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Quarantine lockdown impact on deaths due to heart and cerebrovascular diseases in the United States, between 2019 and 2022

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"Impacto de la cuarentena en las muertes por enfermedades cardíacas y cerebrovasculares en Estados Unidos, entre 2019 y 2022"

Resumen

Antecedentes: A nivel mundial, las cardiopatías isquémicas y los accidentes cerebrovasculares son las principales causas de muerte en los países desarrollados y en vías de desarrollo. Debido a la pandemia por COVID-19, la mayoría de los países tomaron medidas para contener la propagación del virus, evitar el colapso de los sistemas de salud y minimizar las muertes. Si bien estas medidas parecen haber sido efectivas para contener el COVID-19, también pueden haber aumentado las muertes por enfermedades cardíacas y cerebrovasculares debido a la disminución de controles médicos por factores de riesgo, las visitas por emergencias a hospitales y la hospitalización. Objetivo: El objetivo del documento es evaluar el impacto de corto plazo de la cuarentena en las muertes por enfermedades cardíacas y cerebrovasculares no relacionadas con COVID-19 en Estados Unidos, entre 2019 y 2022. Datos y metodología: Sigo una estrategia de identificación de diferencias en diferencias escalonada, utilizando una base de datos de panel que incluye el número de muertes semanales por jurisdicción, las causas de muerte y la intensidad de las medidas tomadas por cada jurisdicción de Estados Unidos para controlar el COVID-19 entre enero 2019 y diciembre 2021. Resultados: Encuentro un efecto positivo y estadísticamente significativo de la cuarentena en las muertes por enfermedades cardíacas y cerebrovasculares. Sin embargo, no hay suficiente confianza en el supuesto de identificación de tendencias paralelas. Implicancias: Es importante analizar el impacto de la cuarentena en diferentes resultados de salud para implementar diseños integrales de políticas en caso de futuras pandemias.

Palabras clave: Cuarentena, impacto, diferencias en diferencias, muertes cardiovasculares, muertes cerebrovasculares, Estados Unidos

"Quarantine lockdown impact on deaths due to heart and cerebrovascular diseases in the United States, between 2019 and 2022"

Abstract

Background: Worldwide, ischemic heart diseases and strokes are the main causes of death in developed and developing countries. Due to the COVID-19 pandemic, most of the countries around the world took stringent measures to contain the virus spread, avoid the collapse of health systems, and minimize deaths. Even though these measures appeared to be effective in reducing the COVID-19 spread, in the short-term quarantine may also have increased deaths due to heart diseases because of a drop in medical checkups for cardiovascular risk factors, emergency visits to hospitals and hospitalization. Objective: The aim of this paper is to assess the short-term impact of stringent COVID-19 quarantine measures on deaths from heart and cerebrovascular diseases not related to COVID-19 in the United States, between 2019 and 2022. Data and methodology: I consider weekly data on the number of deaths by jurisdiction, the causes of death and the intensity of the stringency measures taken by each jurisdiction to control the COVID-19 spread, to construct a panel database from January 2019 to December 2021. With the panel database I follow a staggered difference-in-differences identification strategy. Results: I find a positive and statistically significant effect of lockdowns on deaths due to heart and cerebrovascular diseases. However, there is not enough confidence in the parallel trends' identification assumption. Implications: It is important to further analyze the impact of lockdowns on different health outcomes, in order to implement comprehensive policy designs in the event of future pandemics.

Keywords: Lockdown, quarantine, stringency index, impact, difference-in-differences, deaths, heart diseases, cerebrovascular diseases

Códigos JEL: I11, I12, I18, I38, H75

I. INTRODUCTION

Worldwide, ischemic heart diseases[1] and cerebrovascular diseases (strokes) are the main causes of death in developed and developing countries.[2] In the United States, a total of 647,457 people died because of heart diseases (23% of total deaths), and 146,383 people died because of strokes (5% of total deaths) in 2017.[3]

Due to the COVID-19 pandemic, most of the countries around the world took stringent measures to contain the virus spread, avoid the collapse of health systems, and minimize deaths. Some of the lockdown measures were school, workplaces, and public transport closures; cancellation of public events; meeting restrictions; stay at home requirement; and restrictions to domestic and international traveling.[4]

Even though these measures appeared to be effective in reducing the COVID-19 spread,[5] they had also other consequences. On the one hand, quarantine may have long-term effects on people´s health and increase the risk of cardiovascular disease, mainly related to unhealthy lifestyle (reduced physical activity and unhealthy diet) and anxiety.[6]

[1] Ischemic heart disease is the term given to heart problems caused by narrowed heart (coronary) arteries that supply blood to the heart muscle. When the blood flow to the heart muscle is completely blocked, the heart muscle cells die, which is termed a heart attack or myocardial infarction. *See* Institute of Medicine (US) Committee on Social Security Cardiovascular Disability Criteria. Cardiovascular Disability: Updating the Social Security Listings. Washington (DC): National Academies Press (US); 2010. 7, Ischemic Heart Disease. Available from: https://www.ncbi.nlm.nih.gov/books/NBK209964/.

[2] *See* World Health Organization. The top 10 causes of death, May 24, 2018. Available at https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. Accessed on August 6, 2020).

[3] *See* Heron M. Deaths: Leading causes for 2017. National Vital Statistics Reports; vol 68 no 6. Hyattsville, MD: National Center for Health Statistics. 2019. Available at https://www.cdc.gov/nchs/data/nvsr/nvsr68/nvsr68_06-508.pdf.

[4] *See* Thomas Hale, Sam Webster, Anna Petherick, Toby Phillips, and Beatriz Kira (2020). Oxford COVID-19 Government Response Tracker, Blavatnik School of Government. Available at https://www.bsg.ox.ac.uk/research/research-projects/oxford-covid-19-government-response-tracker.

[5] *See* Nussbaumer-Streit B, Mayr V, Dobrescu AIulia, Chapman A, Persad E, Klerings I, Wagner G, Siebert U, Christof C, Zachariah C, Gartlehner G. Quarantine alone or in combination with other public health measures to control COVID-19: a rapid review. Cochrane Database of Systematic Reviews 2020, Issue 4. Art. No.: CD013574. DOI: 10.1002/14651858.CD013574.

[6] *See* Mattioli, A.V., Ballerini Puviani, M., Nasi, M. et al. COVID-19 pandemic: the effects of quarantine on cardiovascular risk. *Eur J Clin Nutr* 74, 852–855 (2020). https://doi.org/10.1038/s41430-020-0646-z. Available at https://www.nature.com/articles/s41430-020-0646-z#citeas. Accessed on November 1, 2020.

Additionally, in the short term quarantine could also have increased deaths due to heart diseases because of a drop in medical checkups for cardiovascular risk factors, emergency visits to hospitals and hospitalization.

In the United States, during the 10 weeks following the declaration of COVID-19 as a national emergency, emergency visits to hospitals due to heart attacks dropped 23%, visits due to strokes dropped 20%, and visits due to hyperglycemic crises dropped 10%, compared with the preceding 10-week period.[7] The drop in the emergency visits to hospitals could be interpretated as a consequence of three different factors: the stringent restrictions imposed by each state such as "stay at home";[8] the fear of catching the COVID-19 when going to hospitals; [9] and the fall in the economic activity[10], the associated increase in unemployment[11] and the consequent loss of health insurance.

See, also, Bentley, C., Hathaway, N., Widdows, J., Bejta, F., De Pascale, C., Avella, M., ... & Lawson, C. (2011). Nutrition, Metabolism, and Cardiovascular Diseases.

[7] *See* Lange SJ, Ritchey MD, Goodman AB, et al. Potential Indirect Effects of the COVID-19 Pandemic on Use of Emergency Departments for Acute Life-Threatening Conditions — United States, January–May 2020. MMWR Morb Mortal Wkly Rep 2020;69:795–800. DOI: http://dx.doi.org/10.15585/mmwr.mm6925e2. Available at https://www.cdc.gov/mmwr/volumes/69/wr/pdfs/mm6925e2-H.pdf.

[8] *See* Jeffery MM, D'Onofrio G, Paek H, et al. Trends in Emergency Department Visits and Hospital Admissions in Health Care Systems in 5 States in the First Months of the COVID-19 Pandemic in the US. JAMA Intern Med. 2020;180(10):1328–1333. doi:10.1001/jamainternmed.2020.3288. Available at https://jamanetwork.com/journals/jamainternalmedicine/fullarticle/2768777. *See*, also, Belli, Brita. August 2020. Emergency department visits plunged as COVID-19 cases climbed, Yale study finds. Available at https://news.yale.edu/2020/08/03/emergency-department-visits-plunged-covid-19-cases-climbed-study-finds.

