Project Proposal: The COVID-19 Epidemic, Public Health Restrictions, and Mental Health

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Load Packages

```
library(tidyverse)
library(readxl)
library(lubridate)
library(tidymodels)
library(knitr)
library(xtable)
```

Load Data

```
setwd('../')
restrictions_worldwide <- readr::read_csv("data/phsm-severity-data-short.csv")
google_trends <- readr::read_csv("data/google_trends_data_c.csv")
```

Introduction and Data, including Research Questions

From the beginning of the COVID-19 pandemic until now, the global community has suffered social, economic, and medical burdens in unprecedented levels. Though the physical health of individuals has been of paramount concern due to the high infectivity of COVID-19, with 237.88 million cases and 4.85 million deaths in as of October 2021, another burden on individuals, governments, and health systems has manifested itself in the form of rapidly deteriorating mental health (Our World in Data, 2021). It has been widely accepted that as the COVID-19 pandemic has progressed, mental health has decreased (Centers for Disease Control and Prevention, 2021). However, there is a much less comprehensive body of data surrounding how certain mitigation efforts specifically have impacted mental health, and which mental health conditions each restriction affects the most. For example, the Centers for Disease Control and Prevention (2021) acknowledge that social distancing may increase loneliness, stress, and anxiety, but it is less understood if masking is more directly correlated to obsessive compulsive disorder than it is to depression. Therefore, there is a need to fully understand these intricate relationships in order to drive efforts towards creating more individualized mental health treatments, as well as being able to predict what kind of mental health treatment will be needed in response to an increase in any given public health restriction.

Our data analysis will answer the following research question: how do different COVID-19 mitigation efforts correlate to different types of mental illnesses? In doing so, our project will begin to uncover how certain restrictions may impact different mental illness depending on both the type of restriction and the type of mental illness. Our project will make use of two datasets and merge the datasets based on country in order to ensure there are sufficient relationships to explore in the data. The first dataset is of the frequency of different search terms related to mental health from January of 2019 through September of 2021 for a variety of countries. The data was collected from Google Trends and records the popularity of that search term for any given week in a given country. There is a new data value corresponding to each week, where the date collected is marked as the first of the week. This dataset will be used to gauge how concern with certain mental health topics, including anxiety, depression, obsessive compulsive disorder, therapists, and insomnia, has changed over the course of the pandemic. The second dataset tracks implementation of various mitigation efforts in different countries. This dataset was derived from the World Health Organization's tracking of public health and social measures, and indices were calculated on the raw data in order to quantify the intensity of the restriction, whether the restriction is on masks, gatherings, businesses, schools, or travel. This data has daily values from January 2020 through September of 2020. Through a series of data tidying and wrangling steps, the data has been joined on both country and date. Since the search terms are weekly observations whereas restrictions are daily observations, the search term frequency will be kept constant throughout the week, but each observation for restrictions will be observed for changes. This will enable our analysis to observe how daily changes may affect weekly averages without altering or extrapolating data.

Glimpse

```
## Rows: 142,506
## Columns: 11
## $ DATE_START   <chr> "8/20/2020", "9/4/2020", "3/13/2021", "10/18/2020", "4/18~
## $ COUNTRY      <chr> "Yemen", "Belarus", "Egypt", "Uzbekistan", "Finland", "Is~
## $ ISO3         <chr> "YEM", "BLR", "EGY", "UZB", "FIN", "IMN", "MLI", "MYS", "~
## $ WHO_REGION   <chr> "EMRO", "EURO", "EMRO", "EURO", "EURO", "EURO", "AFRO", "~
## $ MASKS        <dbl> 0, 67, 100, 100, 47, 0, 0, 67, 0, 0, 0, 67, 0, 100, 0, 10~
## $ TRAVEL       <dbl> 100, 0, 33, 100, 100, 0, 0, 67, 100, 100, 100, 33, 100, 1~
## $ GATHERINGS   <dbl> 30, 25, 50, 25, 5, 0, 0, 5, 0, 25, 0, 0, 0, 50, 0, 25, 25~
## $ SCHOOLS      <dbl> 25, 25, 25, 75, 25, 0, 50, 80, 25, 0, 25, 0, 25, 30, 25, ~
## $ BUSINESSES   <dbl> 13, 13, 67, 67, 67, 0, 0, 47, 0, 47, 33, 0, 0, 33, 0, 33,~
## $ MOVEMENTS    <dbl> 80, 40, 100, 40, 20, 0, 0, 20, 60, 60, 0, 0, 0, 40, 0, 80~
## $ GLOBAL_INDEX <dbl> 41, 28, 62, 68, 44, 0, 8, 48, 31, 39, 26, 17, 21, 59, 15,~

## Rows: 858
## Columns: 9
## $ week       <chr> "9/26/2021", "9/19/2021", "9/12/2021", "9/5/2021", "8/29/20~
## $ depression <dbl> 75, 80, 72, 70, 67, 61, 69, 67, 66, 68, 69, 68, 64, 67, 70,~
## $ ocd        <dbl> 75, 100, 80, 74, 67, 69, 74, 74, 66, 67, 68, 71, 68, 63, 76~
## $ anxiety    <dbl> 100, 98, 98, 96, 97, 97, 95, 93, 89, 92, 94, 93, 95, 90, 89~
## $ insomnia   <dbl> 81, 80, 83, 77, 79, 70, 85, 84, 82, 78, 73, 75, 70, 74, 81,~
## $ therapy    <dbl> 80, 85, 86, 85, 88, 86, 86, 84, 87, 86, 88, 90, 88, 91, 85,~
## $ nation     <chr> "United States", "United States", "United States", "United ~
## $ COUNTRY    <chr> "United States", "United States", "United States", "United ~
## $ DATE_START <chr> "9/26/2021", "9/19/2021", "9/12/2021", "9/5/2021", "8/29/20~

## Rows: 522
## Columns: 17
## $ COUNTRY      <chr> "Brazil", "Brazil", "Brazil", "Brazil", "Brazil", "Brazil~
## $ DATE_START   <chr> "1/10/2021", "1/12/2020", "1/17/2021", "1/19/2020", "1/24~
## $ ISO3         <chr> "BRA", "BRA", "BRA", "BRA", "BRA", "BRA", "BRA", "BRA", "~
## $ WHO_REGION   <chr> "AMRO", "AMRO", "AMRO", "AMRO", "AMRO", "AMRO", "AMRO", "~
## $ MASKS        <dbl> 47, 0, 47, 0, 47, 0, 47, 47, 0, 47, 47, 47, 47, 47, 47, 4~
## $ TRAVEL       <dbl> 100, 0, 100, 0, 100, 0, 100, 100, 0, 100, 17, 17, 100, 17~
## $ GATHERINGS   <dbl> 30, 0, 30, 0, 30, 0, 30, 30, 0, 5, 5, 5, 5, 5, 5, 5, 30, ~
## $ SCHOOLS      <dbl> 25, 0, 25, 0, 25, 0, 25, 30, 0, 25, 25, 25, 25, 25, 25, 2~
```

```
## $ BUSINESSES   <dbl> 47, 0, 47, 0, 80, 0, 47, 80, 0, 80, 80, 80, 80, 80, 47, 4~
## $ MOVEMENTS    <dbl> 80, 0, 20, 0, 20, 0, 80, 20, 0, 80, 20, 20, 80, 80, 20, 8~
## $ GLOBAL_INDEX <dbl> 55, 0, 45, 0, 50, 0, 55, 51, 0, 56, 32, 32, 56, 42, 41, 5~
## $ depression   <dbl> 36, 41, 37, 46, 35, 40, 37, 33, 39, 40, 39, 37, 39, 39, 3~
## $ ocd          <dbl> 74, 66, 65, 59, 71, 61, 77, 77, 57, 51, 87, 66, 60, 70, 6~
## $ anxiety      <dbl> 87, 67, 86, 69, 86, 73, 86, 87, 67, 70, 74, 82, 71, 74, 7~
## $ insomnia     <dbl> 79, 87, 69, 74, 83, 83, 77, 68, 71, 55, 56, 53, 62, 64, 5~
## $ therapy      <dbl> 78, 83, 81, 85, 80, 84, 76, 74, 80, 86, 91, 88, 86, 80, 7~
## $ date         <date> 2021-01-10, 2020-01-12, 2021-01-17, 2020-01-19, 2021-01-~
```

