**Supplementary material**

**Effects of 2019’s Social Protests on Emergency Health Services Utilization and Case Severity in Santiago, Chile**



**Supplementary statistical methods**

*Bayesian Structural Time-Series Analysis*

To evaluate the effect of social protests on ED service utilization, we used Bayesian structural time series (*BSTS*) models [1] implemented using the *CausalImpact* R package [2]. This approach compares the observed trend of consultations and hospitalizations after the event, with an estimated average change under a hypothetical scenario in which social protests did not occur (i.e., the counterfactual) [3]. The estimated effect is then the difference between the counterfactual and the observed number of consultations and hospitalizations after the social protest of October 18, 2019. The general model can be written as follows:

One advantage of this method is that it allows flexibility in the inference of counterfactuals, temporal evolution, and incremental attributable impact. This estimation is achieved by incorporating features such as level, trends, seasonality, and regression that capture the time-series dynamics [4]. The first two components describe how the hospitalizations and consultations are related to underlying states and how the latent state changes over time. It is referred to as the unobserved trend inherent in time-series data. It is associated with a probability distribution of the noise and random disturbances, which allows incorporating empirical priors on the parameter and transitory or cyclic components to approximate volatility in the series. The third components are the seasonal patterns that capture the associations between multiple fixed periodic events and the number of consultations and hospitalizations. We specified monthly and annual seasonal patterns, based on theoretical backgrounds and the nature of admissions by its different causes (e.g., increased respiratory consultations during the winter season). The fourth component relates to other contemporaneous time-series that can be included as covariates via linear regression. We used as a covariate the circulatory hospitalizations when the outcome was hospitalizationsand consultations series when the outcome was consultations. Due to the length of the time-series, we used a dynamic framework which included the coefficients of time-varying regression, as a way to relax the assumption of stability of the model structure, and in which coefficients change over time according to a random walk process[2].

The model selection process considered alternative specifications in the structure of the time-series for each outcome: Gaussian or studentized distributed noise, different trend drifts such as a random-walk, a semi-local linear trend, a local linear trend, or the inclusion of cyclicity of autoregressive terms. We selected the model with lower cumulative absolute one step ahead errors in the pre-intervention period for each outcome [5]. The models that had lower errors assumed studentized distributions, which are robust against abnormalities such as outliers. This comparison allowed us to choose the specified structure with greater accuracy to match actual trends before social protests in order to strengthen causal inference [6].

Gibbs sampling was performed to produce 30,000 Markov Chain Monte Carlo (MCMC) iterations following a 10% burn-in period. The point effect of social protest and its 95% credible interval was generated as the difference between the estimated forecasts and the observed trend across each iteration [7].

All analyses and graphics were completed using R v 4.0.2.

***Outcome Validity Testing***

We used historical controls to contrast observed ED consultation and hospitalizations in the exposure period; that is, we used the same outcomes in the same hospitals, for the same time of the year, but in a different period (2015-2018).

**Table S1. Summary descriptive table of Hospitalizations and Consultations 2015-2018 vs. 2019**

|  |  |  |
| --- | --- | --- |
| **Outcomes** | **2015-2018** | **2019** |
|  | *N=210* | *N=52* |
| Total Consultations | 3183 [3003;3394] | 2846 [2678;2949] |
| Trauma Consultations | 792 [724;878] | 866 [779;944] |
| Respiratory Consultations | 140 [115;176] | 154 [104;198] |
| Circulatory Consultations | 100 [86.0;121] | 108 [95.8;134] |
| Total Hospitalizations | 284 [264;310] | 300 [286;315] |
| Trauma Hospitalizations | 57.0 [51.0;64.0] | 73.0 [65.0;77.5] |
| Respiratory Hospitalizations | 19.0 [15.0;23.0] | 22.0 [18.8;26.0] |
| Circulatory Hospitalizations | 29.0 [23.0;36.0] | 32.0 [27.5;37.0] |
| Rate of Trauma Hospitalizations per Trauma Consultations (x1,000 population) | 72.0 [62.1;85.1] | 80.6 [72.8;96.8] |
| Respiratory Hospitalizations per Respiratory Consultations (x1,000 population) | 131 [108;161] | 146 [108;187] |

Note. Median, and percentiles 25 and 75 in brackets. Total weeks (n=262).

Figure S1. Comparison of Average Hospitalizations between 2015-2018 vs. 2019



**Figure S2. Comparison of Average Consultations between 2015-2018 vs. 2019**



**Figure S3. Comparison of Average Proportion of Hospitalizations per Consultations (x1,000), between 2015-2018 vs. 2019**



The analytical approach is a novel technique for estimating the causal effect for events in treated units, and consensus on best practice has not yet emerged. The method used and the manner we used the observational data to identify the relationship of interest is always obtained at the cost of assumptions. For this reason, we changed the identification strategy[8].