[9] *See* Lange SJ, Ritchey MD, Goodman AB, et al. Potential Indirect Effects of the COVID-19 Pandemic on Use of Emergency Departments for Acute Life-Threatening Conditions — United States, January–May 2020. MMWR Morb Mortal Wkly Rep 2020;69:795–800. DOI: http://dx.doi.org/10.15585/mmwr.mm6925e2. Available at https://www.cdc.gov/mmwr/volumes/69/wr/mm6925e2.htm.

[10] Real gross domestic product ("GDP") decreased in all 50 states and the District of Columbia in the second quarter of 2020, as real GDP for the nation decreased at an annual rate of 31.4%. The percent change in real GDP in the second quarter ranged from –20.4% in the District of Columbia to –42.2% in Hawaii and Nevada. *See* U.S. Bureau of Economic Analysis. October 2, 2020. Gross Domestic Product by State, 2nd Quarter 2020. Available at https://www.bea.gov/sites/default/files/2020-10/qgdpstate1020_0.pdf.

[11] The seasonally adjusted unemployment rate rose from 3.5% in February 2020 to 14.7% in April 2020. Although it later showed a downward trend, it only returned to pre-pandemic levels in 2022. *See* U.S. Bureau of Labor Statistics. Graphics for Economic News Releases. Civilian unemployment rate. Available at https://www.bls.gov/charts/employment-situation/civilian-unemployment-rate.htm#.

Even though numerous cardiologists argue that the drop in medical consultations and cardiovascular procedures due to quarantine lockdowns may have led to an increase in non-COVID-19 related deaths, [12] there are no methodologically rigorous studies analyzing the stringent policy measures impact on deaths from heart and cerebrovascular diseases.

The research problem is that the short-term impact of quarantine lockdowns on deaths from heart and cerebrovascular diseases in the United States between 2019 and 2022 is unknown.

The aim of this paper is to assess the short-term impact of stringent COVID-19 quarantine measures on deaths from heart and cerebrovascular diseases not related to COVID-19 in the United States, between 2019 and 2022.[13]

[12] *See* Martin Lombardero. ¿De qué nos morimos en Argentina en tiempos de pandemia? *IntraMed*, July 24, 2020. Available at https://www.intramed.net/contenidover.asp?contenidoid=96478. *See*, also, José L. Navarro Estrada y col. Documento de posición Sociedad Argentina de Cardiología – Fundación Cardiológica Argentina: Enfermedad Cardiovascular en tiempos de COVID-19. *Sociedad Argentina de Cardiología*, April 21, 2020. Available at https://www.sac.org.ar/institucional/documento-de-posicion-sac-fca-enfermedad-cardiovascular-en-tiempos-de-covid-19/.

[13] I chose the United States because it has available statistics on causes of death at the state level and shows variability in the policies imposed by each state.

II. RELATED LITERATURE

Even though there are many studies on the impact of lockdowns on the COVID-19 spread and total number of deaths,[14] few studies on cardiovascular diseases have been conducted.

Nef, H.M., Elsässer, A., Möllmann, H. et al. (2021),[15] observed that during the COVID-19 pandemic, hospital admissions for cardiac care declined. However, they noted that effects on mortality were unclear. Therefore, they sought to evaluate the impact of the lockdown period in central Germany on overall and cardiovascular deaths. They collected data of the rates of hospitalization for chronic coronary syndrome, acute coronary syndrome, out of hospital cardiac arrest and the number of deaths per cause from 22 of 24 public health-authorities in central Germany during the pandemic related lockdown period, and compared them to the same time period in 2019. They found that, when compared to the reference non-pandemic period in 2019, catheterization activities dropped 35% and cardiovascular and cardiac mortality increased 8% and 12%, respectively. However, they did not follow a rigorous design to evaluate causality and highlighted that the effect of pandemic-related lockdown and social-distancing restrictions on cardiovascular care and mortality should require further research.

Cené CW, Beckie TM, Sims M, Suglia SF, et al. (2022),[16] reviewed observational and intervention research that examines the impact of social isolation and loneliness on cardiovascular and brain health. They found that evidence is most consistent for a direct association between social isolation and loneliness with coronary heart disease and stroke

[14] *See*, for example, Huang, X., Shao, X., Xing, L., Hu, Y., Sin, D. D., & Zhang, X. (2021). The impact of lockdown timing on COVID-19 transmission across US counties. *EClinicalMedicine*, 38, 101035.
[15] *See* Nef, H.M., Elsässer, A., Möllmann, H. et al. Impact of the COVID-19 pandemic on cardiovascular mortality and catherization activity during the lockdown in central Germany: an observational study. *Clin Res Cardiol* 110, 292–301 (2021). https://doi.org/10.1007/s00392-020-01780-0.
[16] *See* Cené CW, Beckie TM, Sims M, Suglia SF, Aggarwal B, Moise N, Jiménez MC, Gaye B, McCullough LD; on behalf of the American Heart Association Social Determinants of Health Committee of the Council on Epidemiology and Prevention and Council on Quality of Care and Outcomes Research; Prevention Science Committee of the Council on Epidemiology and Prevention and Council on Cardiovascular and Stroke Nursing; Council on Arteriosclerosis, Thrombosis and Vascular Biology; and Stroke Council. Effects of objective and perceived social isolation on cardiovascular and brain health: a scientific statement from the American Heart Association. *J Am Heart Assoc*. 2022;11:e026493. doi: 10.1161/JAHA.122.026493.

mortality. However, they noted that few studies had empirically tested mediating pathways between social isolation, loneliness, and cardiovascular and brain health outcomes using appropriate methods for explanatory analyses, that control for confounders on the associations.

Qi, J., Zhang, D., Zhang, X. et al (2021),[17] using death records from China's Disease Surveillance Points ("DSP") system,[18] and considering information from various news media and government announcements on whether a city implemented strict anti-contagion policies, constructed a daily DSP site-level panel dataset from January 1 to July 31, 2020. They implemented a difference-in-differences design and estimated the short-term impact of lockdowns on the number of deaths from various causes. Contrary to my hypothesis, they found that the number of deaths from cardiovascular diseases dropped by 5.85% when lockdowns were implemented. They explain that the drop in the number of deaths from cardiovascular diseases could be caused by the improvement in the air quality.[19]

My paper contributes to the literature mainly by bringing more evidence of the impact of lockdowns on different non-COVID-19 health outcomes. I consider a different country, a longer period and different data sources than Qi, J., Zhang, D., Zhang, X. et al (2021). I evaluate the impact in the United States between January 1, 2019, and December 4, 2021. I use weekly data on the number of deaths by jurisdiction of occurrence and cause of death, published by the National Center for Health Statistics ("NCHS"), from the Centers for Disease Control and Prevention ("CDC").[20] To quantify whether a state had strict COVID-19 quarantine measures, I consider the "stringency index for display", an index developed

[17] *See* Qi, J., Zhang, D., Zhang, X. et al. Short- and medium-term impacts of strict anti-contagion policies on non-COVID-19 mortality in China. *Nat Hum Behav* 6, 55–63 (2022). https://doi.org/10.1038/s41562-021-01189-3.

[18] It covers more than 324 million people in 605 DSP districts/counties in 321 cities.

[19] The outcome variables were the daily number of non-COVID-19-related deaths. The explanatory variable was a dummy indicating whether lockdowns were implemented in a DSP's city on a particular date. They computed the percentage change by combining the coefficient estimates and the mean values for each cause of death.

[20] *See* National Center for Health Statistics, Centers for Disease Control and Prevention, available at https://www.cdc.gov/nchs/index.htm.

by the Oxford Covid-19 Government Response Tracker ("OxCGRT"), which is based on 9 different types of measures and rescales them to a single value between 0 and 100 (where 100 is the strictest response), for each state on a daily basis.[21] As will be explained in the following sections, the stringency index for display is not a dummy variable that takes value of 0 for no measure and 1 when there was any measure, but instead captures how intense a measure was, allowing me to use a staggered difference-in-differences identification strategy.