Data Analysis Plan

In order to conduct our analysis, we will examine various combinations of mental health search term popularity as explained by the index of public health measure severity. Mental health search term popularity will be used as an indicator for what mental illness is most prevalent during a given time frame, and will be analyzed alongside what restriction was most intense for the same time frame. This relationship will be explored across various countries in order to account for the differences in public health measures that each government enacted throughout the course of the pandemic, as well as determine global averages for mental health search term popularity for each public health measure.

In order to examine if there are some mental health issues that are impacted more strongly by certain public health measures, an analysis of variance (ANOVA) will be conducted on the data. This test will allow for the comparison across multiple means, where each mean is the global averages of mental health search term popularity for each public health measure. We hypothesize that there will be a statistically significant difference among mental illness prevalence as a result of certain public health measures. In order to reject the null hypothesis that there is no difference among certain public health measures disproportionately affecting certain mental illnesses, our p-value for this ANOVA would need to be less that 0.05 for a confidence level of 95%.

Table 1: Summary Statistics for Depression and Anxiety

nation	depression_mean	depression_sd	anxiety_mean	anxiety_sd
Brazil	37.126	3.797	7.409	7.409
India	16.207	9.499	4.659	4.659
Italy	35.747	10.774	8.776	8.776
Mexico	55.851	8.648	8.439	8.439
New Zealand	57.356	13.813	11.478	11.478
United States	75.759	6.457	4.451	4.451

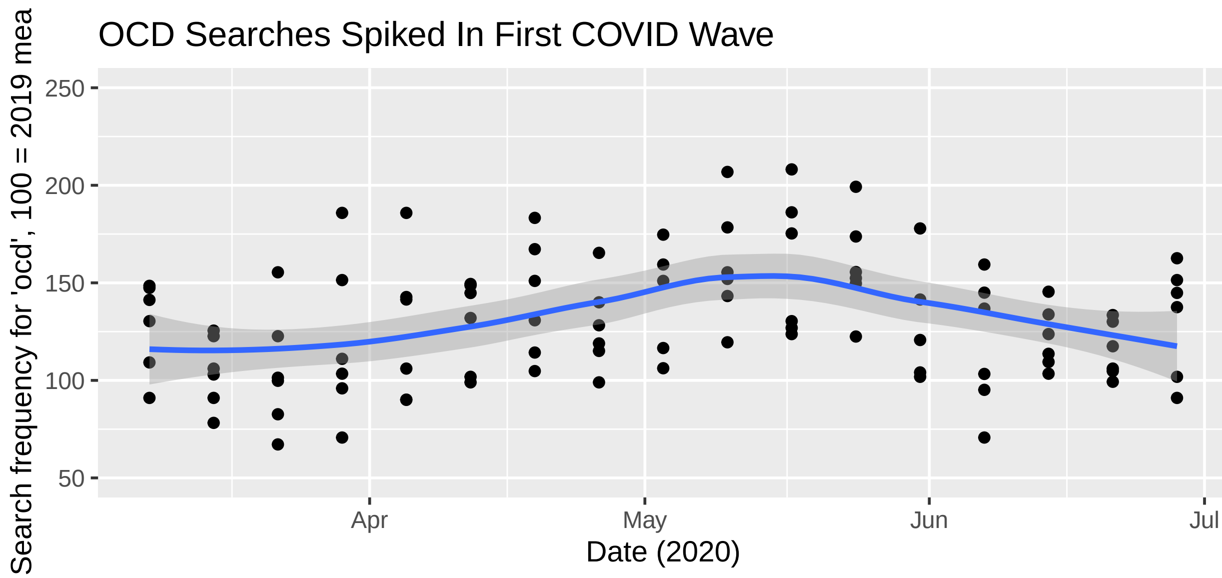
Table 2: Summary Statistics for Therapy, Insomnia and OCD

nation	therapy_mean	therapy_sd	insomnia_mean	insomnia_sd	ocd_mean	ocd_sd
Brazil	83.402	5.645	70.851	11.968	69.563	9.717
India	77.874	7.219	57.816	13.727	67.506	10.580
Italy	56.644	10.005	26.069	9.629	56.667	11.998
Mexico	86.218	5.903	50.540	13.311	34.782	10.474
New Zealand	72.126	9.721	43.023	16.347	35.529	15.378
United States	84.345	4.742	79.609	7.727	71.184	5.858

The tables above summarize the mental health search term frequency data over the period of study from January 2020 through September 2020. The mean of health search term frequency data over this time period were calculated, along with the standard deviation, for the six countries of focus. As seen in Table 1 and Table 2 above, anxiety as a search topic has the lowest mean frequency over the period of study. Therapy appears to have the highest mean frequency over the period of study.

