

Worldwide Bayesian Causal Impact Analysis of Vaccine Administration on Deaths and Cases Associated with COVID-19: A BigData Analysis of 145 Countries

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Abstract

Policy makers and mainstream news anchors have promised the public that the COVID-19 vaccine rollout worldwide would reduce symptoms, and thereby cases and deaths associated with COVID-19. While this vaccine rollout is still in progress, there is a large amount of public data available that permits an analysis of the effect of the vaccine rollout on COVID-19 related cases and deaths. Has this public policy treatment produced the desired effect?

One manner to respond to this question can begin by implementing a Bayesian causal analysis comparing both pre- and post-treatment periods. This study analyzed publicly available COVID-19 data from OWID (Hannah Ritchie and Roser 2020) utilizing the R package *CausalImpact* (Brodersen et al. 2015) to determine the causal effect of the administration of vaccines on two dependent variables that have been measured cumulatively throughout the pandemic: total deaths per million (y_1) and total cases per million (y_2). After eliminating all results from countries with $p > 0.05$, there were 128 countries for y_1 and 103 countries for y_2 to analyze in this fashion, comprising 145 unique countries in total (avg. $p < 0.004$).

Hannah Ritchie, Lucas Rodés-Guirao, Edouard Mathieu, and Max Roser. 2020. "Coronavirus Pandemic (COVID-19)." *Our World in Data*.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74.
<https://doi.org/10.1214/14-aoas788>.

Results indicate that the *treatment* (vaccine administration) has a strong and statistically significant propensity to causally increase the values in either y_1 or y_2 over and above what would have been expected with no treatment. y_1 showed an increase/decrease ratio of (+115/-13), which means 89.84% of statistically significant countries showed an increase in total deaths per million associated with COVID-19 due directly to the causal impact of treatment initiation. y_2 showed an increase/decrease ratio of (+105/-16) which means 86.78% of statistically significant countries showed an increase in total cases per million of COVID-19 due directly to the causal impact of treatment initiation. Causal impacts of the treatment on y_1 ranges from -19% to +19015% with an average causal impact of +463.13%. Causal impacts of the treatment on y_2 ranges from -46% to +12240% with an average causal impact of +260.88%. Hypothesis 1 Null can be rejected for a large majority of countries.

This study subsequently performed correlational analyses on the causal impact results, whose effect variables can be represented as $y_1.E$ and $y_2.E$ respectively, with the independent numeric variables of: *days elapsed since vaccine rollout began* (n_1), *total vaccination doses per hundred* (n_2), *total vaccine brands/types in use* (n_3) and the independent categorical variables *continent* (c_1), *country* (c_2), *vaccine variety* (c_3). All categorical variables showed statistically significant (avg. p : < 0.001) positive Wilcoxon signed rank values ($y_1.E$ V : [c_1 3.04; c_2 : 8.35; c_3 : 7.22] and $y_2.E$ V : [c_1 3.04; c_2 : 8.33; c_3 : 7.19]). This demonstrates that the distribution of $y_1.E$ and $y_2.E$ was non-uniform among categories. The Spearman correlation between n_2 and $y_2.E$ was the only numerical variable that showed statistically significant results ($y_2.E \sim n_2$: ρ : 0.34 C195%[0.14, 0.51],

$p: 4.91e-04$). This low positive correlation signifies that countries with higher vaccination rates do not have lower values for $y2.E$, slightly the opposite in fact. Still, the specifics of the reasons behind these differences between countries, continents, and vaccine types is inconclusive and should be studied further as more data become available. Hypothesis 2 Null can be rejected for $c1$, $c2$, $c3$ and $n2$ and cannot be rejected for $n1$, and $n3$.

The statistically significant and overwhelmingly positive causal impact after vaccine deployment on the dependent variables total deaths and total cases per million should be highly worrisome for policy makers. They indicate a marked increase in both COVID-19 related cases and death due directly to a vaccine deployment that was originally sold to the public as the “key to gain back our freedoms.” The effect of vaccines on *total cases per million* and its low positive association with *total vaccinations per hundred* signifies a limited impact of vaccines on lowering COVID-19 associated cases. These results should encourage local policy makers to make policy decisions based on data, not narrative, and based on local conditions, not global or national mandates. These results should also encourage policy makers to begin looking for other avenues out of the pandemic aside from mass vaccination campaigns.

Some variables that could be included in future analyses might include vaccine lot by country, the degree of prevalence of previous antibodies against SARS-CoV or SARS-CoV-2 in the population before vaccine administration begins, and the Causal Impact of ivermectin on the same variables used in this study.

“Untruth naturally afflicts historical information. There are various reasons that make this unavoidable. One of them is partisanship for opinions and schools. If the soul is impartial in receiving information, it devotes to that information the share of critical investigation the information deserves, and its truth or untruth thus becomes clear. However, if the soul is infected with partisanship for a particular opinion or sect, it accepts without a moment’s hesitation the information that is agreeable to it. Prejudice and partisanship obscure the critical faculty and preclude critical investigation. The result is that falsehoods are accepted and transmitted” (Muhammad ibn Khaldun al-Hadrami 1379, 1–2).

– Ibn Khaldun, 1379 A.D.

Background

Policy makers and mainstream news anchors have promised the public that the vaccine deployment worldwide would reduce symptoms, and thereby cases and deaths. While this vaccine deployment is still in progress, there is a large amount of public data available that permits an analysis of the effect of the vaccine deployment on COVID related cases and deaths. Has public policy treatment produced the desired effect? Responding to this question can begin by implementing a Bayesian Causal analysis comparing both pre and post treatment periods.

This is an important question to respond to due to the vaccine mandates that are being implemented worldwide. People have a right to know if this broad public policy is achieving the desired results. While there are arguments to be made on both sides of this debate, the question of whether a deployment of COVID-19 gene therapy injections cause less death or cases from the virus in any significant way is a testable hypothesis given public data that is now available. With the debates raging over the

Muhammad ibn Khaldun al-Hadrami, Abu Zayd 'Abd ar-Rahman ibn. 1379. *Muqaddimat Ibn Khaldun Li-Kitab Al-'ibar Wa-Diwan Al-Mubtada' Wa-Al-Khabar Fi Ayyam Al-'Arab Wa-Al-'Ajam Wa-Al-Barbar, Wa-Man 'asarahum Min Dhawi Al-Sultan Al-Akbar*. Misr : al-Mataba'ah al-Bahiyah al-Misriyah. http://archive.org/details/McGillLibrary-rbse_isl_kitab-al-ibar_muqaddimah_d16712361900z-16098.

effectiveness, legality, and ethics of these vaccine mandates, a way to continually monitor the effect between vaccine deployment and worldwide COVID-19 associated death and case rates seems an important contribution to this ongoing discussion.

Some previous work has been done on the correlation between vaccination percentage rates or vaccine type and new cases and deaths (Subramanian and Kumar 2021), however this work has yet to prove conclusive or has only looked at correlation in a limited number of countries (Alhinai and Elsidig 2021). Indeed, the correlation numbers are a clue where to look, but they do not determine chronological order and therefore do not determine causation. It could just as well be that high total deaths per million are associated with high vaccination rates simply because those countries with higher death rates may have had a more frightened population ready to take vaccinations, or it could be that countries with high vaccination rates also had high rates of recording new cases and deaths as “COVID-19 associated,” even when there may have been various other comorbidities present in the individual (Disease Control and Prevention 2020). These factors make correlation an important metric, but more of a preliminary clue in the dark of where to look for causation. To find causation on the scale of BigData analysis we must focus on the causal impact of the effects before and after vaccine administration on as many countries in the world as possible, this study looks at 145 countries.

Research Question 1

Specific: Does the ‘beginning of COVID-19 gene therapy injections’ (X) have any statistically significant causal effect in decreasing or increasing *total deaths per million* (y_1) or *total cases per million* (y_2) associated with COVID-19?

Simplified: Does vaccine deployment cause

Subramanian, S. V., and Akhil Kumar. 2021. “Increases in COVID-19 Are Unrelated to Levels of Vaccination Across 68 Countries and 2947 Counties in the United States.” *European Journal of Epidemiology*, September. <https://doi.org/10.1007/s10654-021-00808-7>.

Alhinai, Zaid A., and Nagi Elsidig. 2021. “Countries with Similar COVID-19 Vaccination Rates yet Divergent Outcomes: Are All Vaccines Created Equal?” *International Journal of Infectious Diseases* 110 (September): 258–60. <https://doi.org/10.1016/j.ijid.2021.06.040>.

Disease Control, Centers for, and Prevention. 2020. “Weekly Updates by Select Demographic and Geographic Characteristics.” *National Center for Health Statistics*.

less or more COVID-19 associated cases or death?

Hypothesis 1

H0: X has no statistically significant¹ causal effect on Yx .

HA: X has a statistically significant² causal effect on Yx .

¹ Not statistically significant means a negative or positive causal effect with $p > 0.05$

² Statistically significant means a negative or positive causal effect with $p < 0.05$.

Research Question 2

Specific: Do the statistically significant results of the causal effect on *total deaths per million (y1.E)* or *total cases per million (y2.E)* correlate with any of the following independent variables:

- numerical variables:

- $n1 = \text{days elapsed since vaccine administration}$
- $n2 = \text{total vaccinations per hundred}$
- $n3 = \text{total vaccine types/brands in use}$

- categorical variables:

- $c1 = \text{continent}$
- $c2 = \text{country}$
- $c3 = \text{vaccine type}$

Simplified: Are the results of Research Question 1 associated with either of the following variables? :

1. the length of time vaccines have been in use in a country
2. the number of vaccines they have administered
3. the number of brands/types of vaccines they have administered
4. the continent where the vaccines were administered
5. the country where the vaccines were administered

6. the types of vaccines they have administered

Hypothesis 2

H0: X has no statistically significant³ correlation with yx . E .

HA: X has a statistically significant⁴ correlation with yx . E .

³ Not statistically significant means a correlation between (-0.3 to 0.3) or Wilcoxon $V = 0$ or $p > 0.05$

⁴ Statistically significant means a correlation (> 0.3 or < -0.3) or a positive Wilcoxon V , and $p < 0.05$

Methods

The methods and code to reproduce this study are as follows:

Obtain up to date COVID-19 data from Our World in Data (Hannah Ritchie and Roser 2020)

Hannah Ritchie, Lucas Rodés-Guirao, Edouard Mathieu, and Max Roser. 2020. "Coronavirus Pandemic (COVID-19)." *Our World in Data*.

It is necessary to download the appropriate data sets including:

1. The data from Hannah Ritchie and Roser (2020)⁵ is updated daily and can be downloaded and converted to a data.frame using the R code in this paper, or can be downloaded directly from here as a .csv: <https://covid.ourworldindata.org/data/owid-covid-data.csv>.

Hannah Ritchie, Lucas Rodés-Guirao, Edouard Mathieu, and Max Roser. 2020. "Coronavirus Pandemic (COVID-19)." *Our World in Data*.

2. It was also necessary to convert the data on vaccine types in use by each country (wikipedia 2021)⁶ to a .csv format, this was done with standard spreadsheet techniques in Google Sheets. This data set I have made publicly available here: https://docs.google.com/spreadsheets/d/1egKoaL_vAt_9Jc_WKgr8uZDoxw3xIj9J-Fu33S9sMRL4XQ/edit?usp=sharing

⁵ The data from COVID-19 case and death data from Our World in Data is taken directly from the data provided by Johns Hopkins University.

wikipedia. 2021. "List of COVID-19 Vaccine Authorizations." https://en.wikipedia.org/w/index.php?title=List_of_COVID-19_vaccine_authorizations&oldid=104981676

⁶ The data for vaccine brands and their use in different countries comes from hundreds of sources that have been aggregated by Wikipedia into a comprehensive list

```
# Folder where data is stored, **CHANGE THIS
data_folder <- file.path("./indices[USED]/")

#### UNCOMMENT FOR NEW DATA ####
# Download most recent OWID COVID-19 data s
#url <- "https://covid.ourworldindata.org/c
#name <- "owid-covid-data.csv"
#download.file(url = url, destfile = paste0

## Load the reports ##
```

```

# Set directory to location of CSV files fi
setwd(data_folder)
# Read files without csv
filenames <- gsub("\\.csv$", "", list.files(
# Load all files
for(i in filenames){
  assign(i, read.csv(paste(i, ".csv", sep="
}

```

Clean data and merge datasets

Once all the data is obtained it can be ‘cleaned’ for faster data processing. This involves removing unnecessary variables from the data sets and renaming columns so all variable names are in agreement. This can be done with the R code included in the supplementary material for this report.

Run Causal Analysis for all dependent variables

The R package *CausalImpact* (Brodersen et al. 2015) utilizes a robust series of Bayesian calculations along with predictor data sets to determine the likely trajectory of a trend line had a particular intervention not occurred and then calculates the difference between that projected trend line and the real data line. The authors of the package summarized this impressive set of calculations and its improvements upon previous methods as a,

“...method [that] generalises the widely used difference-in-differences approach to the time-series setting by explicitly modelling the counterfactual of a time series observed both before and after the intervention. It improves on existing methods in two respects: it provides a fully Bayesian time-series estimate for the effect; and it uses model averaging to construct the most appropriate synthetic control for modelling the counterfactual” (Brodersen et al. 2015, 247).

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Effectively, this allows us to look at the past 12–16 months (each country is slightly different) before vaccine administration began, this is called the *pre-intervention*

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural

period, and utilize that data to project where y_1 (total deaths per million) and y_2 (total cases per million) would have been had the intervention of X (vaccine administration) not occurred, what the authors call a “counterfactual” (Brodersen et al. 2015, 248–49). Utilizing this estimated counterfactual and the confidence level associated with that estimation we can then compare it with the actual data available and see if there is any difference. If the projected estimation is higher than the actual results, it will appear as a negative impact, while if the projected estimation is lower than the actual results, it will appear as a positive impact.