[21] *See* Blavatnik School of Government, University of Oxford, Oxford Covid-19 Government Response Tracker, available at https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

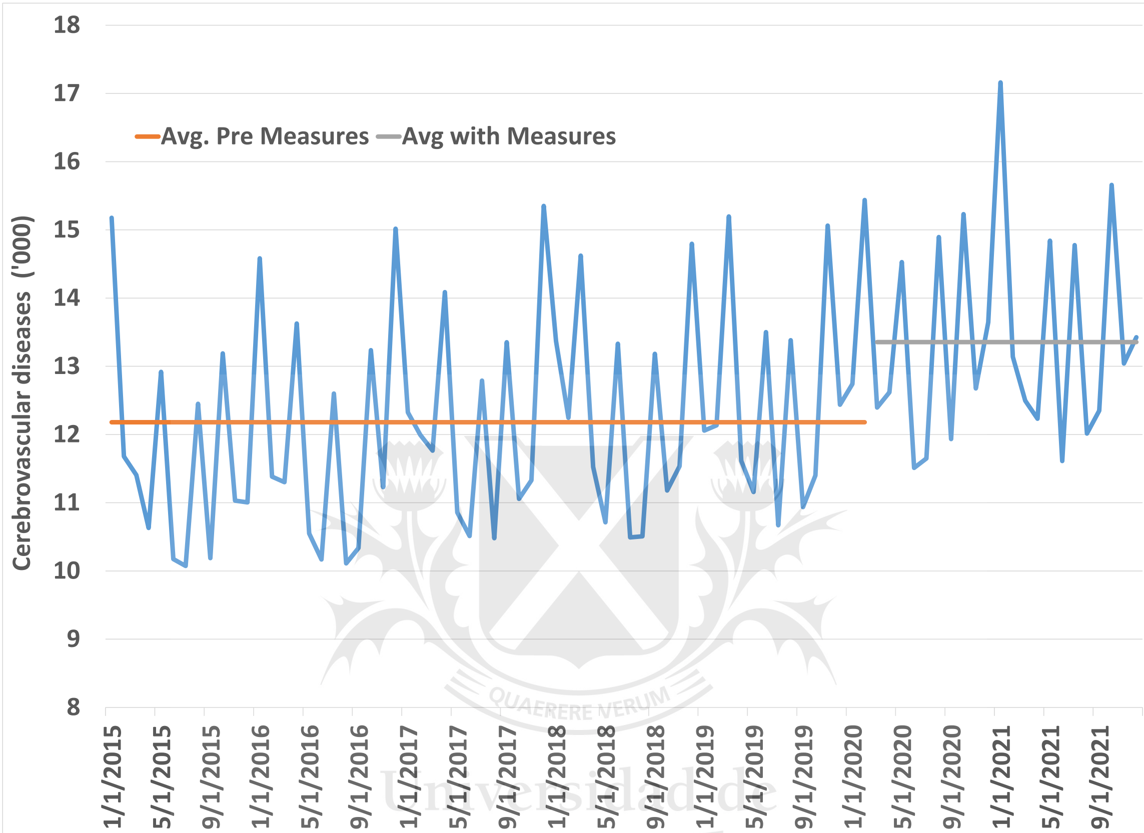
III. DATA

To study the effect of lockdowns on deaths due to heart diseases and strokes I use two sources of data. Firstly, I use a database that includes the weekly number of deaths in the United States, by jurisdiction of occurrence and cause of death, published by the NCHS. Among the causes of death, the database differentiates those related to COVID-19 as a multiple cause or underlying cause of death, and those not related to COVID-19. Diseases of heart and cerebrovascular diseases are two different categories in the database, not related to COVID-19.

As can be seen in Figure I and Figure II below, cerebrovascular and heart diseases increased on average 10%[22] and 6%,[23] respectively, if I compare a pre-measures period (from January 2015 to February 2020) and a period with measures (from March 2020 to December 2021). The difference in means remains even if I remove the outliers (*see* Appendix A.).

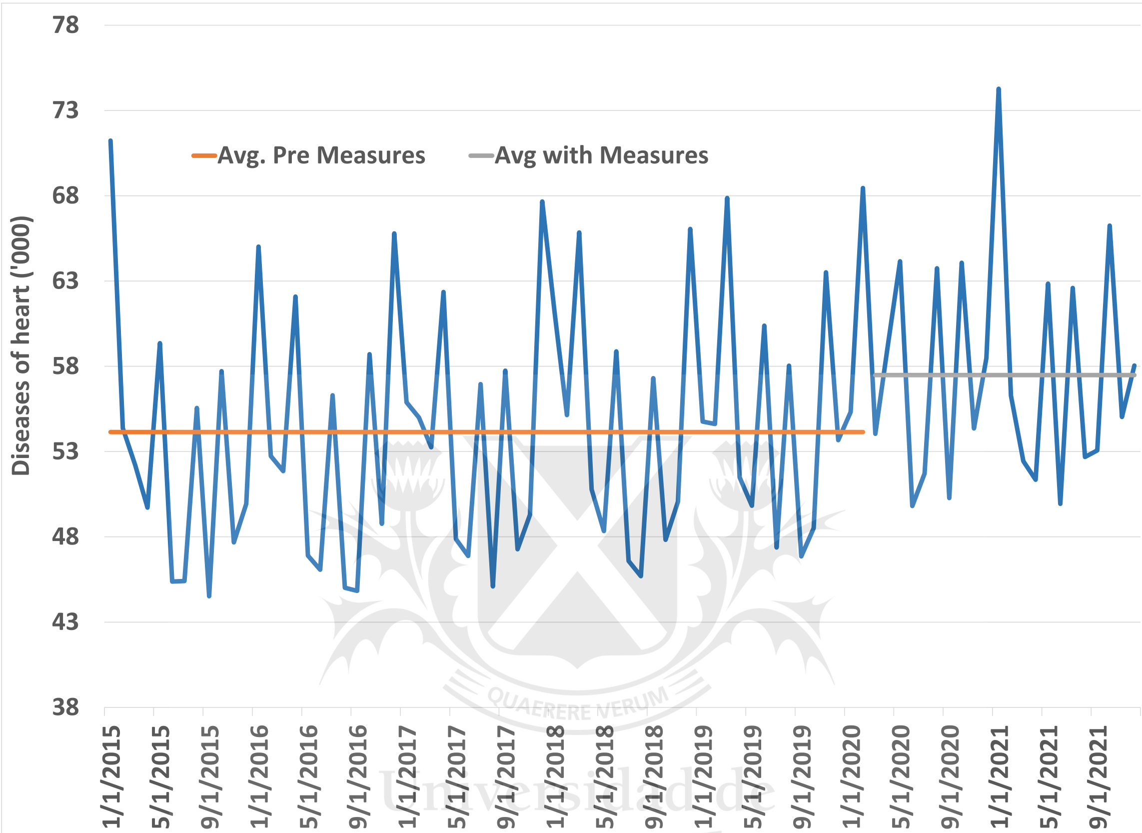
[22] It increased from a monthly average of 12,181 to 13,356 deaths due to cerebrovascular diseases.
[23] It increased from a monthly average of 54,142 to 57,481 deaths due to diseases of heart.

Figure I. Evolution of deaths due to cerebrovascular diseases



Own production based on (i) National Center for Health Statistics. Weekly Counts of Deaths by State and Select Causes, 2014-2019, and (ii) National Center for Health Statistics. Weekly Provisional Counts of Deaths by State and Select Causes, 2020-2022. Accessed on 07/16/2022.

Figure II. Evolution of deaths due to diseases of heart



Own production based on (i) National Center for Health Statistics. Weekly Counts of Deaths by State and Select Causes, 2014-2019, and (ii) National Center for Health Statistics. Weekly Provisional Counts of Deaths by State and Select Causes, 2020-2022. Accessed on 07/16/2022.

Secondly, to quantify whether a state had strict COVID-19 quarantine measures, I consider the stringency index for display. This is an index developed by the OxCGRT, which is based on 9 different types of measures[24] and rescales them to a single value between 0 and 100 (where 100 is the strictest answer), for each state, on a daily basis.[25] Data is collected from publicly available sources such as news articles and government press releases and

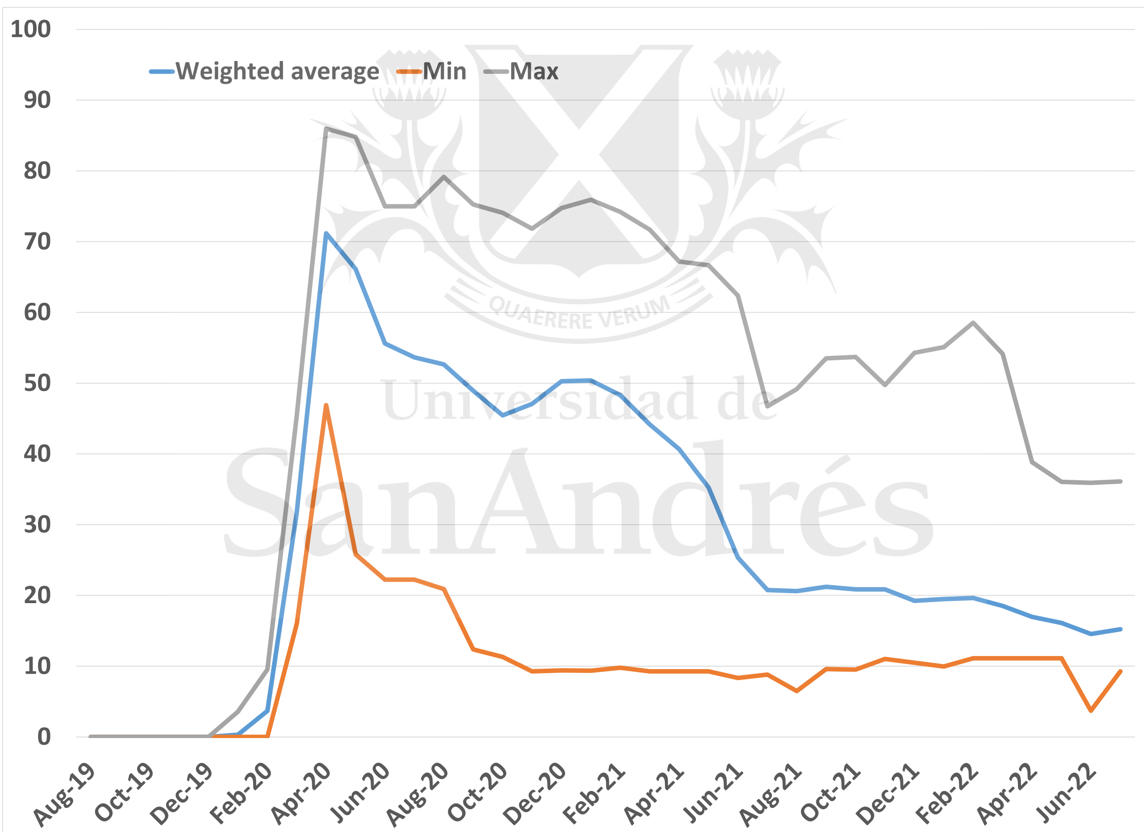
[24] The nine metrics used to calculate the stringency index are: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls. These nine indicators are ordinal, in the sense that they measure policies on a simple scale of severity or intensity.