Interestingly, insomnia and depression as search topics have the greatest range of mean frequencies between each country. For insomnia, there is a range of about 53 points, with the minimum score from Italy and the maximum score from the United States. The United States also holds the highest score for depression search frequency, with a low from India, resulting in a range of 59.

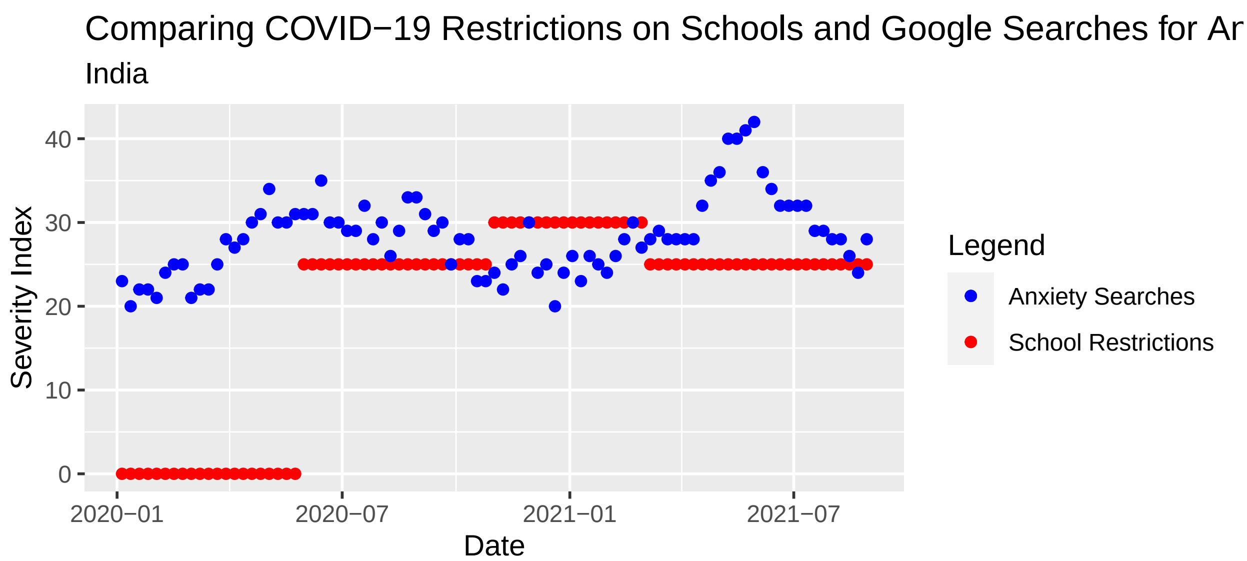
It is important to note that the standard deviations for many of these measurements is fairly high. This is to be expected since the measurments are taken over a time period of rapidly changing social distancing policies and COVID severity across the globe. Further statistical analyses in this report determine how much this affects our understanding of this data.



As the next step in exploratory data analysis, the graph above was created to examine mental health search terms as a function of time, regardless of any COVID restrictions or of any specific country. This graph was made for all search terms, but it was found that the graph for OCD search topic frequency provided the most insight into how individuals' mental state shifted during the pandemic. By using geom_smooth, the line on the plot demonstrates a slight increase in frequency of searching for OCD during the first wave of COVID. From a qualitative standpoint, this increase would align with the notion that individuals became concerned with signs of OCD as much of the population became highly obsessive over cleanliness, which is often understood as OCD in the general population despite this definition being slightly inaccurate. It could also be due to individuals demonstrating signs of a compulsive need to follow certain rituals in order to feel safe from COVID.

Statistical analysis provided further in the report explores the significance, if any, of this increase.

```
new_set %>%
  filter(COUNTRY == "India") %>%
  ggplot() + geom_point(mapping = aes(y = SCHOOLS, x = date, color = "Red")) + geom_point(mapping = aes
```


Comparing COVID−19 Restrictions on Schools and Google Searches for Ar
India
Severity Index
40
30
20
10
0
2020−01
2020−07
2021−01
2021−07
Date
Legend
Anxiety Searches
School Restrictions

Linear Regression

```
US_data <- lim_set %>%
  filter(COUNTRY == "United States")

Brazil_data <- lim_set %>%
  filter(COUNTRY == "Brazil")

Mexico_data <- lim_set %>%
  filter(COUNTRY == "Mexico")

NewZealand_data <- lim_set %>%
  filter(COUNTRY == "New Zealand")

India_data <- lim_set %>%
  filter(COUNTRY == "India")
```

```
# United States

US_relative_therapy_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_therapy ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = US_data

US_relative_therapy_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: USA, Search: Therapy")
```

Table 3: Nation: USA, Search: Therapy

term	estimate	std.error	statistic	p.value
(Intercept)	93.4381	1.8105	51.6102	0.0000
MASKS	0.0706	0.0212	3.3349	0.0013
TRAVEL	0.0109	0.0481	0.2269	0.8211
GATHERINGS	0.1804	0.0680	2.6523	0.0096
SCHOOLS	-0.2416	0.0739	-3.2691	0.0016
BUSINESSES	0.0994	0.0260	3.8175	0.0003
MOVEMENTS	0.0014	0.0200	0.0693	0.9449

```
US_relative_anxiety_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_anxiety ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = US_data

US_relative_anxiety_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: USA, Search: Anxiety")
```