Another aspect of the *CausalImpact* package is the ability to add control variables that are combined into a “synthetic control” (Brodersen et al. 2015) that closely mimic the trend line, but that are exogenous (i.e. have not been affected by the intervention); this allows for even more accurate predictions and normally a lower p-value and a lower standard deviation. To obtain control variable data sets the authors of *CausalImpact* recommend utilizing similar data that did not receive the same treatment, such as a different region or country, any trend line that can closely mimic or even be constant alongside the trend line one is testing (e.g. similar data from an area with no intervention, price charts, stock prices, temperature records, etc.). As there are virtually zero countries that have been unaffected by the vaccines, finding a set of control variables is difficult, though not impossible. Ultimately, this study chose to utilize the data of four countries in Africa (Burkina Faso, Chad, DRC, South Sudan) that were chosen specifically for their low average severity indices since vaccine administration began (i.e. low levels of mandatory mask wearing, social distancing, crowd limitations, travel restrictions, etc.) and for their low vaccination rates. These countries in the author’s estimation best represent a “natural” progression of the virus with

Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

limited vaccine intervention on par with most other nations, making them the least likely to display problems of endogeneity while still acting as valid control groups.

These carefully selected control variables as a synthetic control combined with the formula presented by Brodersen et al. (2015), which utilizes the data pre-intervention as part of its equation to predict the counterfactual, means that the other synthetic control effectively being utilized internally in the equation is a dynamic calculation for each country based on its own individual experience of COVID-19's impacts on total deaths and cases per million *sans* vaccines for, as mentioned above, approximately 12-16 months.

As Brodersen et al. (2015) explained,

“The approach described in this paper inherits three main characteristics from the state-space paradigm. First, it allows us to flexibly accommodate different kinds of assumptions about the latent state and emission processes underlying the observed data, including local trends and seasonality. Second, we use a fully Bayesian approach to inferring the temporal evolution of counterfactual activity and incremental impact. One advantage of this is the flexibility with which posterior inferences can be summarised. Third, we use a regression component that precludes a rigid commitment to a particular set of controls by integrating out our posterior uncertainty about the influence of each predictor as well as our uncertainty about which predictors to include in the first place, which avoids overfitting” (Brodersen et al. 2015, 251)

In other words, by utilizing the data for

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. “Inferring Causal Impact Using Bayesian Structural Time-Series Models.” *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L.

total deaths and cases per million from before vaccines existed and combining that with a synthetic control of countries largely non-participatory in the COVID-19 vaccine program, the R package *CausalImpact* is able to produce a high degree of certainty in the results.⁷ The control countries' average severity indices since vaccine administration and vaccination rates are listed in Table 1.

Scott. 2015.
 "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74.
<https://doi.org/10.1214/14-aos788>.

⁷ average p-value for $y1.E$ = 0.0039783; average p-value for $y2.E$ = 0.00375

This analysis was carried out on all countries in the data set that met the following criteria: (1) more than five observations (i.e. dates), (2) a longer pre intervention period than post intervention period, and (3) no NAs in the observations necessary for calculation.

```
# CAUSAL ANALYSIS -----
# Variables for Function

# Select data frame
df0 <- df_owid
# Create a countries list
countries <- c(unique(df_owid$ISO))
# Folder where plots will be saved
plots.loc <- file.path("./plots/causalImpac

## DEPENDENT VARIABLES

#####
# Here you must declare your variables. It
# for each y variable that you intend to te
# change is where it says ** CHANGE THIS **
#####

# Declare function name and variables
impactReports <- function(df0, countries, p

# Begin for Loop
for (i in countries) {

# Declare Data Frame to Use with Time Serie
df <- df0
df <- dplyr::filter(df, ISO == i) # Use ISC

# Assure the Date column is in the correct
dates <- as.character(df$date) # change to
df$date = as.Date(dates, format="%Y-%m-%d")

# Treatment - Independent Variable
vacc <- dplyr::select(df, date, total_vaccina
vacc <- unique(vacc) # Make sure there are
vacc <- na.omit(vacc) # Make sure there are

# Dependent Variable

## Dependent Variable ** CHANGE THIS **
```

```

df <- dplyr::select(df,date,total_cases_per

df <- unique(df) # only choose unique value
df <- na.omit(df) # remove all

## Dependent Variable ** CHANGE THIS **
dfy <- df$total_cases_per_million

# Obtain Length of Dependent Variable for t
dfyN <- as.numeric(length(dfy))

# Add in data sets that will be used for cr
# This paper ultimately used the four count
# process also included analyzing the resul
# Thus, included here are four other countr
# their conclusion ultimately not being use
# higher standards of deviation suggesting
# This data is included here for full trans
# may like to analyze these other potential

# NOT INCLUDED IN THIS PAPER, BUT INCLUDED
dfy1 <- BDI$total_deaths_per_million[1:df
dfy3 <- HTI$total_deaths_per_million[1:df
dfy5 <- YEM$total_deaths_per_million[1:df
dfy7 <- TZA$total_deaths_per_million[1:df

# SELECTED CONTROL COUNTRIES FOR USE IN CAL
dfy2 <- COD$total_cases_per_million[1:dfyN
dfy4 <- SSD$total_cases_per_million[1:dfyN
dfy6 <- TCD$total_cases_per_million[1:dfyN
dfy8 <- BFA$total_cases_per_million[1:dfyN

# Combine data frames of control countries
dfy <- cbind(dfy,dfy2,dfy4,
             dfy6,dfy8)

# Remove any NA values
dfy <- na.omit(dfy)

# Obtain new Length of data frame of the De
dfyN2 <- as.numeric(nrow(dfy))

# Create time-series from this dataframe
dfx <- df$date[1:dfyN2] # Time Series

# Make sure all data has more than 5 observ
if (length(dfx) < 5 | nrow(dfy) < 5 | nrow(

  # Announce stop and move to next if Logi
cat(paste0("##### stopping ",i," at step 2
next
} else {

#Declare Data Frame Variables
df.ts <- dfx # Dates as characters
df.score <-dfy # Y
df.time <- df$d # Day number

#Calculate Length of data frame
days <- as.Date(max(df.ts)) - as.Date(min(d
days <- as.numeric(days) # Make the string

#Declare time points from data

```

```

time.points <- try(seq.Date(as.Date(min(df.

#Declare time series variables
SCORE.Y <- ts(df.score) # Dependent Variabl
TIME.C <- ts(df.time) # Time Series

#Bind them into test groups
test <- try(zoo(cbind(SCORE.Y, TIME.C), tir

# Announce start of next step
cat(paste0("##### starting ",i," step 3 ##

df <- na.omit(vacc) # Remove any NAs

if (anyNA(df) == TRUE) {

cat(paste0("##### stopping ",i," at step 4
next
} else {

# Treatment Period
treatmentS <- (min(df$date)) # start of tre
treatmentE <- max(df$date) # end of treatme

# Pre-Treatment Period
preperS <- min(dfx) # start of pre-treatmen
preperE <- treatmentS - 1 # end of pre-trea
# Post-Treatment Period
postperS <- (treatmentS) # start of treatme
postperE <- treatmentE # end of treatment p
# Use when you need an exact date
pre.period <- c(preperS,preperE) # declare
post.period <- c(postperS,postperE) # decla

# assure pre-period is longer than post-per
if ((preperE - preperS) < (postperE - postp

# Stop and move to next country if Logic
cat(paste0("##### stopping ",i," at step
next

} else {
cat(paste0("##### calculating ",i,"#####
impact <- try(CausalImpact(test, pre.period
Sys.sleep(1)
x <- "Total Vaccinations Per Million" # CHA
y <- "Total Cases Per Million" # ** CHANGE
cat(paste0("##### plotting ",i,"#####"))
try(print(plot(impact) + # Print the pl
ggplot2::labs(
title = paste0(i, # Title the plot
": Causal Impact Plot",
" | ",
x,
" effect on ",
y),
caption =
paste("Source: Data collected from OWID, an
date())
) +
theme_stata())) # Choose a theme
Sys.sleep(1) # Let plot be created
cat(paste0("##### saving plots and reports

```

```

setwd(plots.loc) # Set the drive to the plc
try(savePlotAsImage(paste0(i,      # Save F
                        "":_Causal_Impact_Pl
                        "_|_",
                        x,
                        "_effect_on_",
                        y,
                        "_Report.png"),
      format = "png",
      width = 1920, # set ratio
      height = 1080))
Sys.sleep(1) # Let plot be saved
try(summary(impact, "report")) # Produce Su
try(summary(impact)) # Produce Summary Repc
report<<-try(capture.output(summary(impact,
report2<<-try(capture.output(summary(impact
try(cat(report, file = paste0(i,      # Writ
                        "": Causal Impact
                        " | ",
                        x,
                        " effect on ",
                        y, "Report.txt"),

try(stargazer(report2,
  summary = FALSE,
  type = "text",
  out = paste0(plots.loc,i,      # h
                "": Causal Impact
                " | ",
                x,
                " effect on ",
                y, "Report2.txt"))

#   }
# }
# }
# }
# }
# }

# RUN FUNCTION -----

# Run this function to produce all the plot
try(impactReports(df0,countries,plots.loc),

```

Extract Causal Analysis results and merge with main dataset

After completing the causal analysis on all countries and printing a report and plot for each country, the data was filtered and cleaned by removing all results with $p > 0.05$ and turning all causal impact results into both whole numbers (ex. $\gamma_1.effect_percent$ for Japan = 48%) and decimals (ex. $\gamma_1.effect_dec$ for Japan = 0.48), both representing the percentage of positive or negative impact in two different forms. This data was then integrated back with the original data frame for further analyses and

data presentation.

```
# ANALYZE CAUSAL IMPACT OUTPUT -----

##### FUNCTION VARIABLE #####
# loc_i = the location of text files for input
# loc_o = the location to output csv and text
# name = name for csv and text documents (as character)
# y = dependent variable (as character)
#####

### Extract necessary data from the Causal Reports

dat.extr.CausalReports <- function(loc_i, loc_o, name, y) {

  ## Data Location
  data_folder <- file.path(loc_i)
  # Set directory to location of CSV files
  setwd(data_folder)
  # Read files without csv
  filenames <- gsub("\\.txt$", "", list.files(data_folder, pattern = "\\.txt$", recursive = TRUE))
  # Create data frame first
  df <- data.frame(matrix(ncol = 2, nrow = length(filenames)))
  # Load all files
  for(i in filenames){
    df0 <- assign(i, readtext(paste(i, ".txt", sep = "")))
    df <- rbind(df, df0)
  }

  ## ISO
  # Extract first three characters to obtain ISO
  df$ISO <- substr(df$doc_id, 1, 3)

  ## p-value
  # Extract all three digit values
  df$p <- str_extract(df$text, "p = 0\\.\\d{3}")
  # Extract all two digit values
  df$p2 <- str_extract(df$text, "p = 0\\.\\d{2}")
  # Replace NAs in three digit values with two digit values
  df$p[is.na(df$p)] <- df$p2[is.na(df$p)]
  # Remove two digit column
  df <- dplyr::select(df, -p2)
  # Remove p = sign and convert to numeric
  df$p <- gsub("p = ", "", df$p) %>% as.numeric()
  # Remove all non-statistically significant
  df <- filter(df, p < 0.05)

  ## % Effect
  # separate this part of the text
  df$effect <- str_extract(df$text, "the response variable")
  # remove this part leaving only the %
  df$effect <- gsub("the response variable", "", df$effect)
  # remove this text or that
  df$effect <- gsub("^ (showed an increase|decrease)", "", df$effect)
  # combine text to make an easy readout for the effect
  df$effect_txt <- paste(df$ISO, ": Vaccine", df$effect)

  ## Interval
  # Extract only % numbers between []
  df$interval <- str_extract(df$text, "\\[\\d+\\.\\d+%\\]")

  ## Effect as Decimal
  # Remove all symbols and convert to numeric
  df$effect <- gsub("%", "", df$effect) %>% as.numeric()
```

```

df$effect_dec <- gsub("%", "", df$effect)
# Turn percentage to decimal
df$effect_dec <- df$effect_dec / 100

## Merge the effect changes and p values
# Select only necessary columns
df5 <- dplyr::select(df, IS0, p, effect, eff
setnames(df5, # Change columns names for
  c("p", "effect", "effect_dec"),
  c(paste0(y, ".p"), paste0(y, ".eff

# Write Data Frame to CSV, change data fran
write.csv(df5,
  paste0(loc_o, name, date(), ".csv"
  na = "",
  fileEncoding = "UTF-8")

# Write statistical table to txt
stargazer(df5, # Export txt
  summary = FALSE,
  type = "text",
  out = paste0(loc_o, name, date(), ".t
}

# RUN FUNCTION
# Variables
loc_i <- file.path("./plots/causalImpact/tc
loc_o <- file.path("./plots/causalImpact/da
name <- "CausalAnalysis-vaccines-by-totalCa
y <- "y2"

# FUNCTION
dat.extr.CausalReports(loc_i, loc_o, name, y)

# Analyze output
df <- read.csv("./plots/causalImpact/data_c
  vaccines-by-totalCasesTue Oc
  as.data.frame()
cntP <- str_count(df$y2.effect, "\\+") # cou
count(cntP) # results

```

Correlation Analysis of Causal Analysis Results

After integrating the results of the Causal Impact Analysis with the original data frame, Research Question 2 was addressed through follow-up correlational analyses. These were calculated with the resulting dependent variables from the Causal Impact Analysis ($y1.E$: $y1.effect_percent$ = effect of vaccine intervention on total deaths per million) and ($y2.E$: $y2.effect_percent$ = effect of vaccine intervention on total cases per million) utilizing *ggstatsplot* (Patil 2021) for all variables listed in Research Question 2.

