**Supplementary material**

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

**Dates with larger social unrest**

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**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 {Scott, 2014 #7} implemented using the *CausalImpact* R package {Brodersen, 2015 #6}. This approach compares the observed trend of consultations and hospitalizations after the event, with an estimated average trend under an hypothetical scenario in which social protests did not occur (i.e., the counterfactual) {Pinilla, 2018 #4}. 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 advantages 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 dynamics of the time series {Harvey, 2007 #1}. 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 to incorporate empirical priors on the parameter and transitory or cyclic components able 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., increase number of 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 were hospitalizations,and consultations series when the outcome were 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{Brodersen, 2015 #6}.

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 or 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 {Koopman, 2000 #15}. The models that had lower errors assumed studentized distributions, which are robust against anomalities such as outliers . This comparison allowed us to choose the specified structure with the greater accuracy to match actual trends before social protests in order to strengthen causal inference {Scott, 2020 #11}.

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 the each iteration {Fragoso, 2018 #2}{Scott, 2014 #7}{Kruschke, 2018 #10}.

All analyses and graphics were completed using R v 4.0.2.

***Outcome Validity Testing***

The validity of results was tested analytically through mean comparison analyses for pre-exposure data and visually by observing the difference between actual and predicted cases in seven-day moving average plots during the pre-exposure time frame.

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).

**References**