Table 4: Nation: USA, Search: Anxiety

term	estimate	std.error	statistic	p.value
(Intercept)	101.6822	1.8172	55.9569	0.0000
MASKS	0.0706	0.0213	3.3207	0.0014
TRAVEL	0.0017	0.0483	0.0354	0.9718
GATHERINGS	0.1011	0.0683	1.4803	0.1427
SCHOOLS	-0.1738	0.0742	-2.3427	0.0216

term	estimate	std.error	statistic	p.value
BUSINESSES	0.0693	0.0261	2.6509	0.0097
MOVEMENTS	0.0428	0.0201	2.1284	0.0364

```
# Brazil

Brazil_relative_ocd_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_ocd ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Brazil_data)

Brazil_relative_ocd_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Brazil, Search: OCD")
```

Table 5: Nation: Brazil, Search: OCD

term	estimate	std.error	statistic	p.value
(Intercept)	101.6838	3.5204	28.8838	0.0000
MASKS	0.1732	0.0755	2.2947	0.0244
TRAVEL	-0.0516	0.0534	-0.9648	0.3376
GATHERINGS	0.1819	0.1557	1.1681	0.2462
SCHOOLS	-0.6105	0.1860	-3.2825	0.0015
BUSINESSES	0.0771	0.0624	1.2347	0.2206
MOVEMENTS	0.1870	0.0694	2.6958	0.0086

```
Brazil_relative_therapy_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_therapy ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Brazil_

Brazil_relative_therapy_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Brazil, Search: Therapy")
```

Table 6: Nation: Brazil, Search: Therapy

term	estimate	std.error	statistic	p.value
(Intercept)	108.1074	1.6076	67.2479	0.0000
MASKS	0.1889	0.0345	5.4795	0.0000
TRAVEL	-0.0760	0.0244	-3.1160	0.0025
GATHERINGS	-0.1496	0.0711	-2.1048	0.0385
SCHOOLS	0.1444	0.0849	1.7004	0.0929
BUSINESSES	-0.0862	0.0285	-3.0224	0.0034
MOVEMENTS	-0.0322	0.0317	-1.0177	0.3119

```
# Mexico

Mexico_dep_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_depression ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Mexi

Mexico_dep_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Mexico, Search: Depression")
```

Table 7: Nation: Mexico, Search: Depression

term	estimate	std.error	statistic	p.value
(Intercept)	103.9686	4.3731	23.7745	0.0000
MASKS	0.5112	0.1493	3.4236	0.0010
TRAVEL	-0.0224	0.0492	-0.4557	0.6499
GATHERINGS	0.4850	0.1531	3.1672	0.0022
SCHOOLS	-1.0561	0.3770	-2.8010	0.0064
BUSINESSES	0.1051	0.0679	1.5477	0.1257
MOVEMENTS	-0.6979	0.2007	-3.4766	0.0008

```
Mexico_relative_insomnia_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_insomnia ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Mexico_

Mexico_relative_insomnia_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Mexico, Search: Insomnia")
```

Table 8: Nation: Mexico, Search: Insomnia

term	estimate	std.error	statistic	p.value
(Intercept)	104.6186	7.6423	13.6894	0.0000
MASKS	-1.7312	0.2610	-6.6339	0.0000
TRAVEL	0.1912	0.0860	2.2221	0.0291
GATHERINGS	-0.4785	0.2676	-1.7881	0.0776
SCHOOLS	3.9493	0.6589	5.9939	0.0000
BUSINESSES	0.0240	0.1187	0.2021	0.8403
MOVEMENTS	1.6124	0.3508	4.5964	0.0000

```
# India

India_relative_insomnia_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_insomnia ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = India_c

India_relative_insomnia_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: India, Search: Insomnia")
```

Table 9: Nation: India, Search: Insomnia

term	estimate	std.error	statistic	p.value
(Intercept)	118.1261	7.2126	16.3777	0.0000
MASKS	0.5406	0.2569	2.1043	0.0385
TRAVEL	-0.2096	0.1877	-1.1171	0.2673
GATHERINGS	0.6567	0.2389	2.7490	0.0074
SCHOOLS	-2.2563	0.5041	-4.4758	0.0000
BUSINESSES	0.4375	0.2233	1.9595	0.0535
MOVEMENTS	0.0890	0.1076	0.8265	0.4110

```
Mexico_relative_ocd_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_ocd ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Mexico_data)

Mexico_relative_ocd_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Mexico, Search: OCD")
```

Table 10: Nation: Mexico, Search: OCD

term	estimate	std.error	statistic	p.value
(Intercept)	138.9079	11.7854	11.7865	0.0000
MASKS	-0.5221	0.4024	-1.2974	0.1982
TRAVEL	-0.0625	0.1327	-0.4709	0.6390
GATHERINGS	-0.3618	0.4127	-0.8768	0.3832
SCHOOLS	0.9272	1.0161	0.9126	0.3642
BUSINESSES	0.2315	0.1830	1.2651	0.2095
MOVEMENTS	0.2300	0.5410	0.4251	0.6719

```
Mexico_relative_therapy_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_therapy ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Mexico_

Mexico_relative_therapy_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Mexico, Search: Therapy")
```

Table 11: Nation: Mexico, Search: Therapy

term	estimate	std.error	statistic	p.value
(Intercept)	100.9349	2.0019	50.4206	0.0000
MASKS	0.0765	0.0684	1.1188	0.2666
TRAVEL	-0.0466	0.0225	-2.0681	0.0419
GATHERINGS	-0.1579	0.0701	-2.2522	0.0271
SCHOOLS	0.2278	0.1726	1.3199	0.1906
BUSINESSES	0.0392	0.0311	1.2602	0.2112
MOVEMENTS	-0.1112	0.0919	-1.2097	0.2299

```
Mexico_relative_anxiety_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_anxiety ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Mexico_

Mexico_relative_anxiety_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: Mexico, Search: Anxiety")
```