Plot Results

Scatter plot and correlational matrix results

Patil, Indrajeet. 2021. "Visualizations with statistical details: The 'ggstatsplot' approach." *Journal of Open Source Software* 6 (61): 3167. <https://doi.org/10.21105/joss.03167>.

were used to analyze the statistical significance of the correlation between the dependent variables and the independent numerical variables. The scatter plots and correlational matrices include the ρ (Spearman) scores and their respective p-values. Dot plots were utilized to show the distribution of the dependent variables with the independent categorical variables, they include the Wilcoxon signed rank value and respective p-value.

Materials

The data used in the following analysis comes from the two data sources mentioned above as well as the R packages that are listed at the end of this report. These results were produced using RStudio Version 1.4.1027 (RStudio Team 2020).

Results

After eliminating all results from countries with $p > 0.05$, there were 128 countries for y_1 and 103 countries for y_2 to analyze in this fashion (avg. p -value < 0.004), 145 unique countries in total. Results indicate that the *treatment* (vaccine administration) has a strong and statistically significant propensity to causally increase the values in either y_1 or y_2 over and above what would have been expected with no treatment. y_1 showed an increase/decrease ratio of (+115/-13), which means 89.84% of statistically significant countries showed an increase in total deaths per million associated with COVID-19 due directly to the causal impact of treatment initiation. y_2 showed an increase/decrease ratio of (+105/-16) which means 86.78% of statistically significant countries showed an increase in total cases per million of COVID-19 due directly to the causal impact of treatment initiation. Causal impacts of the treatment on y_1 ranges from -19% to +19015% with an average causal impact of +463.13%. Causal impacts of the treatment on y_2 ranges from -46% to +12240% with an average causal impact of +260.88%. Hypothesis 1 Null can be

RStudio Team. 2020.
*RStudio: Integrated
Development Environment for
r*. Boston, MA: RStudio,
PBC.
<http://www.rstudio.com/>.

rejected for a large majority of countries.

Causal Impact Results

The results of the *CausalImpact* package were produced as both figures and as automatic report summaries for each country. All figures are included as attached PDFs to this report and all figures can be requested in high quality 1920x1280 .png files from the author free of charge. All report summaries are included as .txt files in the supplementary data to this report.

The following figures and report summaries represent a sample of more than 150 figures produced by this code and data. These examples highlight a variety of countries with decreases, average increases, and substantial increases in deaths and cases associated with COVID-19 as a causal impact of vaccine deployment. Included below select figures is also an example of the report summary that was produced by *CausalImpact*, these report summaries assist in explaining how to interpret each figure from a statistical perspective.

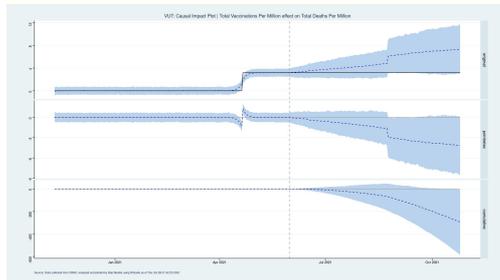
To read these figures one should analyze the three different graphs that are labeled on the right *y* axis as *Original*, *Pointwise*, and *Cumulative*. The *Original* graph represents the actual recorded data as the solid black line; the dashed blue line represents the counterfactual, the predicted trend line had the intervention of vaccine deployment not occurred; and the light blue fill around the counterfactual shows the degree of potential statistical variance, less light blue fill signifies a more accurate counterfactual. The moment of vaccine deployment varies between countries and is represented by the vertical gray dashed line. The *Pointwise* graph shows all of the positive or negative causal impacts by calculating the difference between the counterfactual and the recorded data. Finally, the *Cumulative* graph sums all of the positive or negative causal impacts since the intervention began to show an upward (positive), downward (negative) or neutral (near zero) causal

impact.

$\gamma_{1.E}$: Total Causal Impact from Vaccine Administration on Total Deaths Per Million

Average Decreases

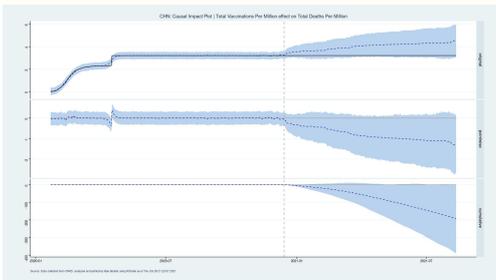
Vanuatu: -39% Vaccine Causal Impact on Total Deaths Per Million



Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 3.18. By contrast, in the absence of an intervention, we would have expected an average response of 5.18. The 95% interval of this counterfactual prediction is [3.22, 7.16]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -2.00 with a 95% interval of [-3.98, -0.038]. For a discussion of the significance of this effect, see below. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 467.46. By contrast, had the intervention not taken place, we would have expected a sum of 761.71. The 95% interval of this prediction is [473.06, 1051.98]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed a decrease of -39%. The 95% interval of this percentage is [-77%, -1%]. This means that the negative effect observed during the intervention period is statistically significant. If the experimenter had expected a positive effect, it is recommended to double-check whether anomalies in the control variables may have caused an overly optimistic expectation of what should have happened in the response variable in the absence of the intervention. The probability of obtaining this effect by

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

chance is very small (Bayesian one-sided tail-area probability $p = 0.025$). This means the causal effect can be considered statistically significant.

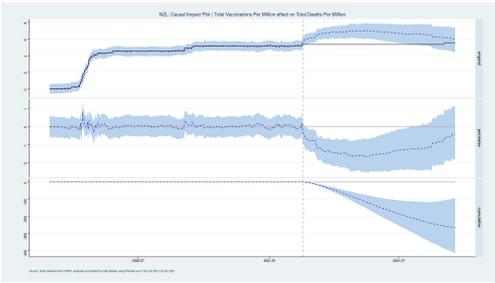


Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 3.21. In the absence of an intervention, we would have expected an average response of 4.01. The 95% interval of this counterfactual prediction is [3.21, 4.83]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is -0.80 with a 95% interval of [-1.62, 0.0011]. For a discussion of the significance of this effect, see below. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 773.57. Had the intervention not taken place, we would have expected a sum of 966.48. The 95% interval of this prediction is [773.30, 1164.21]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed a decrease of -20%. The 95% interval of this percentage is [-40%, +0%]. This means that, although it may look as though the intervention has exerted a negative effect on the response variable when considering the intervention period as a whole, this effect is not statistically significant, and so cannot be meaningfully interpreted. The apparent effect could be the result of random fluctuations that are unrelated to the intervention. This is often the case when the intervention period is very long and includes much of the time when the effect has already worn off. It can also be the case when the intervention period is too short to distinguish the signal from the noise. Finally, failing to find a significant

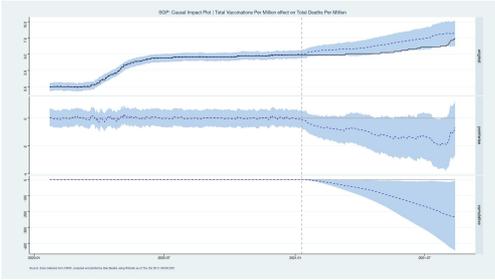
Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

effect can happen when there are not enough control variables or when these variables do not correlate well with the response variable during the learning period. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.026$). This means the causal effect can be considered statistically significant.

New Zealand: -19% Vaccine Causal Impact on Total Deaths Per Million

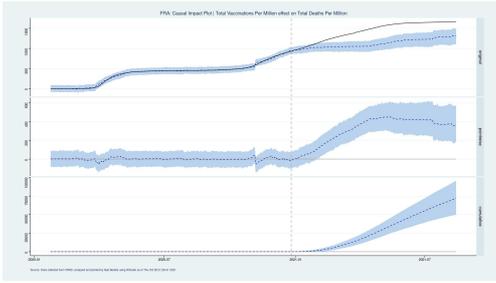


Singapore: -17% Vaccine Causal Impact on Total Deaths Per Million



Average Increases

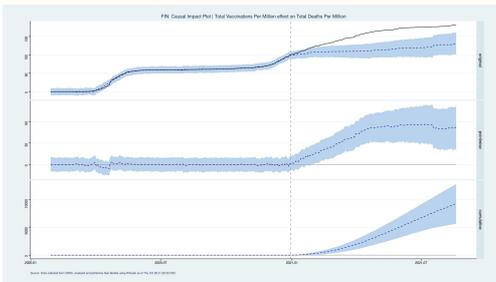
France: +28% Vaccine Causal Impact on Total Deaths Per Million



Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 1.43K. By contrast, in the absence of an intervention, we would have expected an average response of 1.12K. The 95% interval of this counterfactual prediction is [1.02K, 1.22K]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 0.31K with a 95% interval of [0.22K, 0.41K]. For a discussion of the significance of this effect, see below.

Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 330.53K. By contrast, had the intervention not taken place, we would have expected a sum of 258.58K. The 95% interval of this prediction is [234.98K, 280.70K]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +28%. The 95% interval of this percentage is [+19%, +37%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of whether this increase also bears substantive significance can only be answered by comparing the absolute effect (0.31K) to the original goal of the underlying intervention. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). This means the causal effect can be considered statistically significant.

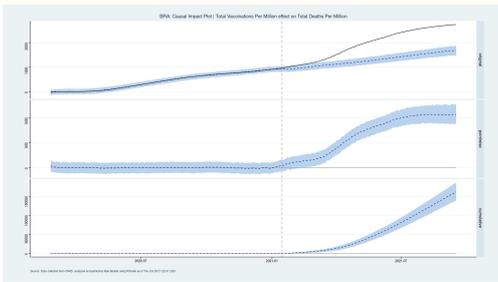
Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aos788>.



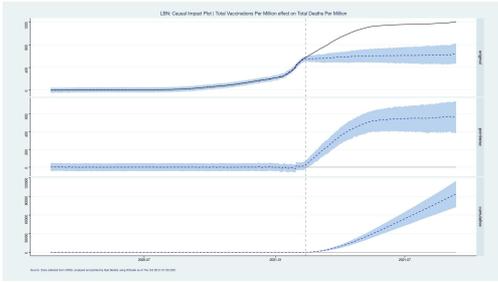
Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 153.55. By contrast, in the absence of an intervention, we would have expected an average response of 113.69. The 95% interval of this counterfactual prediction is [98.50, 129.29]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 39.85 with a 95% interval of [24.26, 55.05]. For a discussion of the significance of this effect, see below. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 35.62K. By contrast, had the intervention not taken place, we would have expected a sum of 26.38K. The 95% interval of this prediction is [22.85K, 29.99K]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +35%. The 95% interval of this percentage is [+21%, +48%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of whether this increase also bears substantive significance can only be answered by comparing the absolute effect (39.85) to the original goal of the underlying intervention. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). This means the causal effect can be considered statistically significant.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aos788>.

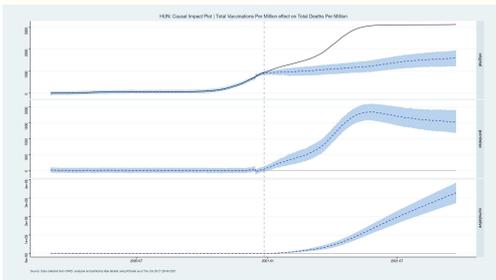
Brazil: +52% Vaccine Causal Impact on Total Deaths Per Million



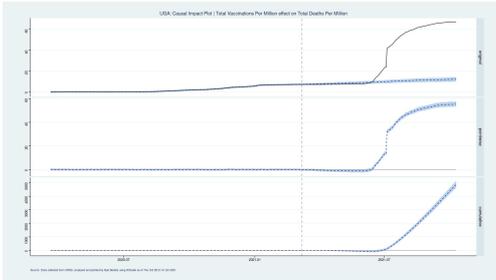
Lebanon: +74% Vaccine Causal Impact on Total Deaths Per Million



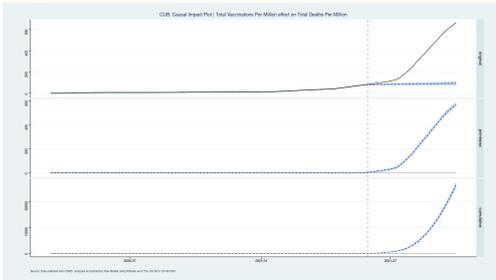
Hungary: +99% Vaccine Causal Impact on Total Deaths Per Million



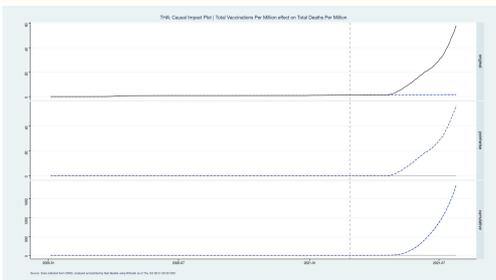
Uganda: +235% Vaccine Causal Impact on Total Deaths Per Million



Cuba: +245% Vaccine Causal Impact on Total Deaths Per Million

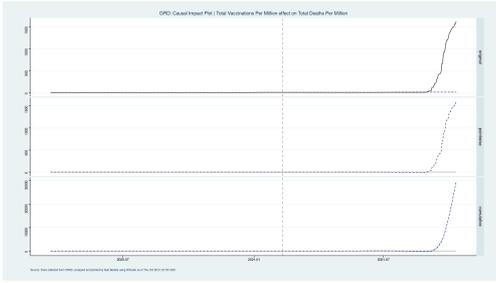


Thailand: +887% Vaccine Causal Impact on Total Deaths Per Million



Elevated Increases

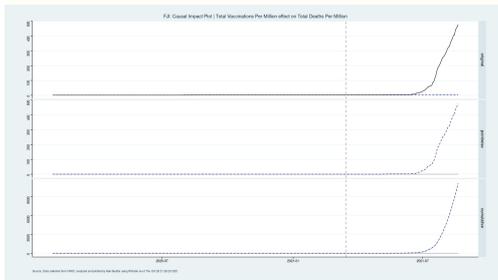
Grenada: +1180% Vaccine Causal Impact on Total Deaths Per Million



Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 132.32. By contrast, in the absence of an intervention, we would have expected an average response of 10.34. The 95% interval of this counterfactual prediction is [8.98, 11.85]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 121.99 with a 95% interval of [120.47, 123.35]. For a discussion of the significance of this effect, see below. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 32.15K. By contrast, had the intervention not taken place, we would have expected a sum of 2.51K. The 95% interval of this prediction is [2.18K, 2.88K]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +1180%. The 95% interval of this percentage is [+1166%, +1193%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of whether this increase also bears substantive significance can only be answered by comparing the absolute effect (121.99) to the original goal of the underlying intervention. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). This means the causal effect can be considered

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aos788>.