We selected another identification strategy to test the associations between social protests and weekly health service utilization. We used the values of the outcomes and control variables of years from 2015 to 2018 as historical controls. Posteriorly, we compared the differences in weekly health services outcomes starting from the 43rd week, using a traditional fixed-effect difference-in-differences analysis as a sensitivity analysis. For the inclusion of seasonal effects of the month, we chose the models with the lowest Root Mean Square Errors (RMSE) among models without monthly terms(1), month as a continuous variable (2), 11 dummy variables of the month (3), month as a quadratic term(4), and sine and cosine of the month scaled to the range 0,1π(5). The selected models for all the outcomes were the models with the month as a dummy variable, except for Trauma Hospitalizations. The model with sine and cosine showed lower errors. Finally, we computed robust standard errors to account for heteroscedasticity and autocorrelation [9] using the *xtscc* command [10] in Stata 16 [11].

**Figure S4. Comparison of Predicted and Actual Trends for Trauma Hospitalizations**



Note. Models without monthly terms (RMSE= 10.44), month as a continuous variable (RMSE= 10.42), 11 dummy variables of the month (RMSE= 9.92), month as a quadratic term(RMSE= 10.46), and sine and cosine of the month scaled to the range 0,1π(RMSE= 9.84).

**Figure S5. Comparison of Predicted and Actual Trends for Respiratory Hospitalizations**

 Note. Models without monthly terms (RMSE= 7.09), month as a continuous variable (RMSE= 7.03), 11 dummy variables of the month (RMSE= 6.31), month as a quadratic term(RMSE= 7.09), and sine and cosine of the month scaled to the range 0,1π(RMSE= 6.33).

**Figure S6. Comparison of Predicted and Actual Trends for Trauma Consultations**

 Note. Models without monthly terms (RMSE= 119.30), month as a continuous variable (RMSE= 119.52), 11 dummy variables of the month (RMSE= 102.70), month as a quadratic term(RMSE= 119.00), and sine and cosine of the month scaled to the range 0,1π(RMSE= 109.60).

**Figure S7. Comparison of Predicted and Actual Trends for Respiratory Consultations**



Note. Models without monthly terms (RMSE= 50.08), month as a continuous variable (RMSE= 48.15), 11 dummy variables of the month (RMSE= 31.04), month as a quadratic term(RMSE= 49.86), and sine and cosine of the month scaled to the range 0,1π(RMSE= 31.78).

**Figure S8. Comparison of Predicted and Actual Trends for Trauma Consultations per Hospitalizations (x1,000)**



Note. Models without monthly terms (RMSE= 17.91), month as a continuous variable (RMSE= 17.88), 11 dummy variables of the month (RMSE= 16.99), month as a quadratic term(RMSE= 17.88), and sine and cosine of the month scaled to the range 0,1π(RMSE= 17.87).

**Figure S9. Comparison of Predicted and Actual Trends for Respiratory Consultations per Hospitalizations (x1,000)**



Note. Models without monthly terms (RMSE= 43.51), month as a continuous variable (RMSE= 42.99), 11 dummy variables of the month (RMSE= 41.28), month as a quadratic term(RMSE= 43.41), and sine and cosine of the month scaled to the range 0,1π(RMSE= 41.74).

**Table S2. Estimated effect of Social Protests in weekly Health Services Utilizations, from fixed effects difference-in-difference models**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Variable** | **Coef** | **CI95% Lower** | **P-value** | **Relative Effect (%)** | **CI95%** |
| Trauma  Hospitalizations a, e | 5.03 | -3.33, 13.38 | 0.233 | 8.31 | -5.49, 22.11 |
| Respiratory  Hospitalizations a | -0.63 | -4.93, 3.67 | 0.769 | -3.10 | -24.12, 17.93 |
| Trauma  Consultations b | -103.10 | -177.91, -28.30 | 0.008 | -12.78 | -22.05, -3.51 |
| Respiratory  Consultations b | -49.17 | -79.68, -18.66 | 0.002 | -31.79 | -51.52, -12.07 |
| Trauma Hospitalizations  per Trauma Consultations (x1,000) c | 24.53 | 12.98, 36.08 | <0.001 | 32.06 | 16.97, 47.15 |
| Respiratory Hospitalizations  per Trauma Consultations (x1000) c | 72.84 | 38.82, 106.86 | <0.001 | 52.93 | 28.21, 77.64 |

Note: Each model included a fixed effect for years. Models also included the following time-varying covariates: (a) Circulatory Hospitalizations, (b) Circulatory Consultations, and (c) Circulatory Hospitalizations per Consultations (x1,000);  
(e) Seasonal effects were included using a sine and cosine term to represent the months.

As seen in Table 1, we found Trauma Hospitalizations did not show statistically significant differences even though it showed the same trend of increment posterior to social protests. For Respiratory Hospitalizations, we found no statistical differences. Notably, we found an association between trauma and respiratory consultations and social protests, which were associated with a significant decrease in the number of respiratory consultations; these decreases were not statistically significant in our primary analysis using the Bayesian Time Series Analysis.

Two main issues may explain the discrepancies in the significance of respiratory consultations between the two methods. First, the difference-in-difference model does not account for potential unobserved confounders over time. Second, the Bayesian Time-Series Analysis can capture more complexities than the difference-in-difference approach. Therefore, it uses more stringent criteria to qualify a coefficient as a statistically significant change in trauma and respiratory consultations.

**References**

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