Table 12: Nation: Mexico, Search: Anxiety

term	estimate	std.error	statistic	p.value
(Intercept)	124.0169	4.0845	30.3629	0.0000
MASKS	0.1912	0.1395	1.3707	0.1743
TRAVEL	0.0435	0.0460	0.9452	0.3474
GATHERINGS	-0.4290	0.1430	-2.9993	0.0036

term	estimate	std.error	statistic	p.value
SCHOOLS	1.3158	0.3521	3.7365	0.0003
BUSINESSES	-0.0662	0.0634	-1.0437	0.2998
MOVEMENTS	-0.2131	0.1875	-1.1368	0.2590

```
NewZealand_relative_ocd_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_ocd ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = NewZealand_c

NewZealand_relative_ocd_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: New Zealand, Search: OCD")
```

Table 13: Nation: New Zealand, Search: OCD

term	estimate	std.error	statistic	p.value
(Intercept)	112.9591	16.3976	6.8888	0.0000
MASKS	NA	NA	NA	NA
TRAVEL	0.0513	0.1642	0.3122	0.7557
GATHERINGS	-0.1562	0.6477	-0.2411	0.8101
SCHOOLS	0.3477	0.2874	1.2101	0.2298
BUSINESSES	-0.3988	0.3586	-1.1122	0.2693
MOVEMENTS	0.0867	1.5186	0.0571	0.9546

```
NewZealand_dep_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_depression ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = NewZe

NewZealand_dep_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: New Zealand, Search: Depression")
```

Table 14: Nation: New Zealand, Search: Depression

term	estimate	std.error	statistic	p.value
(Intercept)	85.8043	6.1572	13.9356	0.0000
MASKS	NA	NA	NA	NA
TRAVEL	0.1367	0.0617	2.2165	0.0295
GATHERINGS	0.2416	0.2432	0.9934	0.3235
SCHOOLS	-0.3181	0.1079	-2.9483	0.0042
BUSINESSES	-0.1054	0.1347	-0.7830	0.4359
MOVEMENTS	0.6475	0.5702	1.1356	0.2595

```
NewZealand_relative_therapy_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_therapy ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = NewZeala

NewZealand_relative_therapy_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: New Zealand, Search: Therapy")
```

Table 15: Nation: New Zealand, Search: Therapy

term	estimate	std.error	statistic	p.value
(Intercept)	104.9165	3.7656	27.8619	0.0000
MASKS	NA	NA	NA	NA
TRAVEL	-0.0165	0.0377	-0.4371	0.6632
GATHERINGS	0.2461	0.1487	1.6545	0.1019
SCHOOLS	0.0821	0.0660	1.2437	0.2172
BUSINESSES	-0.3045	0.0823	-3.6973	0.0004
MOVEMENTS	0.0040	0.3487	0.0115	0.9909

```
NewZealand_relative_anxiety_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_anxiety ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = NewZeala

NewZealand_relative_anxiety_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: New Zealand, Search: Anxiety")
```

Table 16: Nation: New Zealand, Search: Anxiety

term	estimate	std.error	statistic	p.value
(Intercept)	84.3557	5.3406	15.7951	0.0000
MASKS	NA	NA	NA	NA
TRAVEL	0.0537	0.0535	1.0047	0.3181
GATHERINGS	0.3360	0.2110	1.5928	0.1151
SCHOOLS	0.1478	0.0936	1.5793	0.1182
BUSINESSES	0.1676	0.1168	1.4353	0.1551
MOVEMENTS	-0.1052	0.4946	-0.2127	0.8321

```
NewZealand_relative_insomnia_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_insomnia ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = NewZeal

NewZealand_relative_insomnia_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: New Zealand, Search: Insomnia")
```

Table 17: Nation: New Zealand, Search: Insomnia

term	estimate	std.error	statistic	p.value
(Intercept)	103.8355	12.4822	8.3187	0.0000
MASKS	NA	NA	NA	NA
TRAVEL	-0.0641	0.1250	-0.5129	0.6094
GATHERINGS	0.0695	0.4931	0.1410	0.8882
SCHOOLS	-0.2912	0.2187	-1.3312	0.1868
BUSINESSES	0.1570	0.2730	0.5750	0.5669
MOVEMENTS	1.1378	1.1560	0.9842	0.3279

```
India_relative_ocd_reg <- linear_reg() %>%
  set_engine("lm") %>%
```

```
  fit(relative_ocd ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = India_data)

India_relative_ocd_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: India, Search: OCD")
```

Table 18: Nation: India, Search: OCD

term	estimate	std.error	statistic	p.value
(Intercept)	129.9740	5.0571	25.7011	0.0000
MASKS	0.6315	0.1801	3.5060	0.0007
TRAVEL	-0.2281	0.1316	-1.7336	0.0868
GATHERINGS	0.0579	0.1675	0.3458	0.7304
SCHOOLS	-1.2598	0.3535	-3.5644	0.0006
BUSINESSES	-0.0564	0.1566	-0.3603	0.7196
MOVEMENTS	0.0999	0.0755	1.3242	0.1892

```
India_dep_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_depression ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = Indi

India_dep_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: India, Search: Depression")
```

Table 19: Nation: India, Search: Depression

term	estimate	std.error	statistic	p.value
(Intercept)	108.9893	22.9494	4.7491	0.0000
MASKS	0.1275	0.8175	0.1559	0.8765
TRAVEL	0.1556	0.5972	0.2606	0.7951
GATHERINGS	0.6706	0.7601	0.8822	0.3803
SCHOOLS	1.2974	1.6040	0.8088	0.4210
BUSINESSES	-0.6624	0.7105	-0.9324	0.3539
MOVEMENTS	0.0522	0.3424	0.1525	0.8792

```
India_relative_therapy_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_therapy ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = India_da

India_relative_therapy_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: India, Search: Therapy")
```

Table 20: Nation: India, Search: Therapy

term	estimate	std.error	statistic	p.value
(Intercept)	114.4363	2.5684	44.5559	0.0000
MASKS	0.2941	0.0915	3.2152	0.0019
TRAVEL	-0.1772	0.0668	-2.6516	0.0097
GATHERINGS	-0.1074	0.0851	-1.2631	0.2102
SCHOOLS	-0.2459	0.1795	-1.3698	0.1746
BUSINESSES	0.0985	0.0795	1.2394	0.2188