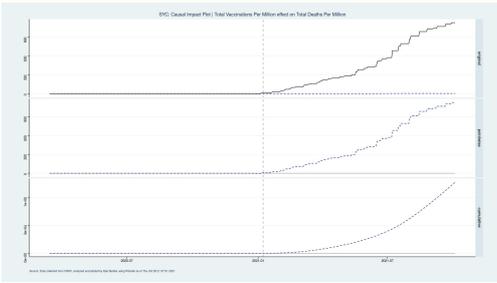
statistically significant.



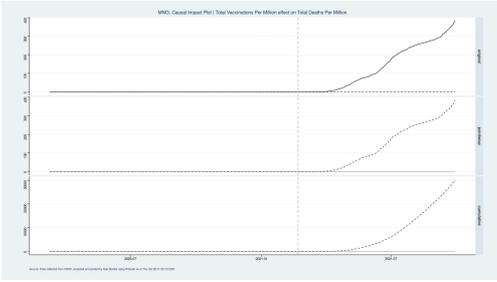
Analysis report {*CausalImpact* (Brodersen et al. 2015)}: During the post-intervention period, the response variable had an average value of approx. 73.75. By contrast, in the absence of an intervention, we would have expected an average response of 2.84. The 95% interval of this counterfactual prediction is [2.19, 3.56]. Subtracting this prediction from the observed response yields an estimate of the causal effect the intervention had on the response variable. This effect is 70.92 with a 95% interval of [70.20, 71.56]. For a discussion of the significance of this effect, see below. Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 11.58K. By contrast, had the intervention not taken place, we would have expected a sum of 0.45K. The 95% interval of this prediction is [0.34K, 0.56K]. The above results are given in terms of absolute numbers. In relative terms, the response variable showed an increase of +2499%. The 95% interval of this percentage is [+2473%, +2522%]. This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of whether this increase also bears substantive significance can only be answered by comparing the absolute effect (70.92) to the original goal of the underlying intervention. The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). This means the causal effect can be considered statistically significant.

Brodersen, Kay H., Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. 2015. "Inferring Causal Impact Using Bayesian Structural Time-Series Models." *Annals of Applied Statistics* 9: 247–74. <https://doi.org/10.1214/14-aoas788>.

Seychelles: +10680% Vaccine Causal Impact on Total Deaths Per Million



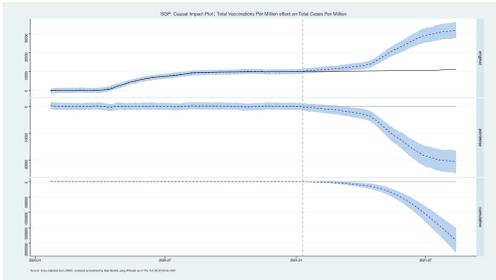
Mongolia: +19015% Vaccine Causal Impact on Total Deaths Per Million



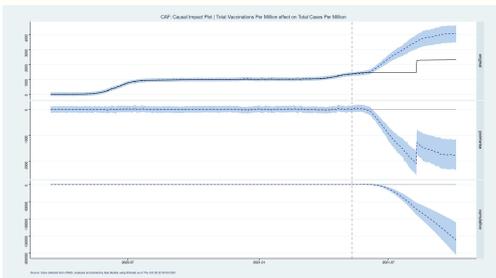
$\gamma_2.E$: Total Causal Impact from Vaccine Administration on Total Cases Per Million

Average Decreases

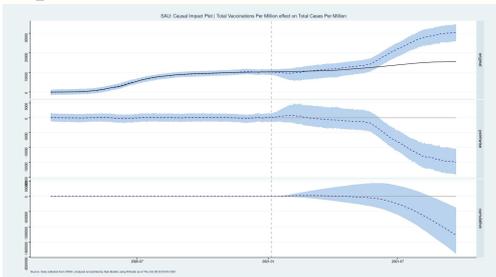
Singapore: -46% Vaccine Causal Impact on Total Cases Per Million



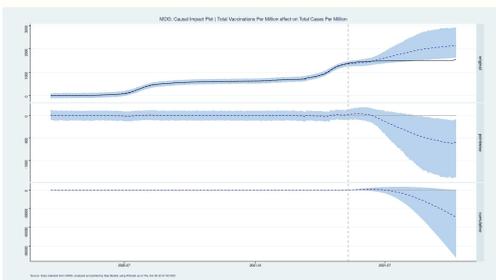
Central African Republic: -38% Vaccine Causal Impact on Total Cases Per Million



Saudi Arabia: -28% Vaccine Causal Impact on Total Cases Per Million

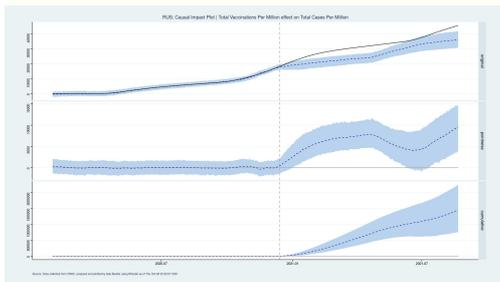


Madagascar: -16% Vaccine Causal Impact on Total Cases Per Million

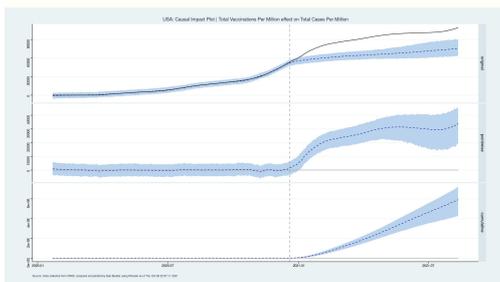


Average Increases

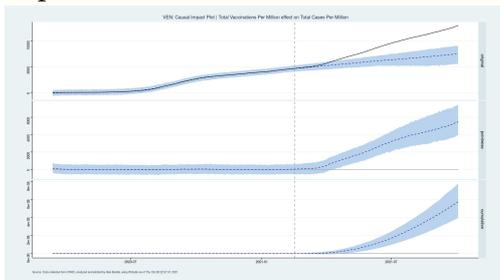
Russia: +22% Vaccine Causal Impact on Total Cases Per Million



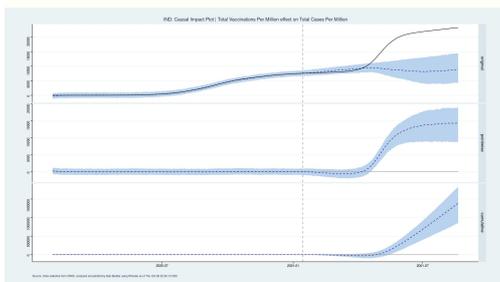
United States: +38% Vaccine Causal Impact on Total Cases Per Million



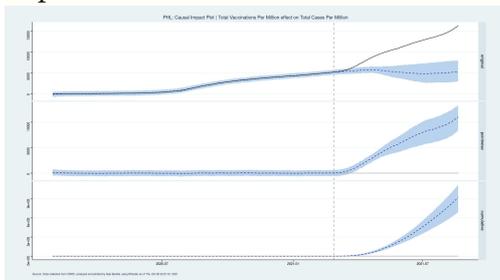
Venezuela: +41% Vaccine Causal Impact on Total Cases Per Million



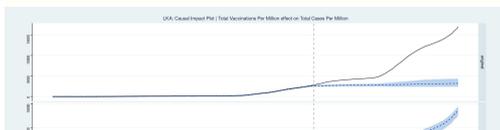
India: +74% Vaccine Causal Impact on Total Cases Per Million



Phillipines: +101% Vaccine Causal Impact on Total Cases Per Million

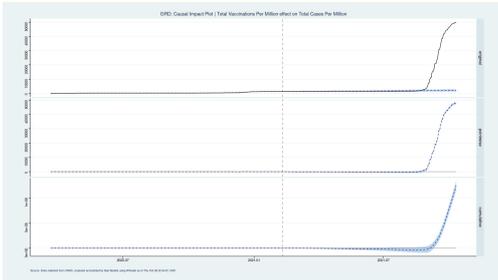


Sri Lanka: +170% Vaccine Causal Impact on Total Cases Per Million

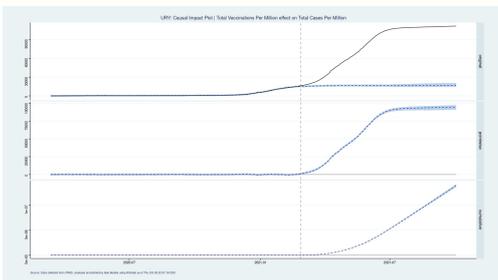




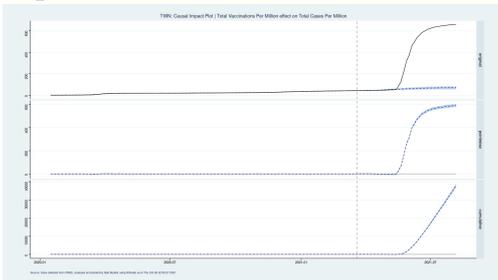
Grenada: +309% Vaccine Causal Impact on Total Cases Per Million



Uruguay: +390% Vaccine Causal Impact on Total Cases Per Million

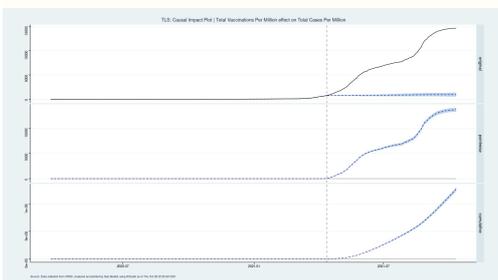


Taiwan: +475% Vaccine Causal Impact on Total Cases Per Million

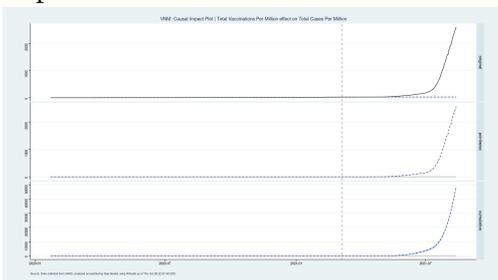


Elevated Increases

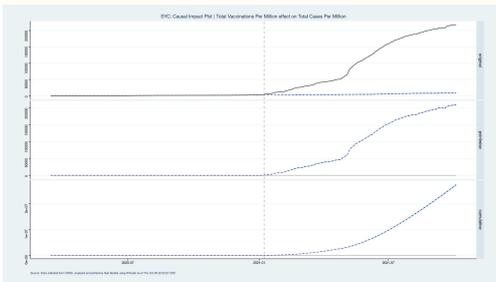
Timor-Leste: +839% Vaccine Causal Impact on Total Cases Per Million



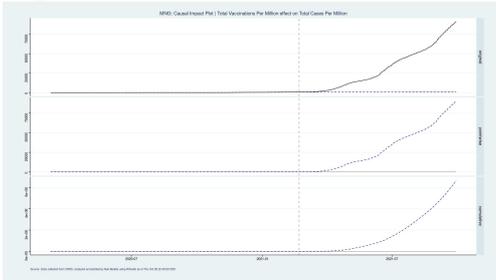
Vietnam: +1099% Vaccine Causal Impact on Total Cases Per Million



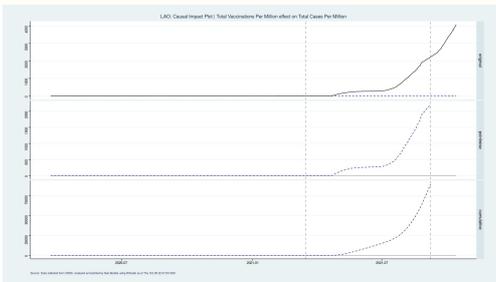
Seychelles: +1978% Vaccine Causal Impact on Total Cases Per Million



Mongolia: +3391% Vaccine Causal Impact on Total Cases Per Million



Laos: +6955% Vaccine Causal Impact on Total Cases Per Million

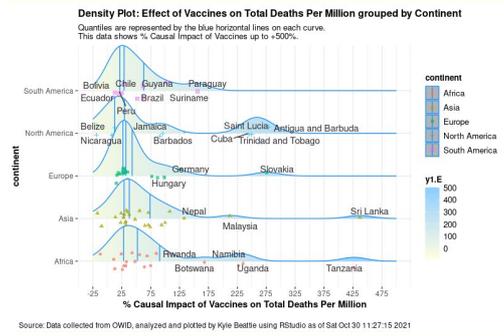


Fiji: +12240% Vaccine Causal Impact on Total Cases Per Million

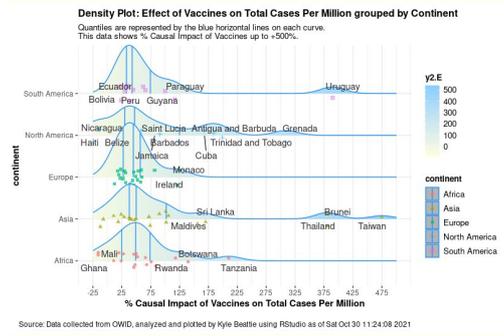


Density Plots

The following density plots and tables present a larger view of the results. The density plots present data for each continent for all countries with results up to +500%.