[25] To bring the index to a weekly basis, I averaged the daily indices on each week.

briefings. These are identified via internet searches by a team of over 50 Oxford University students, staff, collaborators and partners. OxCGRT measures for the United States jurisdictions do not include federal policies that apply to the country as a whole.

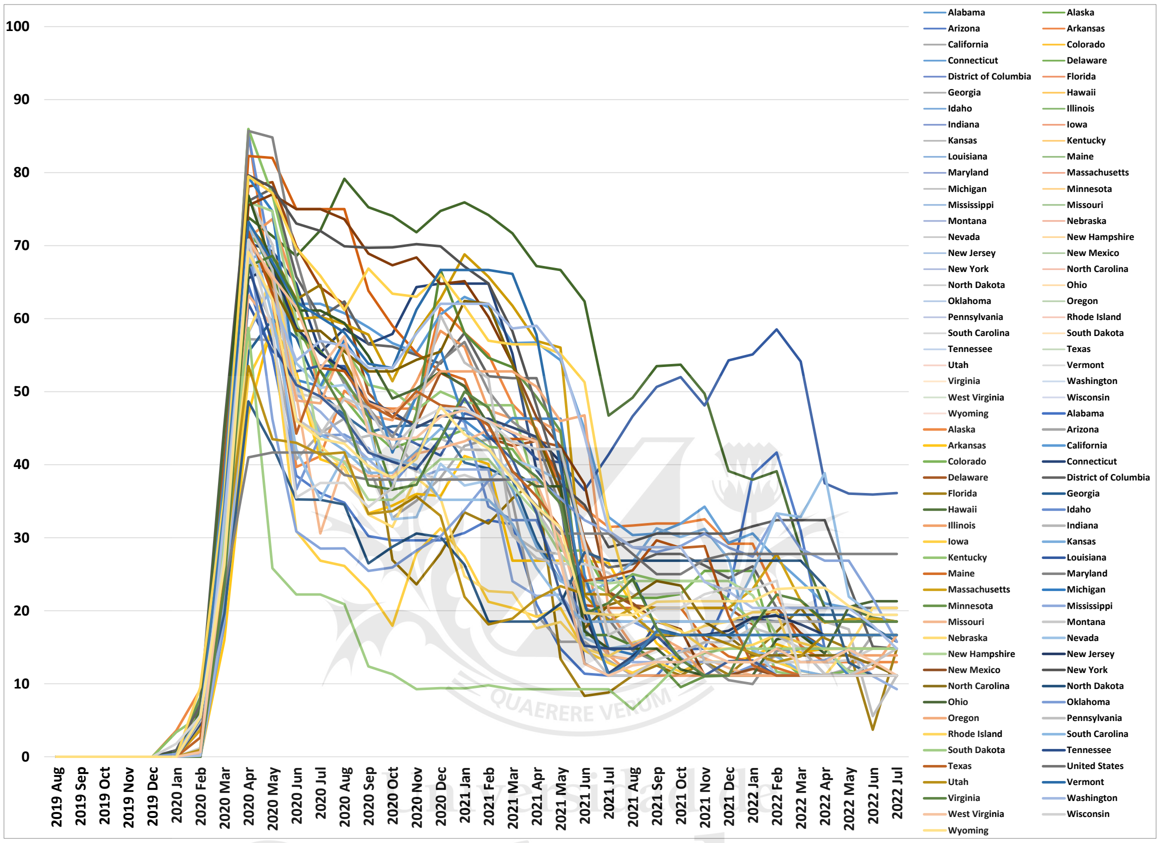
As can be seen in Figure III and Figure IV, stringency measures in the United States begun in January 2020, but each state implemented them in a different moment and a with a specific intensity.

Figure III. COVID-19 policy stringency index evolution and variability



Notes: (i) The average is weighted by State population. (ii) The Max and Min refer to the maximum and minimum value of the stringency index reported at each moment of time, respectively, considering all jurisdictions in the United States. Source: own production based on Oxford COVID-19 Government Response Tracker. Accessed on 07/16/2022. Available on https://github.com/OxCGRT/USA-covid-policy. For population data: 2019 1-year American Community Survey estimates, U.S. Census Bureau. Available at [https://www.governing.com/now/state-population-by-race-ethnicity-data.html.](https://www.governing.com/now/state-population-by-race-ethnicity-data.html)

Figure IV. COVID-19 policy stringency index evolution and variability, by state



Source: own production based on Oxford COVID-19 Government Response Tracker. Accessed on 07/16/2022. Available on https://github.com/OxCGRT/USA-covid-policy.

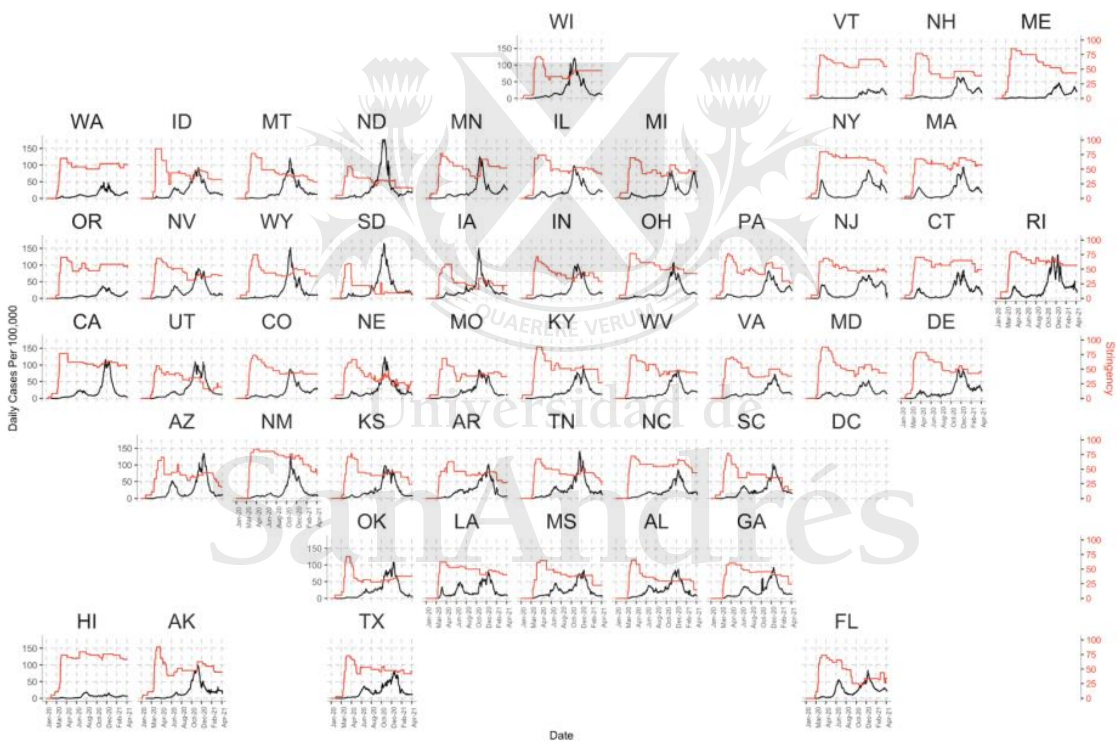
The states with the highest average stringency index between January 2020 and July 2022 are Hawaii (average index of 51), New York (44), Louisiana (43), California (42) and Rhode Island (39). However, the states that reported the highest monthly stringency index were Alaska (86), Kentucky (86), Maryland (86), Idaho (85) and Maine (82), which occurred in April 2020.