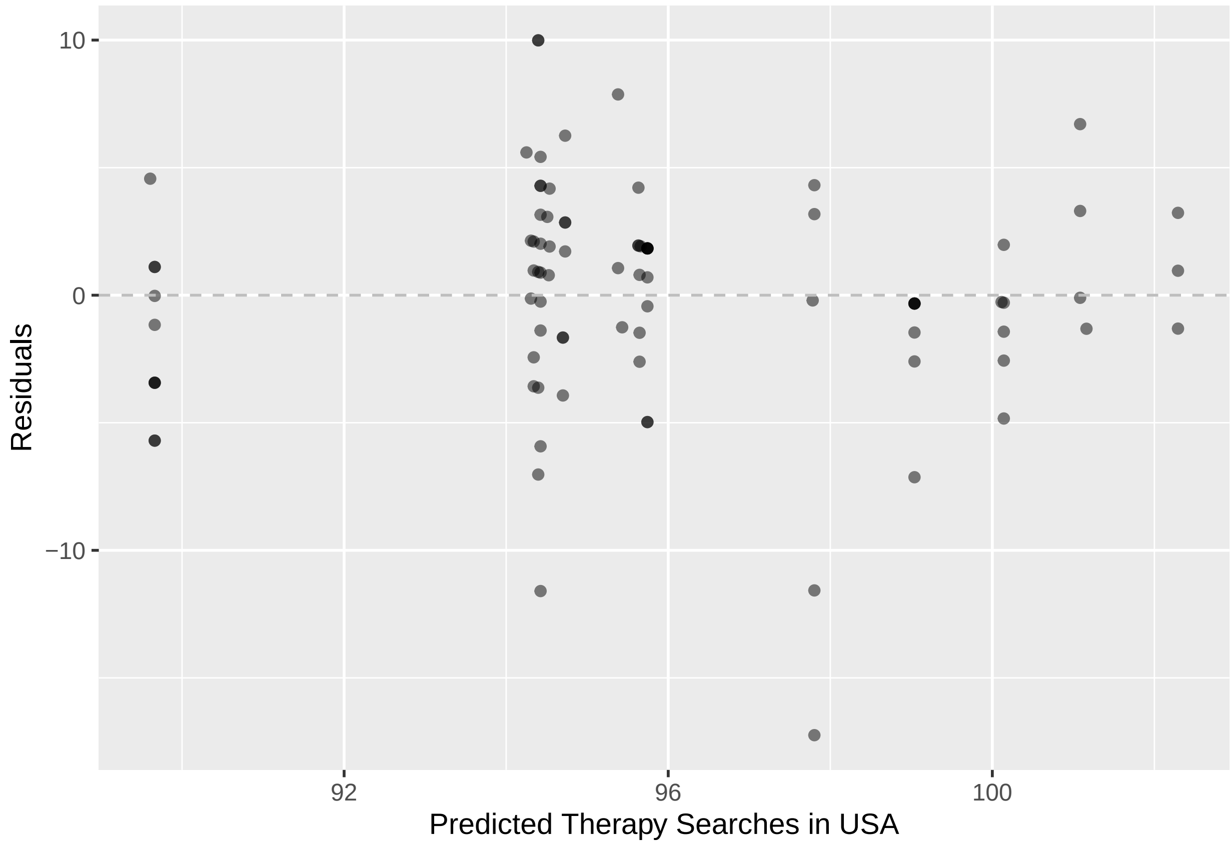
term	estimate	std.error	statistic	p.value
MOVEMENTS	0.0696	0.0383	1.8161	0.0731

```
India_relative_anxiety_reg <- linear_reg() %>%
  set_engine("lm") %>%
  fit(relative_anxiety ~ MASKS + TRAVEL + GATHERINGS + SCHOOLS + BUSINESSES + MOVEMENTS, data = India_da

India_relative_anxiety_reg %>%
  tidy() %>%   knitr::kable(digits=4,caption="Nation: India, Search: Anxiety")
```

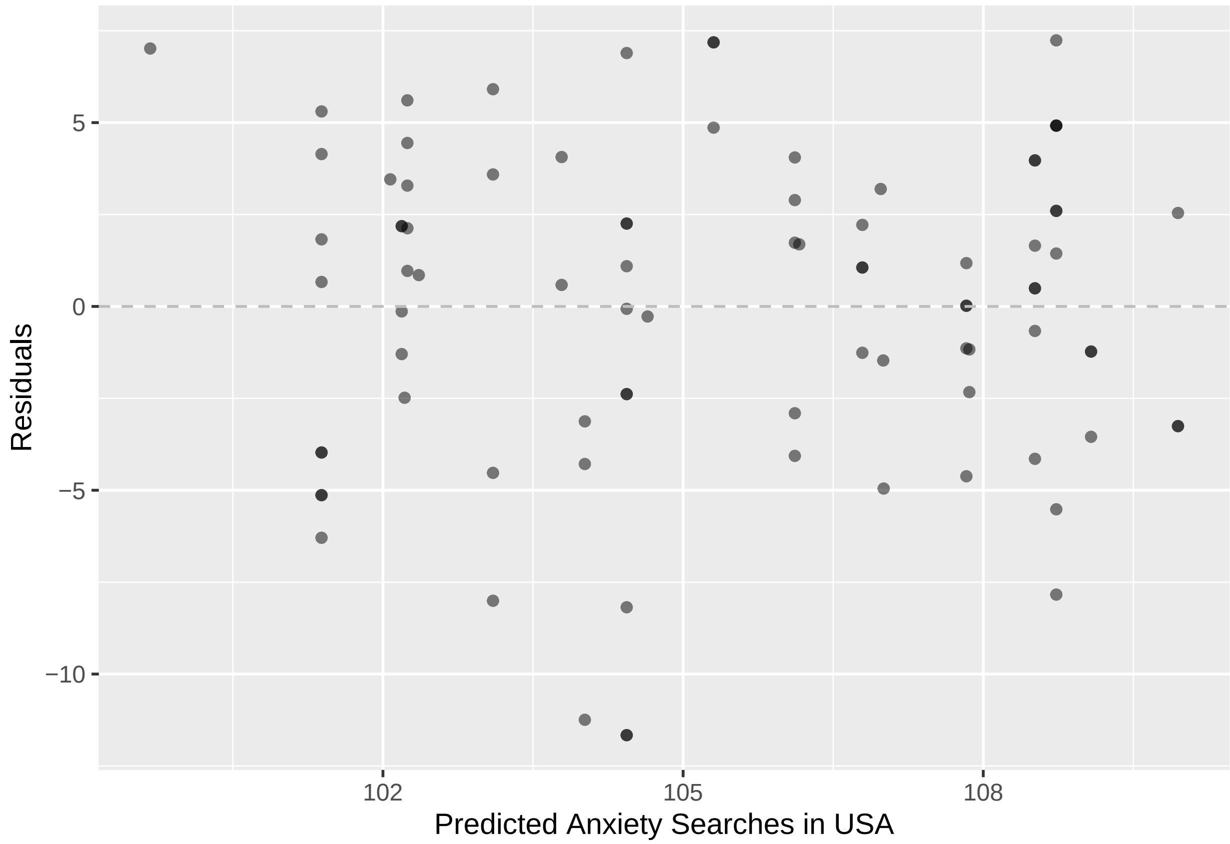
Table 21: Nation: India, Search: Anxiety