Density Plot 1: Effect of Vaccines on Total Deaths Per Million grouped by Continent



Density Plot 2: Effect of Vaccines on Total Cases Per Million grouped by Continent

Tables

The two tables here represent all the countries with statistically significant results, they show the percentage change in y_1 and y_2 as a direct causal impact of vaccine deployment.

X ISO	y1.p y1.effect	y1.effect_dec	Causal Impact of Vaccine Deployment on Total Deaths per Million associated with COVID-19
1 AFG	0.001 +32%	0.32	
2 AGO	0.001 +29%	0.29	
3 ALB	0.001 +35%	0.35	
4 ARE	0.001 +71%	0.71	
5 ARG	0.001 +23%	0.23	
6 ATG	0.001 +279%	2.79	
7 AUS	0.007 -22%	-0.22	
8 AUT	0.005 +26%	0.26	
9 AZE	0.004 +17%	0.17	
10 BGD	0.001 +33%	0.33	
11 BHS	0.019 +13%	0.13	
12 BIH	0.001 +30%	0.30	
13 BLR	0.001 +43%	0.43	
14 BLZ	0.009 -19%	-0.19	
15 BOL	0.027 +13%	0.13	
16 BRA	0.001 +52%	0.52	
17 BRB	0.001 +96%	0.96	
18 BRN	0.001 +65%	0.65	
19 BTN	0.033 +35%	0.35	
20 BWA	0.001 +168%	1.68	
21 CAF	0.046 -12%	-0.12	
22 CAN	0.001 +31%	0.31	
23 CHL	0.001 +29%	0.29	
24 CHN	0.026 -20%	-0.20	
25 CIV	0.001 +43%	0.43	
26 CMR	0.001 +25%	0.25	
27 COL	0.001 +25%	0.25	
28 CPV	0.001 +32%	0.32	
29 CUB	0.001 +245%	2.45	
30 CYP	0.001 +87%	0.87	
31 DEU	0.001 +127%	1.27	
32 DJI	0.001 +27%	0.27	
33 DZA	0.007 -7%	-0.07	
34 ECU	0.030 +11%	0.11	
35 EGY	0.001 +20%	0.20	
36 ESP	0.001 +16%	0.16	
37 ETH	0.001 +19%	0.19	
38 FIN	0.001 +35%	0.35	
39 FJI	0.001 +2499%	24.99	
40 FRA	0.001 +28%	0.28	
41 GAB	0.001 +26%	0.26	
42 GBR	0.001 +35%	0.35	
43 GEO	0.001 +23%	0.23	
44 GHA	0.001 +26%	0.26	
45 GIN	0.001 +56%	0.56	
46 GNB	0.003 +13%	0.13	
47 GRD	0.001 +1180%	11.80	
48 GTM	0.044 +8%	0.08	
49 GUY	0.001 +64%	0.64	
50 HKG	0.030 -13%	-0.13	
51 HND	0.001 +26%	0.26	
52 HRV	0.001 +43%	0.43	
53 HTI	0.002 +11%	0.11	

X ISO	y1.p y1.effect	y1.effect_dec	Causal Impact of Vaccine
54 HUN	0.001 +99%	0.99	
55 IDN	0.001 +100%	1.00	
56 IND	0.001 +29%	0.29	
57 IRL	0.001 +33%	0.33	
58 ITA	0.001 +24%	0.24	
59 JAM	0.001 +91%	0.91	
60 JOR	0.001 +56%	0.56	
61 JPN	0.001 +48%	0.48	
62 KAZ	0.001 +94%	0.94	
63 KEN	0.001 +33%	0.33	
64 KWT	0.001 +24%	0.24	
65 LBN	0.001 +74%	0.74	
66 LBR	0.001 +75%	0.75	
67 LCA	0.001 +250%	2.50	
68 LKA	0.001 +437%	4.37	
69 MAR	0.047 -12%	-0.12	
70 MCO	0.001 +741%	7.41	
71 MDA	0.001 +17%	0.17	
72 MDG	0.021 +11%	0.11	
73 MDV	0.001 +108%	1.08	
74 MEX	0.001 +28%	0.28	
75 MKD	0.001 +28%	0.28	
76 MLI	0.018 +13%	0.13	
77 MLT	0.005 +19%	0.19	
78 MMR	0.001 +71%	0.71	
79 MNE	0.001 +30%	0.30	
80 MNG	0.001 +19015%	190.15	
81 MOZ	0.001 +64%	0.64	
82 MUS	0.001 +69%	0.69	
83 MWI	0.003 +22%	0.22	
84 MYS	0.001 +212%	2.12	
85 NAM	0.001 +227%	2.27	
86 NER	0.029 -12%	-0.12	
87 NIC	0.005 -18%	-0.18	
88 NPL	0.001 +133%	1.33	
89 NZL	0.002 -19%	-0.19	
90 OMN	0.001 +32%	0.32	
91 PAK	0.001 +28%	0.28	
92 PER	0.001 +20%	0.20	
93 PHL	0.001 +38%	0.38	
94 PNG	0.001 +263%	2.63	
95 PRY	0.001 +156%	1.56	
96 PSE	0.004 +14%	0.14	
97 ROU	0.001 +34%	0.34	
98 RUS	0.001 +77%	0.77	
99 RWA	0.001 +107%	1.07	
100 SAU	0.018 -10%	-0.10	
101 SEN	0.001 +43%	0.43	
102 SGP	0.025 -17%	-0.17	
103 SOM	0.005 +24%	0.24	
104 SRB	0.001 +32%	0.32	
105 SUR	0.001 +103%	1.03	
106 SVK	0.001 +276%	2.76	
107 SVN	0.001 +27%	0.27	
108 SWE	0.001 +22%	0.22	
109 SYC	0.001 +10680%	106.80	
110 SYR	0.001 +31%	0.31	
111 TGO	0.001 +24%	0.24	
112 THA	0.001 +887%	8.87	
113 TLS	0.002 +2356%	23.56	
114 TTO	0.001 +266%	2.66	
115 TUN	0.001 +56%	0.56	

X ISO	y1.p y1.effect	y1.effect_dec
116 TUR	0.001 +32%	0.32
117 TWN	0.001 +2767%	27.67
118 TZA	0.001 +427%	4.27
119 UGA	0.001 +235%	2.35
120 UKR	0.001 +43%	0.43
121 URY	0.001 +507%	5.07
122 USA	0.001 +31%	0.31
123 VCT	0.013 +26%	0.26
124 VEN	0.001 +62%	0.62
125 VNM	0.001 +707%	7.07
126 VUT	0.025 -39%	-0.39
127 ZMB	0.001 +85%	0.85
128 ZWE	0.001 +48%	0.48

Causal Impact of Vaccine
Deployment on Total Cases

X ISO	y2.p y2.effect	y2.effect_dec
1 AFG	0.006 -12%	-0.12
2 AGO	0.001 +52%	0.52
3 ALB	0.001 +54%	0.54
4 ARE	0.001 +72%	0.72
5 ARG	0.001 +66%	0.66
6 ATG	0.001 +184%	1.84
7 BGD	0.014 +11%	0.11
8 BHS	0.001 +47%	0.47
9 BIH	0.047 +18%	0.18
10 BLZ	0.042 -14%	-0.14
11 BOL	0.001 +22%	0.22
12 BRA	0.001 +37%	0.37
13 BRB	0.001 +91%	0.91
14 BRN	0.001 +381%	3.81
15 BTN	0.001 +90%	0.90
16 BWA	0.001 +140%	1.40
17 CAF	0.001 -38%	-0.38
18 CAN	0.001 +59%	0.59
19 CHL	0.001 +45%	0.45
20 COG	0.018 -11%	-0.11
21 COL	0.001 +34%	0.34
22 CPV	0.001 +46%	0.46
23 CUB	0.001 +168%	1.68
24 CYP	0.001 +82%	0.82
25 DEU	0.001 +52%	0.52
26 DMA	0.001 +407%	4.07
27 ECU	0.001 +24%	0.24
28 ESP	0.001 +44%	0.44
29 FIN	0.001 +59%	0.59
30 FJI	0.001 +12240%	122.40
31 FRA	0.001 +49%	0.49
32 GBR	0.001 +46%	0.46
33 GEO	0.003 +24%	0.24
34 GHA	0.002 -16%	-0.16
35 GNQ	0.001 -23%	-0.23
36 GRD	0.001 +309%	3.09
37 GTM	0.001 +30%	0.30
38 GUY	0.001 +100%	1.00
39 HND	0.001 +19%	0.19
40 HTI	0.001 -15%	-0.15
41 HUN	0.005 +27%	0.27
42 IDN	0.001 +106%	1.06
43 IND	0.001 +74%	0.74
44 IRL	0.001 +120%	1.20
45 IRN	0.001 +64%	0.64
46 IRQ	0.001 +51%	0.51

Causal Impact of Vaccine
Deployment on Total Cases
per Million associated with
COVID-19

X ISO	y2.p y2.effect	y2.effect_dec	Causal Impact of Vaccine
47 ITA	0.001 +39%	0.39	0.39
48 JAM	0.001 +82%	0.82	0.82
49 JOR	0.001 +53%	0.53	0.53
50 JPN	0.001 +45%	0.45	0.45
51 KAZ	0.001 +38%	0.38	0.38
52 KEN	0.001 +28%	0.28	0.28
53 KHM	0.001 +5808%	58.08	58.08
54 KNA	0.001 +1051%	10.51	10.51
55 KOR	0.001 +49%	0.49	0.49
56 KWT	0.001 +50%	0.50	0.50
57 LAO	0.001 +6955%	69.55	69.55
58 LBN	0.001 +47%	0.47	0.47
59 LBR	0.001 +20%	0.20	0.20
60 LBY	0.001 +31%	0.31	0.31
61 LCA	0.001 +125%	1.25	1.25
62 LKA	0.001 +170%	1.70	1.70
63 MCO	0.001 +124%	1.24	1.24
64 MDA	0.007 +12%	0.12	0.12
65 MDG	0.024 -16%	-0.16	-0.16
66 MDV	0.001 +156%	1.56	1.56
67 MEX	0.001 +41%	0.41	0.41
68 MKD	0.003 +23%	0.23	0.23
69 MLI	0.027 +11%	0.11	0.11
70 MLT	0.001 +46%	0.46	0.46
71 MMR	0.037 +39%	0.39	0.39
72 MNE	0.001 +20%	0.20	0.20
73 MNG	0.001 +3391%	33.91	33.91
74 MOZ	0.001 +46%	0.46	0.46
75 MRT	0.001 -22%	-0.22	-0.22
76 MUS	0.001 +536%	5.36	5.36
77 MYS	0.001 +102%	1.02	1.02
78 NAM	0.001 +84%	0.84	0.84
79 NGA	0.024 -15%	-0.15	-0.15
80 NIC	0.001 -25%	-0.25	-0.25
81 NLD	0.001 +31%	0.31	0.31
82 NPL	0.001 +39%	0.39	0.39
83 OMN	0.027 +42%	0.42	0.42
84 PAK	0.029 -7%	-0.07	-0.07
85 PER	0.001 +30%	0.30	0.30
86 PHL	0.001 +101%	1.01	1.01
87 PNG	0.001 +191%	1.91	1.91
88 PRY	0.001 +117%	1.17	1.17
89 PSE	0.002 +19%	0.19	0.19
90 RUS	0.001 +22%	0.22	0.22
91 RWA	0.001 +118%	1.18	1.18
92 SAU	0.003 -28%	-0.28	-0.28
93 SDN	0.001 -29%	-0.29	-0.29
94 SEN	0.001 +24%	0.24	0.24
95 SGP	0.001 -46%	-0.46	-0.46
96 SLE	0.017 -10%	-0.10	-0.10
97 SMR	0.001 +25%	0.25	0.25
98 SRB	0.001 +32%	0.32	0.32
99 SUR	0.001 +62%	0.62	0.62
100 SVK	0.001 +29%	0.29	0.29
101 SVN	0.001 +58%	0.58	0.58
102 SWE	0.001 +60%	0.60	0.60
103 SWZ	0.001 +36%	0.36	0.36
104 SYC	0.001 +1978%	19.78	19.78
105 SYR	0.001 +29%	0.29	0.29
106 TGO	0.001 +76%	0.76	0.76
107 THA	0.001 +381%	3.81	3.81
108 TLS	0.001 +839%	8.39	8.39

X ISO	y2.p	y2.effect	y2.effect_dec	Causal Impact of Vaccine
109 TTO	0.001	+199%	1.99	0.001
110 TUN	0.001	+68%	0.68	0.001
111 TWN	0.001	+475%	4.75	0.001
112 TZA	0.001	+210%	2.10	0.001
113 UGA	0.001	+48%	0.48	0.001
114 UKR	0.001	+32%	0.32	0.001
115 URY	0.001	+390%	3.90	0.001
116 USA	0.001	+38%	0.38	0.001
117 VCT	0.001	+35%	0.35	0.001
118 VEN	0.001	+41%	0.41	0.001
119 VNM	0.001	+1099%	10.99	0.001
120 ZMB	0.001	+66%	0.66	0.001
121 ZWE	0.001	+50%	0.50	0.001

Categorical Variables - Dot plots of variables $y1.E$, $y2.E$, $c1$, $c2$, and $c3$

To test and display categorical variables, dot plots were created using the R package *ggstatsplot* (Patil 2021). These plots demonstrate the distribution of vaccine effect across *continent*, *country* and *vaccine brands in use in each country*. As this data is non-parametric, these charts also present the Wilcoxon signed rank value (V) to demonstrate whether the differences between groups is different from the null of 0. This demonstrates whether different continents, countries, or vaccine brands show different levels of $y1.E$ or $y2.E$ or whether the effect of vaccine administration was uniform.