It is important to note that the OxCGRT authors not only find an overall variation in the stringency between states, but also that the stringency of states' policy response varied substantially relative to their daily rate of COVID-19 cases.[26] As Figure V shows, states

[26] *See* Hallas, L., Hatibie, A., Koch, R., Majumdar, S., Pyarali, M., Wood, A., & Hale, T. (2021). Variation in US states' COVID-19 policy responses. Blavatnik School of Government, p. 20.

displayed clear spikes in the number of COVID-19 cases during November 2020 and January 2021, that were sometimes met with increased policy stringency (*e.g.*, Pennsylvania and Virginia), and others with unchanging or even decreasing policy stringency (*e.g.*, Alabama and Georgia). Other states, such as Vermont and Hawaii, maintained relatively high policy stringency throughout the pandemic's first year as cases remained relatively low.

Figure V. Daily COVID-19 cases (seven-day running average) and state stringency



Source: Hallas, L., Hatibie, A., Koch, R., Majumdar, S., Pyarali, M., Wood, A., & Hale, T. (2021). Variation in US states' COVID-19 policy responses. Blavatnik School of Government, Figure V.

IV. IDENTIFICATION STRATEGY

Given the panel database with the weekly (i) number of deaths due to heart diseases and strokes for each state in the United States between January 1, 2019, and December 4, 2021; and (ii) the intensity of the measures taken by each state to control the COVID-19 spread, I follow a staggered difference-in-differences identification strategy[27] with the following specifications:

$$(1) \quad D_{st} = \alpha_s + \gamma_t + \beta I_{st} + \varepsilon_{st}$$

Where,

a. D_{st} are the deaths from cerebrovascular and heart diseases in state *s* and week *t*.

b. α_s is the state s fixed effect, that captures the different deaths levels between states, and other potentially time invariant omitted variables.

c. γ_t is the weekly fixed effect in week *t*, that captures changes that affect all states in the same way, each time.

d. I_{st} is a stringency index that captures the lockdown measures in state *s* and week *t*. This is an index that goes from 0 to 100 and takes a value of 0 when there are no pro-quarantine measures and 100 when the quarantine measures are the strictest.

β is the parameter of interest. To interpret β causally, the following assumptions must be done:

a. Stable Unit Treatment Value Assumption (SUTVA): lockdown measures taken by a particular state do not change the behavior of people in another state.

[27] A staggered Difference-In-Differences design is a special case of the general Difference-In-Differences set up, where the adoption date at which units are first exposed to the policy may vary by unit, and units can switch back and forth between being exposed or not to the treatment.

b. Parallel trends assumption: deaths from cerebrovascular and heart diseases should have evolved in the same way as before the quarantine if no measures had been taken.

c. No movement of individuals between states because of lockdown measures.

d. People in each state follow the rules established by the authorities.

e. Stringency measure's timing are orthogonal to cerebrovascular and heart diseases.

f. Stringency measures are unrelated to COVID-19 number of cases in the same State (*see* section "VI. Discussion" for the possible implication of this relationship).

Standard errors are clustered at the state level, to relax the assumption of independence of the errors and replace it with the assumption of independence between clusters. Therefore, the errors can be correlated within clusters.

IV.1 PARALLEL TRENDS ASSUMPTION

One of the most important identification assumptions in a difference-in-differences approach is that the controls have evolved from a pre-treatment period to a post-treatment period in the same way that the treated would have behaved if they had not been treated. This means, in the absence of treatment, the variation between before and after the treatment period in the controls is a good counterfactual of what the change in the treatment group would have been if the treatment had not existed. While this assumption cannot be tested because it is unobservable (*i.e.*, it is impossible to see if the trends would have been the same in the absence of treatment), I can check if the trends before treatment were the same between controls and treated. Observing backward periods, I can analyze if the evolution was similar and the difference between treated and controls remained constant, in order to assume that it would have continued constant after the treatment.

In this study, all the states were eventually treated, *i.e.*, all of them had lockdown measures, but the measures took place in different moments and with different intensities. Therefore I took a different approach to check if there is confidence in the parallel trend assumption. When the sample includes many periods, the difference-in-differences model lends itself to a test for causality in the spirit of Granger (1969).[28] The Granger idea is to see whether causes happen before consequences and not *vice versa*. In this context, Granger causality testing means a check on whether, conditional on state and year effects, past I_{st} (lags) predict D_{st} while future I_{st} (leads) do not. If I_{st} causes D_{st} but not *vice versa*, then leads should not matter in the following equation:

$$(2)\quad D_{st} = \alpha_s + \gamma_t + \sum_{\tau=q^-}^{q^+} \beta^\tau I_{st}^\tau + \varepsilon_{st}$$

Where,

a. D_{st} are the deaths caused by cerebrovascular and heart diseases in state *s* and week *t*.

b. α_s is the state s fixed effect, that captures the different deaths levels between states, and other potentially time invariant omitted variables.

c. γ_t is the weekly fixed effect in time *t*, that captures changes that affect states in the same way, each time.

d. I_{st}^τ captures the intensity of the measures if the measure *I* was taken τ periods before or after the D_{st} occurrence, where $q < 0$ are the lags or post-treatment effects and $q > 0$ are the leads or anticipatory effects.

[28] *See* Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press, Chapter 5.2.1. Regression DD. *See*, also, Granger, Clive W. J. (1969): "Investigating Causal Relation by Econometric and Cross-Sectional Method", Econometrica, 37, 424-438.

e. ε_{st} is the error term.

β^{τ} measures the effect of $I_{s,t+\tau}$ on D_{st}. Given that the idea is to see whether causes happen before consequences and not *vice versa*, to be confident in the assumption of parallel pretreatment trends, every β^{τ} with positive τ must not be statistically different from zero, and the coefficients must be "near" zero. For example, a mobility restriction in *t* must not affect deaths caused by cerebrovascular and heart diseases of τ weeks before. I set q^{+} and q^{-} equal to 30.[29]

[29] *See* Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press, Chapter 5.2.1. Regression DD.

V. RESULTS

The identification strategy results show that the stringency measures have on average a positive and statistically significant effect on deaths from heart and cerebrovascular diseases; *i. e.* lockdown measures appear to have increased deaths due to heart diseases and strokes in the same week the measures were taken.

If I interpret the coefficients in Table I below causally, a unit change in the average stringency index[30] in every state would cause 11 and 3 weekly deaths from heart and cerebrovascular diseases, respectively, countrywide.

Table I. Short-term effect of quarantine on deaths due to heart diseases and strokes

VARIABLES	(1) Quarantine effect on deaths due to heart diseases	(2) Quarantine effect on deaths due to strokes
Stringecy Index	0.220*** (0.0585)	0.0584*** (0.0134)
Constant	251.3*** (1.392)	57.64*** (0.320)
Observations	7,803	7,803
Number of Jction	51	51
R-squared	0.014	0.018
State FE	YES	YES
Week FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: Own production.

In addition, the effect of quarantine on deaths due to heart diseases and strokes appears to be not only short-term but also long-lasting. If I follow the same regression but consider

[30] The average stringency index between January 2019 and December 2021 is 23.79.

the effect of the lockdown measures on deaths occurring 30 weeks later, I still find positive and statistically significant effects.

Table II. Medium-term effect of quarantine on deaths from heart diseases and strokes

VARIABLES	(1) Quarantine effect on deaths due to heart diseases	(1) Quarantine effect on deaths due to strokes
Stringecy Index t-30	0.178*** (0.0599)	0.0795*** (0.0162)
Constant	253.0*** (1.168)	57.48*** (0.316)
Observations	7,803	7,803
Number of Jction	51	51
R-squared	0.010	0.038
State FE	YES	YES
Week FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Source: own production