term	estimate	std.error	statistic	p.value
(Intercept)	94.1356	4.5351	20.7572	0.0000
MASKS	0.3905	0.1615	2.4173	0.0179
TRAVEL	-0.0961	0.1180	-0.8144	0.4178
GATHERINGS	0.0148	0.1502	0.0987	0.9216
SCHOOLS	-0.6451	0.3170	-2.0352	0.0451
BUSINESSES	0.2298	0.1404	1.6365	0.1057
MOVEMENTS	0.0138	0.0677	0.2036	0.8392

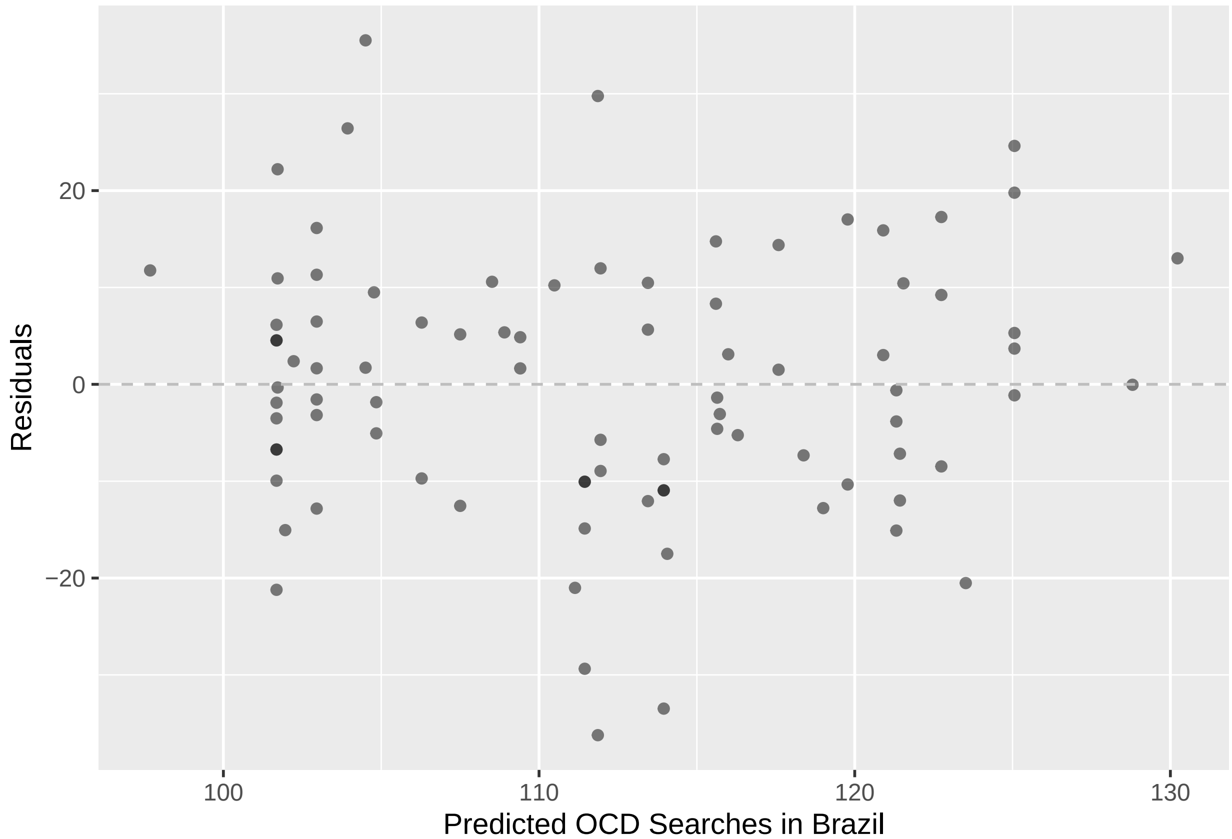
```
US_therapy_aug <- augment(US_relative_therapy_reg$fit)

ggplot(US_therapy_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Therapy Searches in USA", y = "Residuals")
```