Patil, Indrajeet. 2021. "Visualizations with statistical details: The 'ggstatsplot' approach." *Journal of Open Source Software* 6 (61): 3167. <https://doi.org/10.21105/joss.03167>.

Numerical Variables - Correlation Matrix and Scatterplot of $y_1.E$, $y_2.E$, n_1 , n_2 , and n_3

As this data is non-parametric, all significant correlation calculations are presented with Spearman's ρ (*rho*). This correlation matrix shows how all numerical variables relate to one another. The stronger the correlation, the bluer the box appears, if there is an X over the number that means it has a p-value > 0.05 and is not statistically significant. The only statistically significant result of importance for this study is the correlation between *total vaccinations per hundred people* and *effect of vaccine intervention on total cases per million* ($\rho: 0.3384496, p: 9.7^{-4}$).

Correlation Matrix

Spearman Scatterplot of y2.E ~ n2

The scatter plot shown here provides the following detailed information for the only statistically significant correlation among independent numerical variables:

- Correlation coefficient (r) = The strength of the relationship.
- p-value = The significance of the relationship.
- Histogram with kernel density estimation and rug plot.
- Scatter plot with fitted line.

Discussion

Increase in Death and Cases as a Causal Impact of Vaccine Administration

Countries with few COVID-19 deaths in the year 2020 appear to have fared the worst of all countries after vaccine administration (e.g. Thailand, Vietnam, Mongolia, Taiwan, Seychelles, Cambodia, etc.). The causal impact results from vaccine administration seen in these countries of hundreds or thousands of percentage increases in total deaths and cases per million are also the causal impact results we can be most statistically confident in due to the direct increase of COVID-19 associated deaths and cases after vaccine administration, where prior to vaccine administration there were few or none. Notably, the results we can be least statistically confident about are many of the results suggesting a negative causal impact from vaccine administration (e.g. Saudi Arabia, China, Nigeria, Belize, etc.).

Some might try to argue that these results indicate a rise in cases and deaths associated with COVID-19 of those who have not taken COVID-19 experimental gene therapy injections, or that perhaps these deaths are as a result of some new more contagious variant such as Delta. As to the first point, while this data is still inconclusive, especially on a worldwide scale as was this study's focus, there is beginning to emerge a pattern of a similar amount of cases and deaths of COVID-19 in relation to the population that is vaccinated as is evidenced by public records from Public Health England and the Israeli Ministry of Health. In addition, if that counterargument were true, we would expect to see countries with higher vaccination rates also have lower (or negative) impacts from vaccine administration on rates of cases and deaths associated with COVID-19. Instead, we see the opposite, a low positive correlation ($\rho: 0.34, p < 0.001$) between *total vaccinations per*

hundred and the impact of vaccine administration on cases associated with COVID-19. These results concur with the fact that the vaccines only offer a low absolute risk reduction (ARR) (0.8–1.9%) (Olliaro, Torreale, and Vaillant 2021) in the first place and have been shown to wane over time to an even lower ARR (Levin et al. 2021; Chemaitelly et al. 2021; Wang et al. 2021).

To the latter point, the calculations in the *CausalImpact* package and the code presented above accounted for the differing dates when the vaccine administration started in each country and it is not likely that the Delta variant arrived in each of these countries precisely at the time each vaccine administration also started. Rather, it is more likely that the vaccine administration causes a bottleneck effect in each region and helps to create even more deadly variants as Ausschuss et al. (2021), Bossche (2021), and Ricke and Malone (2020) all warned, which may translate into a rise in cases and deaths associated with COVID-19 as a result of the causal impact of vaccine administration.

Farr's Law, Gompertz Function

As noted by other authors (Pacheco-Barrios et al. 2020), many countries that reported high cases and deaths associated with COVID-19 during 2020 and early 2021 showed a standard example of Farr's Law and/or the Gompertz Function when viewed cumulatively per capita as an inverse Gompertz function (Haynes and Kulkarni 2021) or when predicted as a "best straight line" (Levitt, Scaiewicz, and Zonta 2020). In other words, these countries appeared to have largely achieved natural immunity by late spring of 2021 in the Northern Hemisphere, which is why many of their trend lines go flat for a time. Unfortunately, once the vaccine administration started for the general population, or shortly thereafter, those trend lines began to increase again in many

Olliaro, Piero, Els Torreale, and Michel Vaillant. 2021. "COVID-19 Vaccine Efficacy and Effectiveness—the Elephant (not) in the Room." *The Lancet Microbe*.

Levin, Einav G, Yaniv Lustig, Carmit Cohen, Ronen Fluss, Victoria Indenbaum, Sharon Amit, Ram Doolman, et al. 2021. "Waning Immune Humoral Response to BNT162b2 Covid-19 Vaccine over 6 Months." *New England Journal of Medicine*.
<https://doi.org/10.1056/nejmoa2114583>.

Chemaitelly, Hiam, Patrick Tang, Mohammad R Hasan, Sawsan AlMukdad, Hadi M Yassine, Fatiha M Benslimane, Hebah A Al Khatib, et al. 2021. "Waning of BNT162b2 Vaccine Protection Against SARS-CoV-2 Infection in Qatar." *New England Journal of Medicine*.
<https://doi.org/10.1101/2021.08.25.21262584>.

Wang, Zijun, Fabian Schmidt, Yiska Weisblum, Frauke Muecksch, Christopher O Barnes, Shlomo Fink, Dennis Schaefer-Babajew, et al. 2021. "mRNA Vaccine-Elicited Antibodies to SARS-CoV-2 and Circulating Variants." *Nature* 592 (7855): 616–22.
<https://doi.org/10.1101/2021.01.15.426911>.

Ausschuss, Stiftung Corona, Dr. Reiner Fuellmich, Dr. Wolfgang Woodard, and Dr. Luc Montagnier. 2021. "Prof. Dr. Med. Luc Montagnier (IN ENGLISH) Full Interview June 2021."
<https://www.youtube.com/watch?v=Nd5yFvU3mpg>.

Bossche, Geert Vanden. 2021. "Open Letter to All Authorities, Scientists and Experts Around the World." *Geert Vanden Bossche*.
<https://www.geertvandenbossche.org/post/opencall>.

countries, and unnaturally so in the middle or towards the end of summer in the Northern hemisphere or in countries where previously there had been very few if any cases or deaths. Normally, seasonal die off from pneumonia, influenza, or COVID-19 is in the winter, so this spike that appears in many countries after vaccine administration at this time of the year or in countries with no previous outbreaks is highly suspect as not being a natural trend, but rather vaccine-induced.

These results are consistent with the waning effect of COVID-19 vaccine protection mentioned above, the amount of “breakthrough” cases we are currently witnessing (Musser et al. 2021), and the overwhelming and historically unprecedented quantity of reports of vaccine adverse events in the Vaccine Adverse Events Reporting System (VAERS), over 16,000 reported deaths as of writing this report (Health and Services 2021), suggesting a highly untested vaccine. At the same time, the robust, durable, and long-lasting natural immunity that occurs with infection from SARS-CoV or SARS-CoV-2 (Majdoubi et al. 2021) combined with extremely low absolute risk reduction (0.8-1.9%) (Olliaro, Torreale, and Vaillant 2021) from available vaccines, make the risks of these vaccines likely outweigh the benefits for most if not all of the population.

At the very least, these results suggest that COVID-19 vaccine administration as a public policy over 80% of the time does not have a statistically significant causal impact of lowering total deaths or cases per million, but rather a statistically significant impact in increasing total deaths or cases per million associated with COVID-19 over and above what would have been expected if no vaccines were ever administered.

Obviously, the results here will be shocking

Ricke, Darrell, and Robert W Malone. 2020. “Medical Countermeasures Analysis of 2019-nCoV and Vaccine Risks for Antibody-Dependent Enhancement (ADE).” *Available at SSRN 3546070*.

Pacheco-Barrios, Kevin, Alejandra Cardenas-Rojas, Stefano Giannoni-Luza, and Felipe Fregni. 2020. “COVID-19 Pandemic and Farr’s Law: A Global Comparison and Prediction of Outbreak Acceleration and Deceleration Rates.” *PloS One* 15 (9): e0239175. <https://doi.org/10.1371/journal.pone.0239175>.

Haynes, Kingsley E, and Rajendra Kulkarni. 2021. “Modeling Region Based Regimes for COVID-19 Mitigation: An Inverse Gompertz Approach to Coronavirus Infections in the USA, New York, and New Jersey.” *Regional Science Policy & Practice*.

Levitt, Michael, Andrea Scaiewicz, and Francesco Zonta. 2020. “Predicting the Trajectory of Any Covid19 Epidemic from the Best Straight Line.” *medRxiv*. <https://doi.org/10.1101/2020.06.26.20140814>.

Musser, James M, Paul A Christensen, Randall J Olsen, Scott Wesley Long, Sishir Subedi, James J Davis, Parsa Hodjat, Debbie R Walley, Jacob C Kinsky, and Jimmy D Gollihar. 2021. “Delta Variants of SARS-CoV-2 Cause Significantly Increased Vaccine Breakthrough COVID-19 Cases in Houston, Texas.” *medRxiv*.

Health, and Human Services. 2021. “Vaccine Adverse Event Reporting System 2021 Dataset.” <https://vaers.hhs.gov/data.html>.

Majdoubi, Abdelilah, Christina Michalski, Sarah E O’Connell, Sarah Dada, Sandeep Narpala, Jean Gelin, Disha Mehta, et al. 2021. “A Majority of Uninfected Adults Show

to many who have perhaps been paying more attention to official government/media narrative rather than on the ground data and evidence. However, for those that have been paying attention to the pleas, warnings, and publicly voiced frustrations of many of the brightest and bravest minds in the scientific, medical and investigative community (e.g. Dr. Luc Montagnier (Ausschuss et al. 2021), Dr. Michael Yeadon (Yeadon 2020; Borger et al. 2021), Dr. Robert Malone (Ricke and Malone 2020), Dr. Wolfgang Woodard (Wodarg and Scarlattilaan 2020), Dr. Geert Vanden Bossche (Bossche 2021), Dr. Peter McCullough (Bruno et al. 2021), and over 860,000 others (Kulldorff, Gupta, and Bhattacharya 2020; Kampf and Kulldorff 2021)) or have been studying the raw data themselves, these results likely come as no surprise.

Vaccine Mandates

If they ever were ethical, which this author disagrees with strongly based on scientific, medical, and research ethics that regard the patient rights to informed consent and non-prejudicial refusal of treatment or experimentation as iterated and agreed to under the Nuremberg Code (Code 1998), Helsinki Accords (Association and others 2009), and the Human Rights Declaration on Bioethics (UNESCO 2019) as inalienable, essential, and non-negotiable, vaccine mandates under these conditions and results are beyond unethical at this point, they are clearly discriminatory and likely criminal, a determination courts and lawyers will ultimately decide.

The results of this study taken together demonstrate a product that directly causes more COVID-19 associated cases and deaths than otherwise would have existed with zero vaccines. Consequently, these experimental gene therapy injections known as COVID-19 vaccines cannot be mandated by any public policy that intends to continue following the regulations of the

Preexisting Antibody Reactivity Against SARS-CoV-2." *JCI Insight* 6 (8).

Olliaro, Piero, Els Torreele, and Michel Vaillant. 2021. "COVID-19 Vaccine Efficacy and Effectiveness—the Elephant (not) in the Room." *The Lancet Microbe*.

Ausschuss, Stiftung Corona, Dr. Reiner Fuellmich, Dr. Wolfgang Woodard, and Dr. Luc Montagnier. 2021. "Prof. Dr. Med. Luc Montagnier (IN ENGLISH) Full Interview June 2021." <https://www.youtube.com/watch?v=Nd5yFvU3mpg>.

Yeadon, Michael. 2020. "Lies, Damned Lies and Health Statistics—the Deadly Danger of False Positives." *Lockdown Scept. URL* <https://Lockdownsceptics.Org/Lies-Damned-Lies-and-Health-Statistics-the-Deadly-Danger-of-False-Positives/> (accessed 10.6. 20).

Borger, Pieter, Bobby Rajesh Malhotra, Michael Yeadon, Clare Craig, Kevin McKernan, Klaus Steger, Paul McSheehy, et al. 2021. "Addendum to the Corman-Drosten Review Report."

Ricke, Darrell, and Robert W Malone. 2020. "Medical Countermeasures Analysis of 2019-nCoV and Vaccine Risks for Antibody-Dependent Enhancement (ADE)." Available at SSRN 3546070.

Wodarg, Wolfgang, and Domenico Scarlattilaan. 2020. "Petition/Motion for Administrative/Regulatory Action Regarding Confirmation of Efficacy End Points and Use of Data in Connection with the Following Clinical Trial (s): Phase III-Eudract Number: 2020-002641-2. Corona-Ausschuss. De." http://enformtk.u-aizu.ac.jp/views/docs/EMA_FDA_Petition.pdf.

Bossche, Geert Vanden. 2021. "Open Letter to All Authorities, Scientists and

Nuremberg Code (Code 1998), the Helsinki Accords (Association and others 2009), and the Human Rights Declaration on Bioethics (UNESCO 2019).

Limitations

There exist limitations with this study including: (1) potentially inaccurate publicly recorded data (2) the causal impact measures only the vaccine effect on COVID-19 related cases and death and not all-cause mortality (3) data for COVID-19 related cases and death largely do a poor job differentiating between vaccinated and non-vaccinated individuals (4) the predictor sets can be debated over (5) a lack of pre-intervention data for some countries prevents analysis of more countries.

