group. In Fig. [5A](#page-9-0) we compare results with the 80 and 90 cutoff, using official census data (only years 2002 and 2017), We observe that the 90 cutoff leads to consistently slightly higher life expectancies, with a difference that appears higher for older ages. Importantly, in [5B](#page-9-0),C we also include other estimates, for reference. We observe large discrepancies in year 2017 when comparing official census and official projections. Once more, this is an indication that official projections are not accurate, as they become inconsistent in 2017 (i.e., official projections in year 2017 are far from official census in the same year).

Main results with alternative estimates In the main text we have used the cohort survival projection method. Here, we present results using the other two alternative methods. Figs. [5](#page-10-0) and [6](#page-10-1) correspond to Exhibits 1 and 2 in the main text, respectively. Figs. [7](#page-11-0) and [8](#page-12-0) complement Exhibit 3, and likewise, Figs. [9](#page-13-0) and [10](#page-14-0) complement Exhibit 4.

5 Additional results

Fig[.11](#page-15-0) supplements Exhibit 4 by showing the relation between life expectancy and poverty in non-urban municipalities. No clear consistent pattern is observed. Also, in Fig. [12](#page-16-0) we show the corresponding decreases of life expectancy over time as a function of poverty, in urban and non-urban setups. This figure is complemented by Fig. [13,](#page-17-0) which shows an even stronger correlation when using crowdedness as covariate, and Figs. [14](#page-18-0) and [15,](#page-19-0) which show sensitivity of Fig. [12](#page-16-0) to changes in the projection methodology.

Metropolitana 36 13 3 52 Los Ríos 1 7 4 12

> Nuble 2 6 12 20 Chile 68 124 147 339

Arica y Parinacota $\begin{array}{cccc} 0 & 1 & 3 & 4 \end{array}$

Table 1: Number of municipalities for each strata (urban, rural) in our design, for each region.

References

- 1. J. Berdegué, E. Jara, F. Modrego, X. Sanclemente, A. Schejtman, *Rimisp, Santiago* (2009).
- 2. M. Alexander, E. Zagheni, M. Barbieri, *Demography* 54, 2025 (2017).
- 3. G. E. Mena, *et al.*, *Science* 372 (2021).
- 4. I. N. de Estadísticas, Estimaciones y proyecciones de la población de chile 2002-2035 a nivel comunal. documento metodológico (2019 [Online].).

Region	Urban	Rural	Excluded	Total
Tarapaca	299843	0	30715	330558
Antofagasta	0	552790	54744	607534
Atacama	448784	251371	57431	757586
Coquimbo	880647	787549	139030	1807226
Valparaíso	0	223516	62652	286168
O'Higgins	275211	477699	161645	914555
Maule	369493	559301	116156	1044950
Biobio	946952	504405	105448	1556805
La Araucanía	282415	522213	140985	945613
Los Lagos	407362	262009	159337	828708
Aysen	0	81777	20233	102010
Magallanes	θ	153069	12304	165373
Metropolitana	6273435	809613	29760	7112808
Los Ríos	166080	181799	36958	384837
Arica y Parinacota	0	221364	4704	226068
Nuble	215646	152749	100611	469006
Chile	10565868	5741224	1232713	17539805

Table 2: Total populations for each region for each strata (urban, rural) in our design.

Table 3: Names of all urban (red), rural (blue) and excluded (black) municipalities of each region.

Figure 1: A. Time evolution of life expectancy, including the excluded municipalities collapsed as a super-municipality. B. Same as A, but with likelihood of dying before reaching 65.

Figure 2: Yearly deaths for each municipality (colored lines) grouped by region (different plots). Lines that are also dotted are the ones for which anomalies existed in recording, leading to sudden drops and/or increases around 2004, presumably due to coding errors. These were excluded in the neighboring years (Talcahuano, Hualpén, Diego de Almagro, Talca, Alto Hospicio, Chillán Viejo).

Figure 3: Comparison of various life expectancy estimates, for years 2017-2020. All of these use 80 as cutoff age for population counts. In A we compare cohort survival projection with the one that makes the population constant from 2017 on. In B we compare official projections with cohort survival projection. In C we compare official projection with the one that has constant population.

Figure 4: Comparison of several life expectancy estimates, only for census years (2002, 2017). In A we compare estimates based on census data but different age cutoffs. When using 90 as cutoff, life expectancies appear slightly higher. In B we compare the official census data with 80 cutoff with official projections in that year. We note that discrepancies become more significant in year 2017, indicating the need for an alternative methodology. In C we compare official census (80 as cutoff age) with our cohort survival projection method. They are in close agreement, as they are both based on official census data, and not projections.

Figure 5: Time evolution of life expectancy, using our three estimators, Exhibit 1 in main text coincides with A.

Figure 6: Time evolution probability of not surviving up to 65 years, using our three estimators. Exhibit 2 in main text coincides with A.

Figure 7: Year-to-year relative changes in Gini, where we have assumed that population after 2017 remained constant (equal to the one provided by census). Bars represent 75% credible intervals. This figure supplements Exhibit 3 in the main text.

Figure 8: Year-to-year relative changes in Gini, where we have used the official census projections. Bars represent 75% credible intervals. This figure supplements Exhibit 3 in the main text.

$-2015-2019-2020$

Figure 9: A Life expectancy between 20 and 65 and **B** and life expectancy at 65 as a function of poverty and gender, for urban municipalities. Bars represent 95% credible intervals. These estimates are based on the method that fixed population counts at values in 2017 for years 2017, 2018, 2019 and 2020, and may be compared with Exhibit 4 in the main text.

\div 2015-2019 \div 2020

Figure 10: A Life expectancy between 20 and 65 and B and life expectancy at 65 as a function of poverty and gender, for urban municipalities. These estimates are based on the official census projections and may be compared with Exhibit 4 in the main text.

\div 2015-2019 \div 2020

Figure 11: A Life expectancy between 20 and 65 and B and life expectancy at 65 as a function of poverty and gender, for non-urban municipalities. These are similar to results in Exhibit 4 in the main text, but correlations vanish when focusing on non-urban municipalities.

Figure 12: Declines in life expectancy at birth (A), life expectancy between 20 and 65 (B), and life expectancy at 65 (C) as a function of proportion of population that lives in poverty. Each dot is a municipality, separated by gender (colors) Urban and non-urban municipalities are shown in first and second row, respectively. A strong effect appears in urban setups, and the correlation is stronger in for life expectancy between 20 and 65.

Figure 13: Declines in life expectancy at birth (A), life expectancy between 20 and 65 (B), and life expectancy at 65 (C) as a function of proportion of population that lives in a crowded home. Each dot is a municipality, separated by gender(colors) Urban and non-urban municipalities are shown in first and second row, respectively.

Figure 14: Same as [12] but with population estimates for years 2017, 2018, 2019, 2020 all equal to population counts in 2017 as given by census.

Figure 15: Same as $\boxed{12}$ but with population estimates given by official projections.