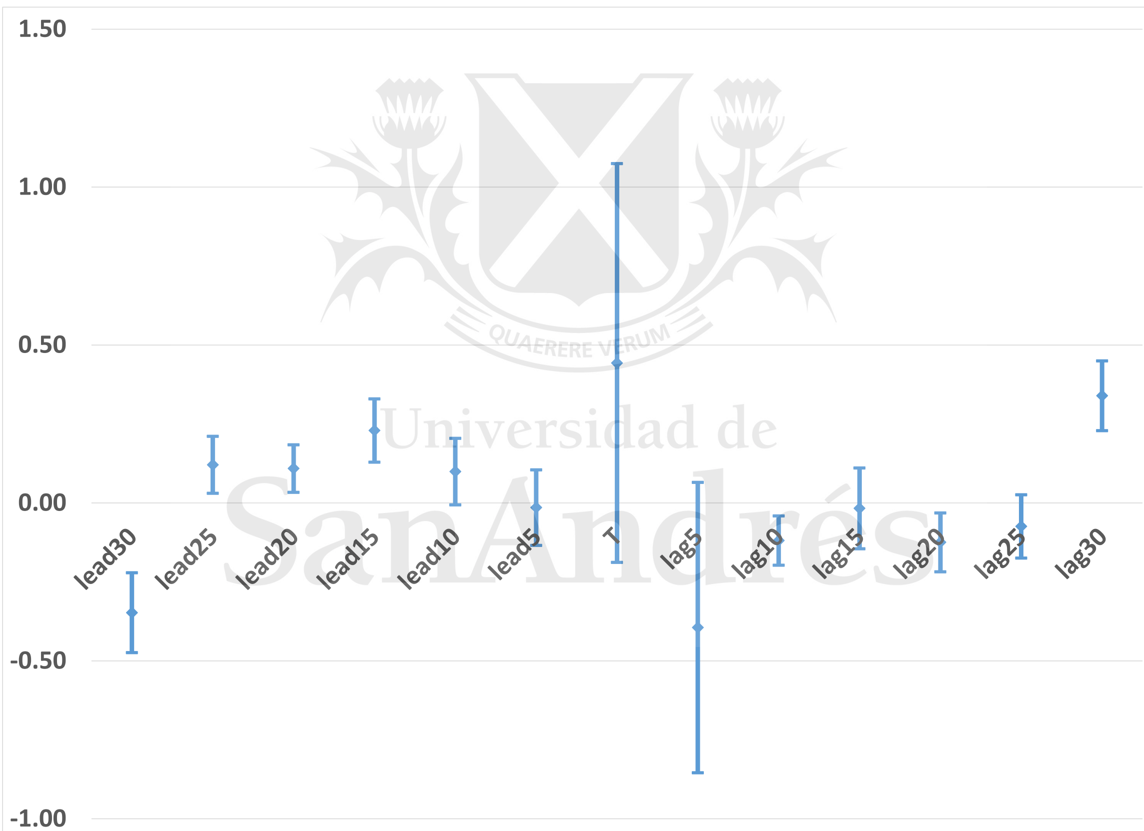
V.1 PARALLEL TRENDS ASSUMPTION

In Figure VI and Figure VII below, I show the results of running the specification (2) for deaths due to heart diseases and strokes as dependent variables, respectively. From the results, it is not possible to be confident in the parallel trends identification assumption:

a. Deaths due to heart diseases: the coefficients statistically different from zero with a 95% confidence interval are leads 30, 25, 20 and 15 (β^{30}, β^{25} , β^{20} and β^{15}) and lags 10, 20 and 30 (β^{-10} , β^{-20} and β^{-30}). On the one hand, that leads are statistically different from zero remove confidence that pre-treatment trends are parallel. Additionally, that lag 30 is positive and lags 10 and 20 are negative may be a counterintuitive result, which may also remove confidence in the results.

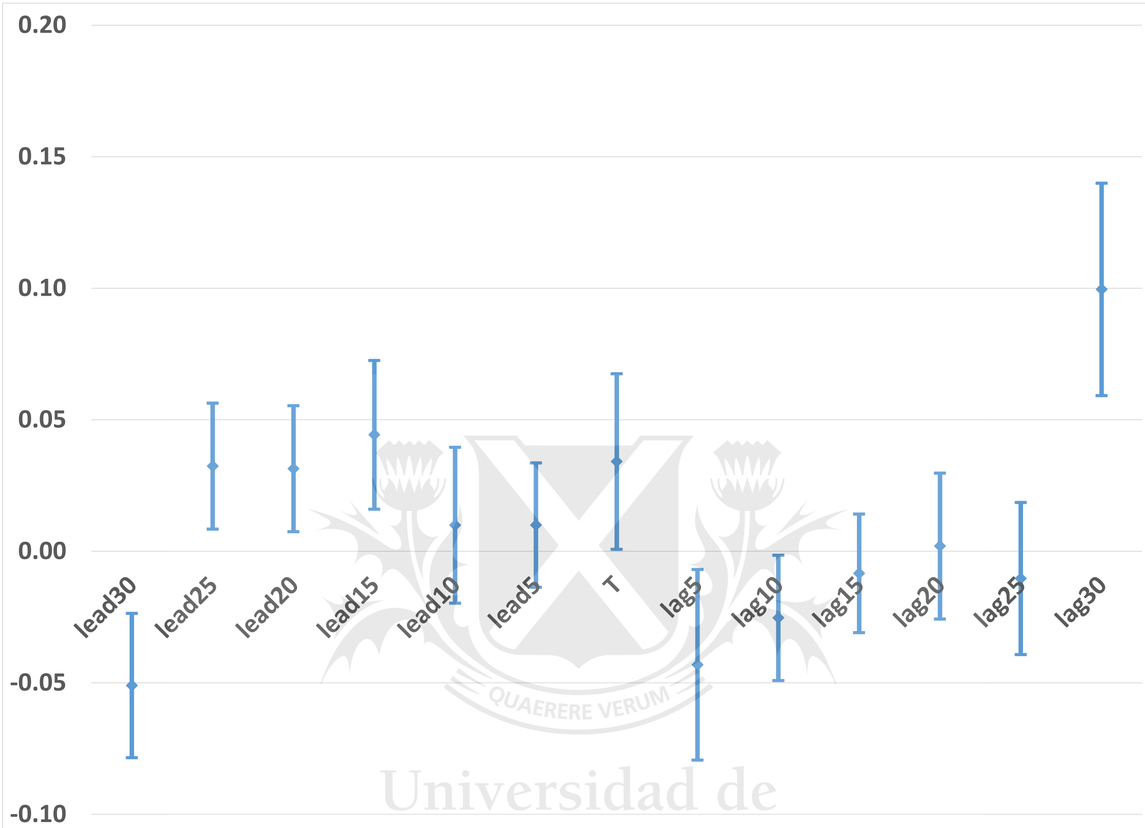
b. <u>Deaths due to strokes</u>: the fact that that leads 30, 25, 20 and 15 (β^{30}, β^{25} , β^{20} and β^{15}) are statistically different from zero with a 95% confidence interval removes confidence in the parallel pre-treatment trends assumption. That β^{0} and β^{-30} are statistically different from zero and have a different sign than β^{-5} and β^{-10}, which are also statistically different from zero, remove confidence in the results as a whole.

Figure VI. Parallel trends - Effect of quarantine on deaths due to heart diseases



Note: the lines represent the range of values where the coefficient can be with a 95% of confidence. Source: Own production.

Figure VII. Parallel trends - Effect of quarantine on stroke deaths



Note: the lines represent the range of values where the coefficient can be with a 95% of confidence. Source: Own production.

VI. DISCUSSION

One of the reasons why there is not enough confidence in the parallel trends' assumption could be that the stringency index considers nine variables and not all of them might be as relevant to the outcome of interest, such as school closures or international travel controls. To address this potential issue, I adjusted the index to include only the most relevant variables that could affect access to medical checkups: closures of public transport, stay-at-home requirements, workplace closures and restrictions on public gatherings.[31] However, the use of the adjusted stringency index shows similar results to those obtained with the original index: although the β (parameter of interest) estimates are statistically significant and take a higher positive value when running equation (1) with the adjusted index than with the original index,[32] there are still estimates of the leads ($\beta^{q>0}$) with statistically significant values when running equation (2) with the adjusted index.[33] In Appendix B. I show the results of running equations (1) and (2) using the adjusted stringency index.

The fact that there is not enough confidence in the parallel trends' assumption may arise from three other main causes that could bias the parameter of interest. Firstly, one of the assumptions is that people did not stop going to emergency visits in hospitals because of fear of catching COVID-19, but only because of the lockdown measures imposed by the state. According to research conducted by Anderson, K.; McGinty E.; et al (2021), adults in the United States attributed missed care primarily to medical practice being closed (either temporarily or permanently) during the early months of the pandemic (63% of the

[31] The adjusted index, like the original, is rescaled to a single value between 0 and 100 (being 100 the strictest answer), for each state, on a daily basis. To bring the index to a weekly basis, I averaged the daily indices on each week.

[32] Running equation (1) with the adjusted stringency index returns a β estimate of: 0.249 for deaths due to heart diseases (compared to 0.220 using the original index); and 0.0591 for deaths due to strokes (compared to 0.0584 using the original index), both with a p-value lower than 0.01.