As to the first limitation, whether the public data being provided by certain countries is 100% accurate is a matter for another study. Here it is important to use the public data available because this is the data that the world is using to determine COVID-19 government policies. This is the data that is quoted daily by government officials, journalists, and scientists alike. The results presented here are based on that data in its unadulterated form.

Regarding the second limitation, future research will utilize the methods formulated in this study to analyze all-cause mortality or specific-cause mortality data, making this R script highly versatile for future research.

Third, the publicly available data for COVID-19 related cases and death does a poor job at differentiating between vaccinated and non-vaccinated individuals making it an important category to study within this context, however one that should be performed on a smaller-scale case study if valid data should be made available. This study, while recognizing the urgent importance of the outcomes for this variable, could not perform large-scale data

Experts Around the World.” *Geert Vanden Bossche*.
<https://www.geertvandenbossche.org/post/opencall>.

Bruno, Roxana, Peter A Mccullough, Teresa Forcades I Vila, Alexandra Henrion-Caude, Teresa Garcia-Gasca, Galina P Zaitzeva, Sally Priester, et al. 2021. “SARS-CoV-2 Mass Vaccination: Urgent Questions on Vaccine Safety That Demand Answers from International Health Agencies, Regulatory Authorities, Governments and Vaccine Developers.” *Authorea Preprints*.

Kulldorff, Martin, Sunetra Gupta, and Jay Bhattacharya. 2020. “Great Barrington Declaration.” *Great Barrington Declaration* 4.

Kampf, Gunter, and Martin Kulldorff. 2021. “Calling for Benefit-Risk Evaluations of COVID-19 Control Measures.” *The Lancet* 397 (10274): 576–77.

Code, Nuremberg. 1998. “The Nuremberg Code. 1949.” *The Ethics of Biomedical Research. An International Perspective*. Oxford University Press, New York, 213.

Association, World Medical, and others. 2009. “Declaration of Helsinki. Ethical Principles for Medical Research Involving Human Subjects.” *Jahrbuch Für Wissenschaft Und Ethik* 14 (1): 233–38.
<https://doi.org/10.1515/9783110208856.233>.

UNESCO. 2019. “Universal Declaration on Bioethics and Human Rights.” *UNESCO*.
<https://en.unesco.org/themes/ethics-science-and-technology/bioethics-and-human-rights>.

Code, Nuremberg. 1998. “The Nuremberg Code. 1949.” *The Ethics of Biomedical Research. An International Perspective*. Oxford University Press, New York, 213.

analysis with data that is so sparse and ill-defined worldwide. Unfortunately, much of the data surrounding this variable is highly politicized at this moment in time and is therefore difficult to obtain in large enough quantities in an unbiased fashion.

Fourth, the use of predictor data sets is a complicated business, however; the decisions made here to include data sets from four African countries (Burkina Faso, Chad, Democratic Republic of the Congo, and South Sudan) whose populations and governments have largely abstained from mass vaccination provides, in this author's estimation, a more natural synthetic control with the least endogeneity interference possible. Additionally, by using total deaths and cases per million over time the trend line is much more consistent than looking at the dramatic ups and downs of new deaths/cases per million thus allowing for a more accurate and robust predictive capability for the counterfactual.

Finally, as some countries were not reporting data last year, or stopped reporting data at a certain point, there is limited pre-intervention data for these countries from 2020 with which to use for the Causal Impact Analysis. An analysis of those countries will have to be done separately.

Future Research

This study provides various suggestions for different forms of future research on this topic.

As mentioned above, a future study utilizing these methods, but looking at all-cause mortality rates rather than total deaths/cases per million will provide better pre-intervention data (as it goes back decades in some cases), which will be useful for prediction of trend lines. It will also provide a better understanding of the overall causal impact of COVID-19 vaccine administration on the general health of the population rather than just the

Association, World Medical, and others. 2009. "Declaration of Helsinki. Ethical Principles for Medical Research Involving Human Subjects." *Jahrbuch Für Wissenschaft Und Ethik* 14 (1): 233–38. <https://doi.org/10.1515/9783110208856.233>.

UNESCO. 2019. "Universal Declaration on Bioethics and Human Rights." *UNESCO*. <https://en.unesco.org/themes/ethics-science-and-technology/bioethics-and-human-rights>.

causal impact on COVID-19 associated deaths and cases.

An effort to obtain non-politicized raw data surrounding deaths and cases associated with COVID-19 in vaccinated and non-vaccinated individuals after vaccine administration began in each country will be vital for further accurate analysis of this important variable. This will allow us to distinguish between the effects of both the vaccines and the variants, but it must be done in a fashion that categorizes individuals properly. In this author's estimation, the proper categorization should be as follows: *Group 1: vaccinated* = anyone who has had any COVID-19 gene therapy injection at any moment following injection; *Group 2: non-vaccinated* = anyone who has never had any COVID-19 gene therapy injection.

Given the recent announcement by the Japanese Ministry of Health about their reasoning for rejecting a batch of 2.6 million Moderna vaccines because it contained a “metallic foreign substance that reacts to magnets” (Urasaki and Nomura 2021), the possibility of different vaccines or batches having different effects due to contamination must be considered in any future analyses.

Additionally, the more we learn about natural immunity suggests that many populations may have had previous antibodies to SARS and SARS-like viruses, which may affect the vaccine impact.

It should be recalled this study only represents a snapshot in time, as such, future data points as they become available can be reviewed utilizing the calculation methodology explained in this paper to see if there are any changes in the results over time.

Finally, due to the announcement of the use of ivermectin by the Tokyo Medical Association and the state of Uttar Pradesh in India and the dramatic reduction in cases

Urasaki, Yumiko, and Yuko Nomura. 2021. “1.6m Moderna Doses Withdrawn in Japan over Contamination.” *Nikkei Asia*.

<https://asia.nikkei.com/Spotlight/Coronavirus/COVID-vaccines/1.6m-Moderna-doses-withdrawn-in-Japan-over-contamination>.

and deaths after administration (Seth 2021; Hannah Ritchie and Roser 2020), and based on other promising research in repurposing ivermectin for use against COVID-19 (Santin et al. 2021) a similar study to that presented here could be done to understand the causal impact of mass ivermectin administration as has been practiced now in Japan, India, Peru, and El Salvador, aside from the many tropical countries that administer ivermectin bi-yearly as a malaria prophylactic. Should enough countries adopt this policy and should the data become available in the future, this would be a worthwhile causal impact analysis to pursue.

Data Availability

All results, data, plots, and R code are included in this study for the easy replication by others. To access all files please refer to this Google Drive link: <https://drive.google.com/drive/folders/1xOphw78-BhsMly09lpxCVPZ-WGieMSqO?usp=sharing>

A PDF version of this study can be accessed here:

<https://drive.google.com/file/d/1DLlRa9rUqvW9pG1vNEsWMEydWwsmSMbe/view?usp=sharing>

All *CausalImpact* figures as compiled into multiple PDF pages can be downloaded here:

<https://drive.google.com/file/d/1lX3NVqY-sbxVLM81lgK5f6I5ny9c6zGL/view?usp=sharing>

This author welcomes suggestions on how to improve any aspect of the methodology utilized in this study, please refer questions, suggestions, or criticism to Kyle A. Beattie kbeattie@ualberta.ca.

Seth, Maulshree. 2021. "Uttar Pradesh Government Says Early Use of Ivermectin Helped to Keep Positivity, Deaths Low." *The Indian Express*. <https://indianexpress.com/article/cities/lucknow/uttar-pradesh-government-says-ivermectin-helped-to-keep-deaths-low-7311786/>.

Hannah Ritchie, Lucas Rodés-Guirao, Edouard Mathieu, and Max Roser. 2020. "Coronavirus Pandemic (COVID-19)." *Our World in Data*.

Santin, Alessandro D, David E Scheim, Peter A McCullough, Morimasa Yagisawa, and Thomas J Borody. 2021. "Ivermectin: A Multifaceted Drug of Nobel Prize-Honored Distinction with Indicated Efficacy Against a New Global Scourge, COVID-19." *New Microbes and New Infections*, 100924.

References

- R (Version 4.0.3; R Core Team 2020) and the R-packages *AICcmodavg* (Version 2.3.1; Mazerolle 2020), *anytime* (Version 0.3.9; Eddelbuettel 2020), *broom* (Version 0.7.9; Robinson, Hayes, and Couch 2020), *car* (Version 3.0.10; Fox and Weisberg 2019; Fox, Weisberg, and Price 2020), *carData* (Version 3.0.4; Fox, Weisberg, and Price 2020), *cluster* (Version 2.1.0; Maechler et al. 2019), *corpus* (Version 0.10.2; Perry 2020), *correlation* (Version 0.6.1; Makowski et al. 2020), *corrplot2017* (Wei and Simko 2017), *data.table* (Version 1.14.0; Dowle and Srinivasan 2020), *dplyr* (Version 1.0.7; Wickham et al. 2020), *finalfit* (Version 1.0.3; Harrison, Drake, and Ots 2020), *flextable* (Version 0.6.6; Gohel 2020), *forcats* (Version 0.5.1; Wickham 2020a), *Formula* (Version 1.2.4; Zeileis and Croissant 2010), *fpc* (Version 2.2.9; Hennig 2020), *GGally* (Version 2.1.2; Schloerke et al. 2020), *ggcorrplot* (Version 0.1.3; Kassambara 2019), *ggplot2* (Version 3.3.5; Wickham 2016), *ggpubr* (Version 0.4.0; Kassambara 2020), *ggraph* (Version 2.0.5; Pedersen 2020), *ggrepel* (Version 0.9.1; Slowikowski 2020), *ggstatsplot* (Version 0.8.0; Patil 2021), *ggthemes* (Version 4.2.4; Arnold 2019), *ggvis* (Version 0.4.7; Chang and Wickham 2019), *ggwordcloud* (Version 0.5.0; Le Pennec and Slowikowski 2019), *Hmisc* (Version 4.5.0; Harrell Jr, Charles Dupont, and others. 2020), *igraph* (Version 1.2.6; Csardi and Nepusz 2006), *kableExtra* (Version 1.3.4; Zhu 2020), *KernSmooth* (Version 2.23.20; Wand 2020), *knitr* (Version 1.36; Xie 2015), *lattice* (Version 0.20.44; Sarkar 2008), *lsr* (Version 0.5; Navarro 2015), *NLP* (Version 0.2.1; Hornik 2018), *nortest* (Version 1.0.4; Gross and Ligges 2015), *papaja* (Version 0.1.0.9997; Aust and Barth 2020), *pdfutils* (Version 3.0.1; Ooms 2020), *PerformanceAnalytics* (Version 2.0.4; Peterson and Carl 2020), *plm* (Version 2.4.1; Croissant and Millo 2008; Millo 2017), *plyr* (Version 1.8.6; Wickham et al. 2020; Wickham 2011), *psych* (Version 2.1.6; Revelle 2020; Makowski 2018), *psycho*
- R Core Team. 2020. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Mazerolle, Marc J. 2020. *AICcmodavg: Model Selection and Multimodel Inference Based on (q)AIC(c)*. <https://cran.r-project.org/package=AICcmodavg>.
- Eddelbuettel, Dirk. 2020. *Anytime: Anything to 'POSIXct' or 'date' Converter*. <https://CRAN.R-project.org/package=anytime>.
- Robinson, David, Alex Hayes, and Simon Couch. 2020. *Broom: Convert Statistical Objects into Tidy Tibbles*.
- Fox, John, and Sanford Weisberg. 2019. *An R Companion to Applied Regression*. Third. Thousand Oaks CA: Sage. <https://socialsciences.mcmaster.ca/jfox/Books/Companion/>.
- Fox, John, Sanford Weisberg, and Brad Price. 2020. *carData: Companion to Applied Regression Data Sets*. <https://CRAN.R-project.org/package=carData>.
- Fox, John, Sanford Weisberg, and Brad Price. 2020. *carData: Companion to Applied Regression Data Sets*. <https://CRAN.R-project.org/package=carData>.
- Maechler, Martin, Peter Rousseeuw, Anja Struyf, Mia Hubert, and Kurt Hornik. 2019. *Cluster: Cluster Analysis Basics and Extensions*.
- Perry, Patrick O. 2020. *Corpus: Text Corpus Analysis*. <https://CRAN.R-project.org/package=corpus>.
- Makowski, Dominique, Mattan S. Ben-Shachar, Indrajeet Patil, and Daniel Lüdtke. 2020. "Methods and Algorithms for Correlation Analysis in r." *Journal of Open Source Software* 5 (51): 2306. <https://doi.org/10.21105/joss.02306>.

(Version 0.6.1; Makowski 2018), *purrr* (Version 0.3.4; Henry and Wickham 2020), *quanteda* (Version 3.0.0; Benoit et al. 2018), *RColorBrewer* (Version 1.1.2; Neuwirth 2014), *readr* (Version 2.0.1; Wickham, Hester, and Francois 2018), *readtext* (Version 0.80; Benoit and Obeng 2020), *rvest* (Version 1.0.1; Wickham 2020b), *see* (Version 0.6.4; Lüdecke et al. 2020), *SnowballC* (Version 0.7.0; Bouchet-Valat 2020), *stringr* (Version 1.4.0; Wickham 2019), *survival* (Version 3.2.13; Terry M. Therneau and Patricia M. Grambsch 2000), *tesseract* (Version 4.1.1; Ooms 2019), *text2vec* (Version 0.6; Selivanov, Bickel, and Wang 2020), *tibble* (Version 3.1.5; Müller and Wickham 2020), *tidyr* (Version 1.1.4; Wickham 2020c), *tidytext* (Version 0.3.1; Silge and Robinson 2016), *tidyverse* (Version 1.3.1; Wickham et al. 2019), *tinylabels* (Version 0.2.1; Barth 2021), *tm* (Version 0.7.8; Feinerer, Hornik, and Meyer 2008), *topicmodels* (Version 0.2.12; Grün and Hornik 2011), *wordcloud* (Version 2.6; Le Pennec and Slowikowski 2019; Fellows 2018), *xml2* (Version 1.3.2; Wickham, Hester, and Ooms 2020), *xtable* (Version 1.8.4; Gohel 2020; Dahl et al. 2019), *xts* (Version 0.12.1; Ryan and Ulrich 2020), and *zoo* (Version 1.8.9; Zeileis and Grothendieck 2005)

Wei, Taiyun, and Viliam Simko. 2017. *R Package "corrplot": Visualization of a Correlation Matrix*. <https://github.com/taiyun/corrplot>.