[33] With a confidence interval of 95%, running equation (2) using the adjusted stringency index returns statistically significant β^{30}, β^{15}, and β^{10} estimates for deaths due to heart diseases; and statistically significant β^{30}, β^{20}, and β^{15} estimates for deaths due to strokes.

sample) and, secondarily, to fear of COVID-19 exposure (57% of the sample).[34] Therefore, most of the people who missed medical check-ups would have attended if they had been available, although there is a certain proportion who still would not have done so because they were not sure they would not be infected under the given conditions. A way to control this identification concern could be to add a variable that captures people's fear of catching COVID-19; *e.g.*, the number of COVID-19 cases in each week and state. However, any variable included in this way would also be a dependent variable of the lockdown measure and hence a *bad control*.[35]

Secondly, another identification concern is that measures such as workplace closures and stay-at-home requirements had a direct positive effect in unemployment.[36] If people stop going to hospitals for emergency visits because they lost their employment and could not afford the visit, and the lockdown measures caused unemployment, the parameter of interest β could be biased. Anderson, K.; McGinty E.; et al (2021), find that 7% of an adult sample in the United States attributed missed care to the financial repercussions of the COVID-19 pandemic. However, it is not possible to add the weekly unemployment in the regression because is a dependent variable of the lockdown measures and would also be a *bad control.*

[34] *See* Anderson KE, McGinty EE, Presskreischer R, Barry CL. Reports of Forgone Medical Care Among US Adults During the Initial Phase of the COVID-19 Pandemic. JAMA Netw Open. 2021;4(1):e2034882. doi:10.1001/jamanetworkopen.2020.34882. Available at https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2775366.

[35] Angrist and Pischke (2009, p.64) state the following:

> *Some variables are bad controls and should not be included in a regression model, even when their inclusion might be expected to change the short regression coefficients. Bad controls are variables that are themselves outcome variables in the notional experiment at hand. That is, bad controls might just as well be dependent variables too. Good controls are variables that we can think of having been fixed at the time the regressor of interest was determined.*

See Angrist, J. and Pischke, J.-S. (2009). Mostly harmless econometrics: an empiricists guide. Princeton: Princeton University Press.

[36] *See* footnote 11.

Finally, the stringency measure's timing may not be orthogonal to the number of deaths from cerebrovascular and heart disease: the timing of easing restrictions could have been affected by concerns about the increase in deaths from these causes.

For the reasons addressed above, that β is positive and statistically different from zero in equation (1) is not enough to be confident in its interpretation as a causal effect.

VII. CONCLUSION

Although the stringent policy measures appear to be effective in reducing the COVID-19 spread and avoid the collapse of health systems, they have also reduced medical checkups for cardiovascular risk factors, emergency visits to hospitals, and hospitalizations.

In this paper I analyze the short-term impact of stringent COVID-19 quarantine measures on deaths from heart and cerebrovascular diseases in the United States between January 2019 and December 2021, following a staggered difference-in-differences identification strategy. Even though I find a positive and statistically significant effect, there is not enough confidence in the parallel trends' identification assumption. One of the reasons for the lack of confidence is the impossibility of adding two key variables in the regression because of being bad controls: the fear of catching COVID-19 when going to the physician and unemployment. The other reason is that the timing of easing restrictions could have been affected by concerns about the number of deaths from cerebrovascular and heart disease.

Given the lack of rigorous studies conducted, it is important to further analyze the impact of lockdowns on different health outcomes, in order to implement future comprehensive policy designs in the event of a future pandemic. To this end, practitioners and public health officials should (i) maintain available resources and ensure critical health services continuity; (ii) emphasize the importance of visiting emergency departments for serious symptoms, illnesses, and injuries that cannot be managed in other settings; and (iii) assure the public that emergency departments implement infection prevention and control guidelines to ensure the safety of patients and health care personnel.

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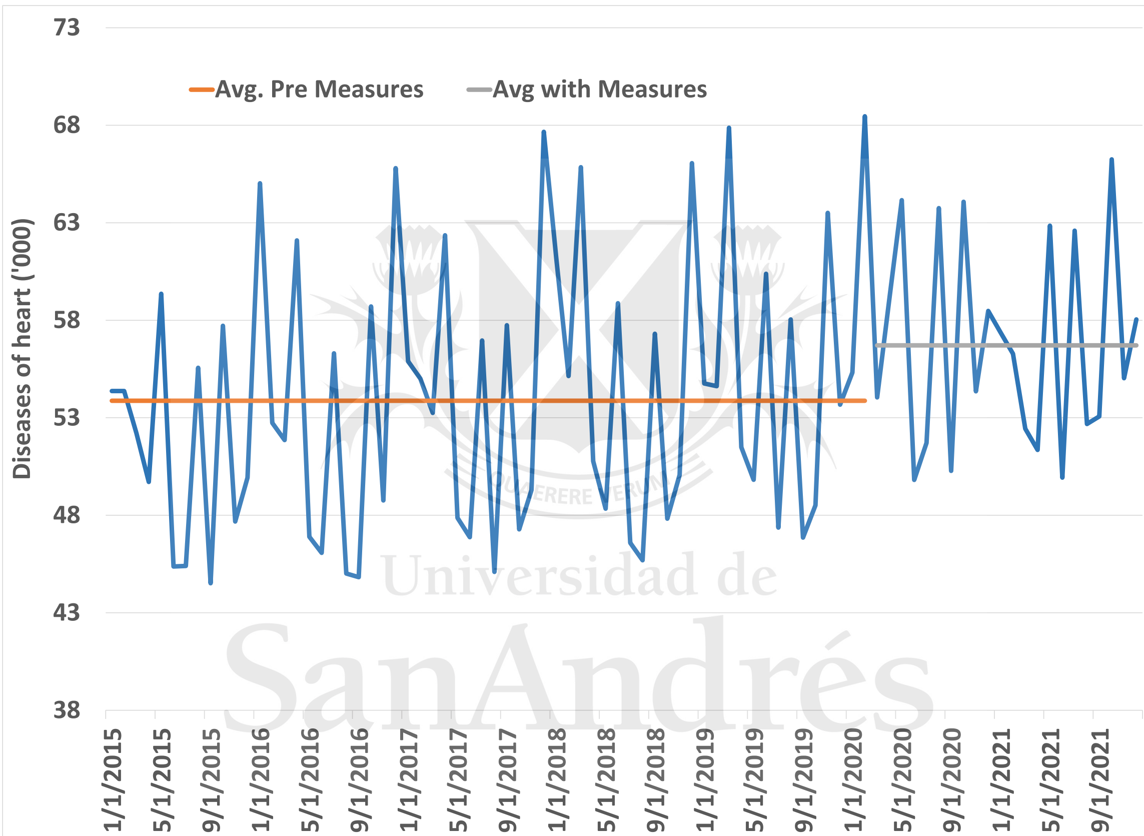
IX. APPENDIX A.

The difference in the averages of deaths before and after the beginning of the lockdown measures remains even if I remove the outliers for January 2015 and January 2021.[37]

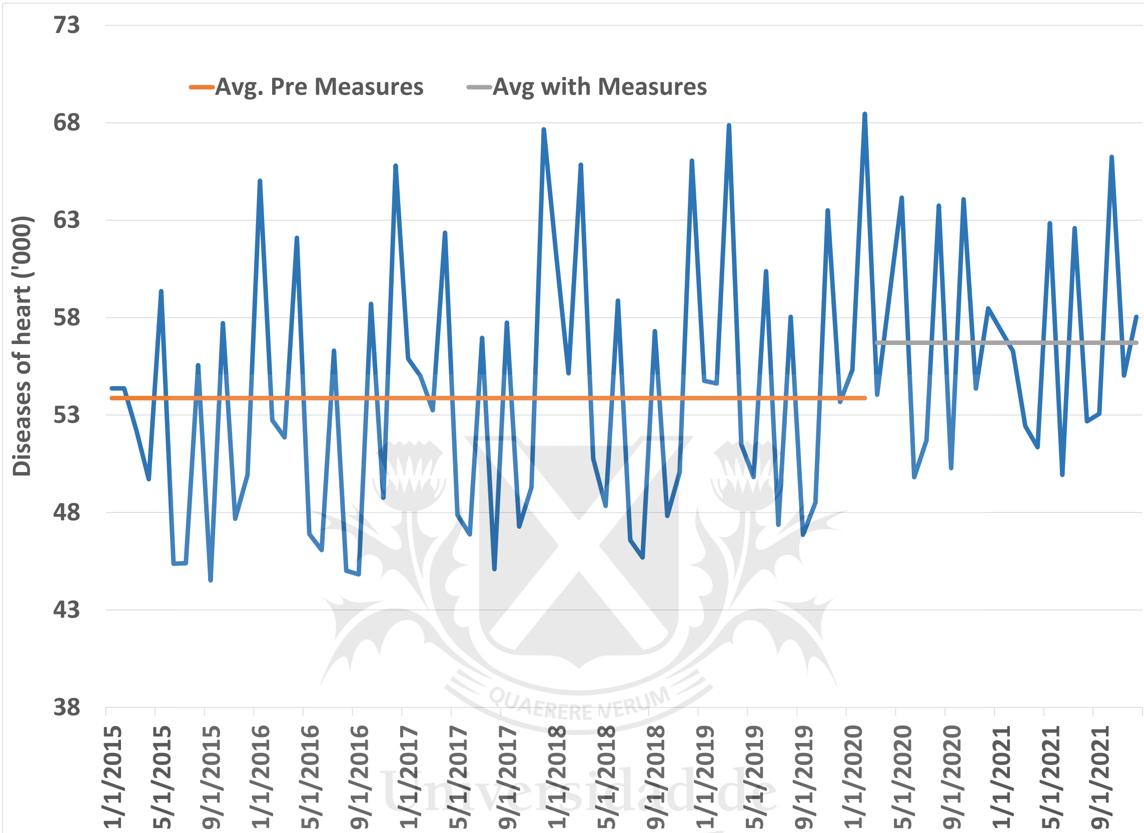
Figure VIII. Evolution of deaths due to cerebrovascular diseases. Outliers removed.



Note: outliers for January 2015 and January 2021 were removed. Own production based on (i) National Center for Health Statistics. Weekly Counts of Deaths by State and Select Causes, 2014-2019, and (ii) National Center for Health Statistics. Weekly Provisional Counts of Deaths by State and Select Causes, 2020-2022. Accessed on 07/16/2022.

[37] Removing outliers, deaths due to cerebrovascular diseases increase from a monthly pre-measures average of 12,124 to a post-treatment average of 13,184. Deaths due to diseases of heart increase from a monthly pre-measures average of 53,870 to a post-treatment average of 56,713.

Figure IX. Evolution of deaths due to diseases of heart. Outliers removed.



Note: outliers for January 2015 and January 2021 were removed. Own production based on (i) National Center for Health Statistics. Weekly Counts of Deaths by State and Select Causes, 2014-2019, and (ii) National Center for Health Statistics. Weekly Provisional Counts of Deaths by State and Select Causes, 2020-2022. Accessed on 07/16/2022.

X. APPENDIX B.

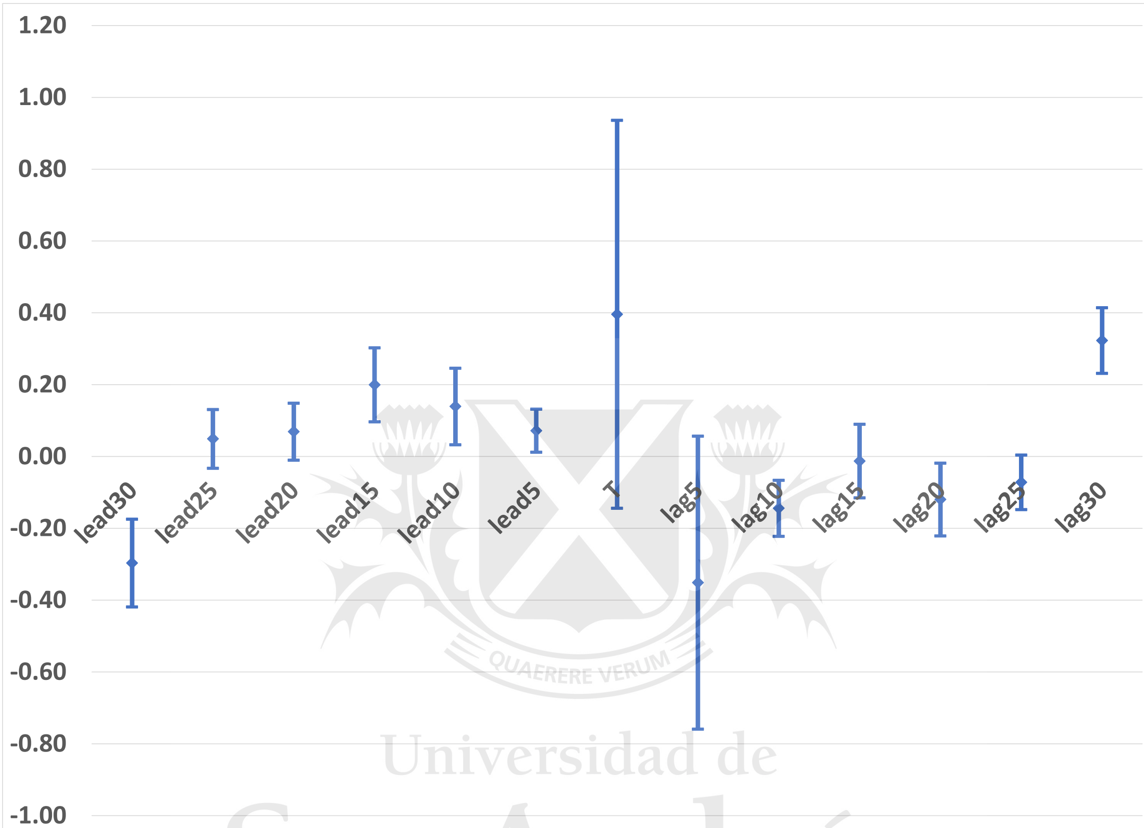
Table III. Quarantine effect on deaths from heart diseases and strokes (Adj. Index)

VARIABLES	(1) Quarantine effect on deaths due to heart diseases	(2) Quarantine effect on deaths due to strokes
Adj. Stringency Index	0.249***	0.0591***
	(0.0786)	(0.0132)
Constant	252.1***	57.98***
	(1.393)	(0.234)
Observations	7,803	7,803
R-squared	0.015	0.016
Number of Jction	51	51
State FE	YES	YES
Week FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

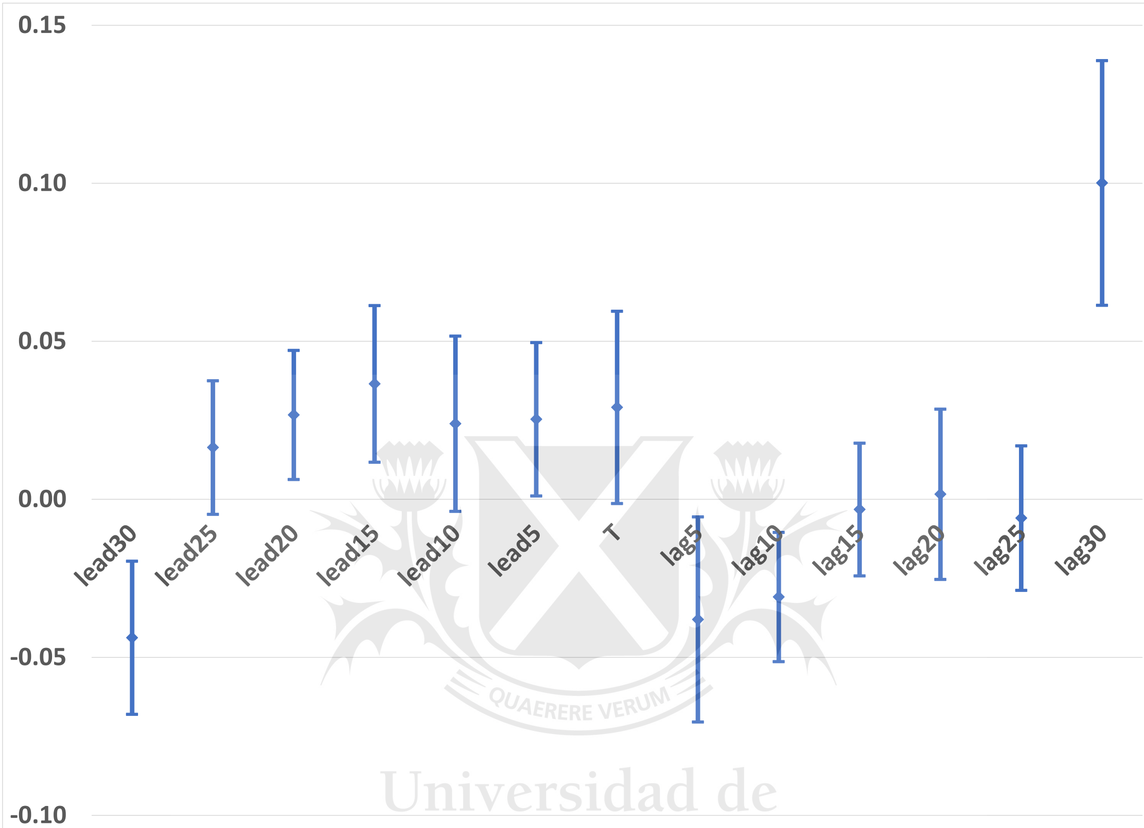
Source: Own production.

Figure X. Parallel trends - Effect of quarantine on deaths due to heart diseases (Adjusted Index)



Note: the lines represent the range of values where the coefficient can be with a 95% of confidence. Source: Own production.

Figure XI. Parallel trends - Effect of quarantine on stroke deaths (Adjusted Index)



Note: the lines represent the range of values where the coefficient can be with a 95% of confidence. Source: Own production.