Dowle, Matt, and Arun Srinivasan. 2020. *Data.table: Extension of 'data.frame'*. <https://CRAN.R-project.org/package=data.table>.

Wickham, Hadley, Romain François, Lionel Henry, and Kirill Müller. 2020. *Dplyr: A Grammar of Data Manipulation*. <https://CRAN.R-project.org/package=dplyr>.

Harrison, Ewen, Tom Drake, and Riinu Ots. 2020. *Finalfit: Quickly Create Elegant Regression Results Tables and Plots When Modelling*. <https://CRAN.R-project.org/package=finalfit>.

Gohel, David. 2020. *Flextable: Functions for Tabular Reporting*. <https://CRAN.R-project.org/package=flextable>.

Wickham, Hadley. 2020a. *Forcats: Tools for Working with Categorical Variables (factors)*. <https://CRAN.R-project.org/package=forcats>.

Zeileis, Achim, and Yves Croissant. 2010. "Extended Model Formulas in R: Multiple Parts and Multiple Responses." *Journal of*

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The conclusions presented here are my sincere attempt to arrive at some truth of the matter at hand. Ultimately, God knows best where the truth lies.

Statistical Software 34 (1):
1–13.
<https://doi.org/10.18637/jss.v034.i01>.

Hennig, Christian. 2020.
Fpc: Flexible Procedures for Clustering.
<https://CRAN.R-project.org/package=fpc>.

Schloerke, Barret, Di Cook, Joseph Larmarange, Francois Briatte, Moritz Marbach, Edwin Thoen, Amos Elberg, and Jason Crowley. 2020. *Ggally: Extension to 'ggplot2'*.
<https://CRAN.R-project.org/package=Ggally>.

Kassambara, Alboukadel. 2019. *Ggcorrplot: Visualization of a Correlation Matrix Using 'ggplot2'*.
<https://CRAN.R-project.org/package=ggcorrplot>.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York.
<https://ggplot2.tidyverse.org>.

Kassambara, Alboukadel. 2020. *Ggpubr: 'ggplot2' Based Publication Ready Plots*. <https://CRAN.R-project.org/package=ggpubr>.

Pedersen, Thomas Lin. 2020. *Ggraph: An Implementation of Grammar of Graphics for Graphs and Networks*.
<https://CRAN.R-project.org/package=ggraph>.

Slowikowski, Kamil. 2020. *Ggrepel: Automatically Position Non-Overlapping Text Labels with 'ggplot2'*.
<https://CRAN.R-project.org/package=ggrepel>.

Patil, Indrajeet. 2021. "Visualizations with statistical details: The 'ggstatsplot' approach." *Journal of Open Source Software* 6 (61): 3167.
<https://doi.org/10.21105/joss.03167>.

Arnold, Jeffrey B. 2019. *Ggthemes: Extra Themes, Scales and Geoms for 'ggplot2'*. <https://CRAN.R-project.org/package=ggthemes>.

Chang, Winston, and Hadley Wickham. 2019. *Ggvis: Interactive Grammar of Graphics*.
<https://CRAN.R-project.org/package=ggvis>.

Le Penec, Erwan, and Kamil Slowikowski. 2019. *Ggwordcloud: A Word Cloud Geom for 'ggplot2'*. <https://CRAN.R-project.org/package=ggwordcloud>.

Harrell Jr, Frank E, with contributions from Charles Dupont, and many others. 2020. *Hmisc: Harrell Miscellaneous*. <https://CRAN.R-project.org/package=Hmisc>.

Csardi, Gabor, and Tamas Nepusz. 2006. "The Igraph Software Package for Complex Network Research." *InterJournal Complex Systems*: 1695. <http://igraph.org>.

Zhu, Hao. 2020. *kableExtra: Construct Complex Table with 'kable' and Pipe Syntax*. <https://CRAN.R-project.org/package=kableExtra>.

Wand, Matt. 2020. *KernSmooth: Functions for Kernel Smoothing Supporting Wand & Jones (1995)*. <https://CRAN.R-project.org/package=KernSmooth>.

Xie, Yihui. 2015. *Dynamic Documents with R and Knitr*. 2nd ed. Boca Raton, Florida: Chapman; Hall/CRC. <https://yihui.org/knitr/>.

Sarkar, Deepayan. 2008. *Lattice: Multivariate Data Visualization with r*. New York: Springer. <http://lmdvr.r-forge.r-project.org>.

Navarro, Daniel. 2015. *Learning Statistics with r: A Tutorial for Psychology Students and Other Beginners. (version 0.5)*. Adelaide, Australia: University of Adelaide. <http://ua.edu.au/ccs/teaching/lsr>.

Hornik, Kurt. 2018. *NLP: Natural Language Processing Infrastructure*. <https://CRAN.R-project.org/package=NLP>.

Gross, Juergen, and Uwe Ligges. 2015. *Nortest: Tests for Normality*. <https://CRAN.R-project.org/package=nortest>.

Aust, Frederik, and Marius Barth. 2020. *papaja: Create APA Manuscripts with R*

Markdown.

<https://github.com/crsh/papaja>.

Ooms, Jeroen. 2020.
*Pdftools: Text Extraction,
Rendering and Converting of
PDF Documents*.
[https://CRAN.R-
project.org/package=pdfutils](https://CRAN.R-project.org/package=pdfutils).

Peterson, Brian G., and
Peter Carl. 2020.
*PerformanceAnalytics:
Econometric Tools for
Performance and Risk
Analysis*. [https://CRAN.R-
project.org/package=PerformanceAnalytics](https://CRAN.R-project.org/package=PerformanceAnalytics).

Croissant, Yves, and
Giovanni Millo. 2008.
“Panel Data Econometrics
in R: The plm Package.”
Journal of Statistical Software
27 (2): 1–43.
<https://doi.org/10.18637/jss.v027.i02>.

Millo, Giovanni. 2017.
“Robust Standard Error
Estimators for Panel
Models: A Unifying
Approach.” *Journal of
Statistical Software* 82 (3):
1–27.
<https://doi.org/10.18637/jss.v082.i03>.

Wickham, Hadley, Romain
François, Lionel Henry, and
Kirill Müller. 2020. *Dplyr:
A Grammar of Data
Manipulation*.
[https://CRAN.R-
project.org/package=dplyr](https://CRAN.R-project.org/package=dplyr).

Wickham, Hadley. 2011.
“The Split-Apply-
Combine Strategy for Data
Analysis.” *Journal of
Statistical Software* 40 (1):
1–29.
<http://www.jstatsoft.org/v40/i01/>.

Revelle, William. 2020.
*Psych: Procedures for
Psychological, Psychometric,
and Personality Research*.
Evanston, Illinois:
Northwestern University.
[https://CRAN.R-
project.org/package=psych](https://CRAN.R-project.org/package=psych).

Makowski, Dominique.
2018. “The Psycho
Package: An Efficient and
Publishing-Oriented
Workflow for
Psychological Science.”
*Journal of Open Source
Software* 3 (22): 470.
<https://doi.org/10.21105/joss.00470>.

Makowski, Dominique.
2018. “The Psycho
Package: An Efficient and
Publishing-Oriented

Workflow for
Psychological Science.”
*Journal of Open Source
Software* 3 (22): 470.
<https://doi.org/10.21105/joss.00470>.

Henry, Lionel, and Hadley
Wickham. 2020. *Purrr:
Functional Programming
Tools*. [https://CRAN.R-
project.org/package=purrr](https://CRAN.R-project.org/package=purrr).

Benoit, Kenneth, Kohei
Watanabe, Haiyan Wang,
Paul Nulty, Adam Obeng,
Stefan Müller, and Akitaka
Matsuo. 2018. “Quanteda:
An r Package for the
Quantitative Analysis of
Textual Data.” *Journal of
Open Source Software* 3 (30):
774.
<https://doi.org/10.21105/joss.00774>.

Neuwirth, Erich. 2014.
*RColorBrewer: ColorBrewer
Palettes*. [https://CRAN.R-
project.org/package=RColorBrewer](https://CRAN.R-project.org/package=RColorBrewer).

Wickham, Hadley, Jim
Hester, and Romain
Francois. 2018. *Readr: Read
Rectangular Text Data*.
[https://CRAN.R-
project.org/package=readr](https://CRAN.R-project.org/package=readr).

Benoit, Kenneth, and
Adam Obeng. 2020.
*Readtext: Import and
Handling for Plain and
Formatted Text Files*.
[https://CRAN.R-
project.org/package=readtext](https://CRAN.R-project.org/package=readtext).

Wickham, Hadley. 2020b.
*Rvest: Easily Harvest (scrape)
Web Pages*.
[https://CRAN.R-
project.org/package=rvest](https://CRAN.R-project.org/package=rvest).

Lüdecke, Daniel, Mattan S.
Ben-Shachar, Philip
Waggoner, and Dominique
Makowski. 2020. “See:
Visualisation Toolbox for
'easystats' and Extra
Geoms, Themes and Color
Palettes for 'ggplot2'.”
CRAN.
<https://doi.org/10.5281/zenodo.3952153>.

Bouchet-Valat, Milan.
2020. *SnowballC: Snowball
Stemmers Based on the c
'libstemmer' UTF-8 Library*.
[https://CRAN.R-
project.org/package=SnowballC](https://CRAN.R-project.org/package=SnowballC).

Wickham, Hadley. 2019.
*Stringr: Simple, Consistent
Wrappers for Common String
Operations*.
[https://CRAN.R-
project.org/package=stringr](https://CRAN.R-project.org/package=stringr).

Terry M. Therneau, and
Patricia M. Grambsch.
2000. *Modeling Survival
Data: Extending the Cox
Model*. New York:
Springer.

Ooms, Jeroen. 2019.
*Tesseract: Open Source OCR
Engine*. [https://CRAN.R-
project.org/package=tesseract](https://CRAN.R-project.org/package=tesseract).

Selivanov, Dmitriy,
Manuel Bickel, and Qing
Wang. 2020. *Text2vec:
Modern Text Mining
Framework for r*.
[https://CRAN.R-
project.org/package=text2vec](https://CRAN.R-project.org/package=text2vec).

Müller, Kirill, and Hadley
Wickham. 2020. *Tibble:
Simple Data Frames*.
[https://CRAN.R-
project.org/package=tibble](https://CRAN.R-project.org/package=tibble).

Wickham, Hadley. 2020c.
Tidyr: Tidy Messy Data.
[https://CRAN.R-
project.org/package=tidyr](https://CRAN.R-project.org/package=tidyr).

Silge, Julia, and David
Robinson. 2016. "Tidyttext:
Text Mining and Analysis
Using Tidy Data Principles
in r." *JOSS* 1 (3).
<https://doi.org/10.21105/joss.00037>.

Wickham, Hadley, Mara
Averick, Jennifer Bryan,
Winston Chang, Lucy
D'Agostino McGowan,
Romain François, Garrett
Grolemund, et al. 2019.
"Welcome to the
tidyverse." *Journal of Open
Source Software* 4 (43): 1686.
<https://doi.org/10.21105/joss.01686>.

Barth, Marius. 2021.
*tinylabls: Lightweight
Variable Labels*.
<https://github.com/mariusbarth/tinylabls>.

Feinerer, Ingo, Kurt
Hornik, and David Meyer.
2008. "Text Mining
Infrastructure in r." *Journal
of Statistical Software* 25 (5):
1–54.
<http://www.jstatsoft.org/v25/i05/>.

Grün, Bettina, and Kurt
Hornik. 2011.
"topicmodels: An R
Package for Fitting Topic
Models." *Journal of
Statistical Software* 40 (13):
1–30.
<https://doi.org/10.18637/jss.v040.i13>.

Le Pennec, Erwan, and
Kamil Slowikowski. 2019.
*Ggwordcloud: A Word Cloud
Geom for 'ggplot2'*.

<https://CRAN.R-project.org/package=ggwordcloud>.

Fellows, Ian. 2018.
Wordcloud: Word Clouds.

<https://CRAN.R-project.org/package=wordcloud>.

Wickham, Hadley, Jim Hester, and Jeroen Ooms. 2020. *Xml2: Parse XML*.

<https://CRAN.R-project.org/package=xml2>.

Gohel, David. 2020.
Flextable: Functions for Tabular Reporting.

<https://CRAN.R-project.org/package=flextable>.

Dahl, David B., David Scott, Charles Roosen, Arni Magnusson, and Jonathan Swinton. 2019. *Xtable: Export Tables to LaTeX or HTML*. <https://CRAN.R-project.org/package=xtable>.

Ryan, Jeffrey A., and Joshua M. Ulrich. 2020.
Xts: eXtensible Time Series.

<https://CRAN.R-project.org/package=xts>.

Zeileis, Achim, and Gabor Grothendieck. 2005. "Zoo: S3 Infrastructure for Regular and Irregular Time Series." *Journal of Statistical Software* 14 (6): 1–27.

<https://doi.org/10.18637/jss.v014.i06>.