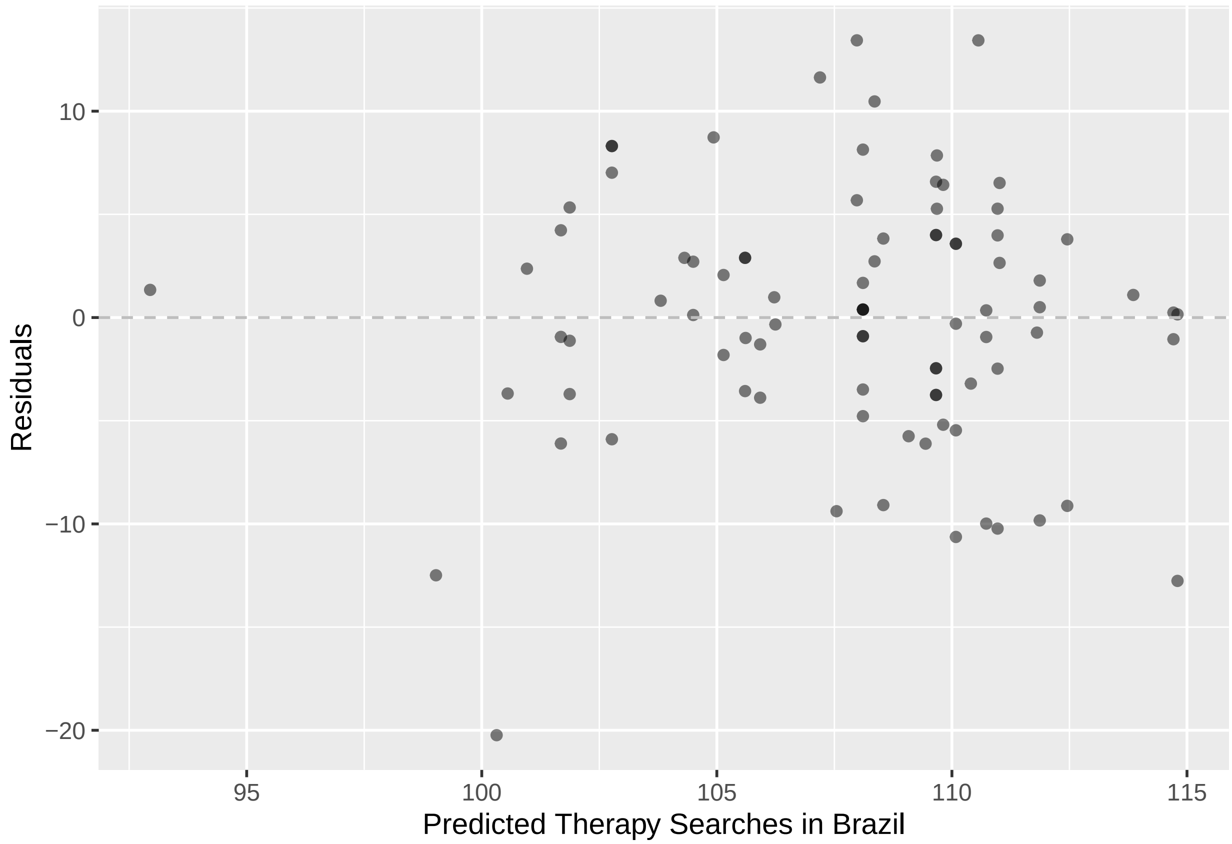

```r
US_anxiety_aug <- augment(US_relative_anxiety_reg$fit)

ggplot(US_anxiety_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Anxiety Searches in USA", y = "Residuals")
```



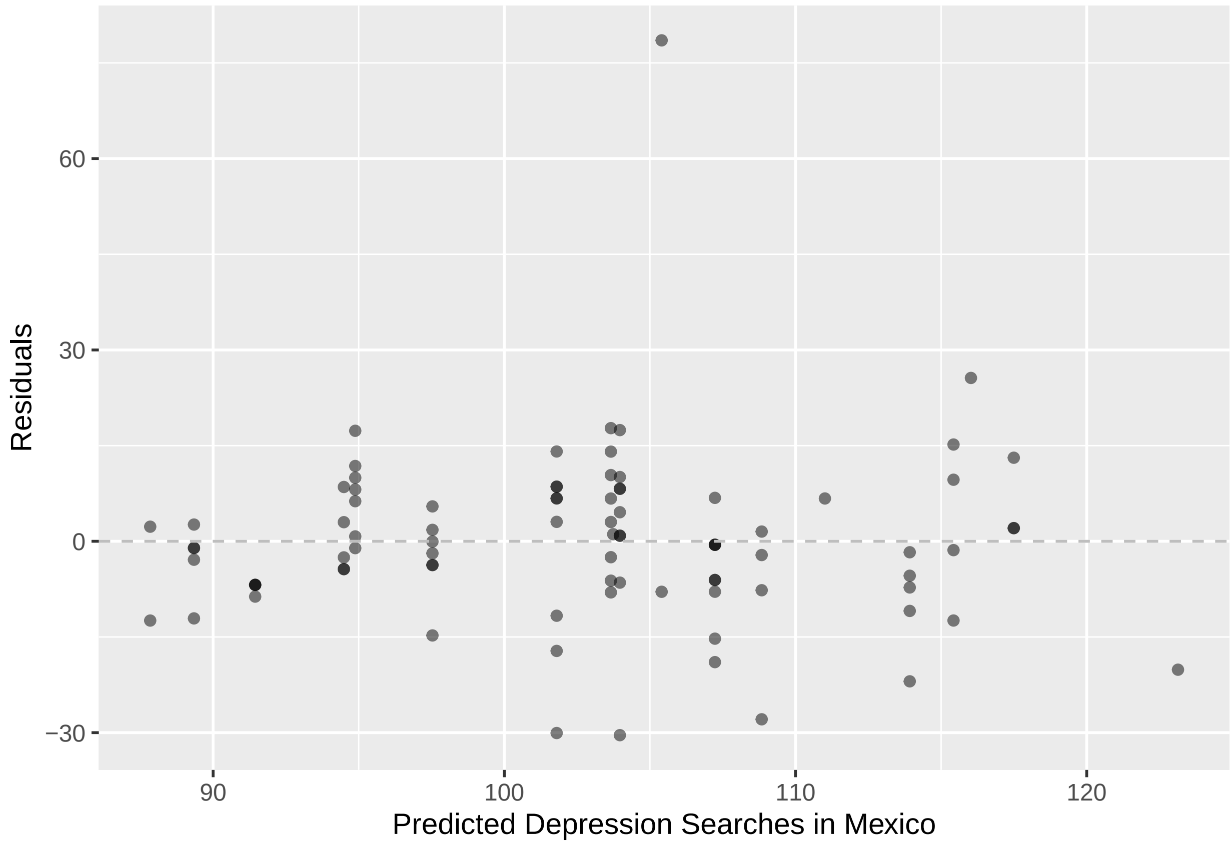

```
Brazil_ocd_aug <- augment(Brazil_relative_ocd_reg$fit)

ggplot(Brazil_ocd_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted OCD Searches in Brazil", y = "Residuals")
```



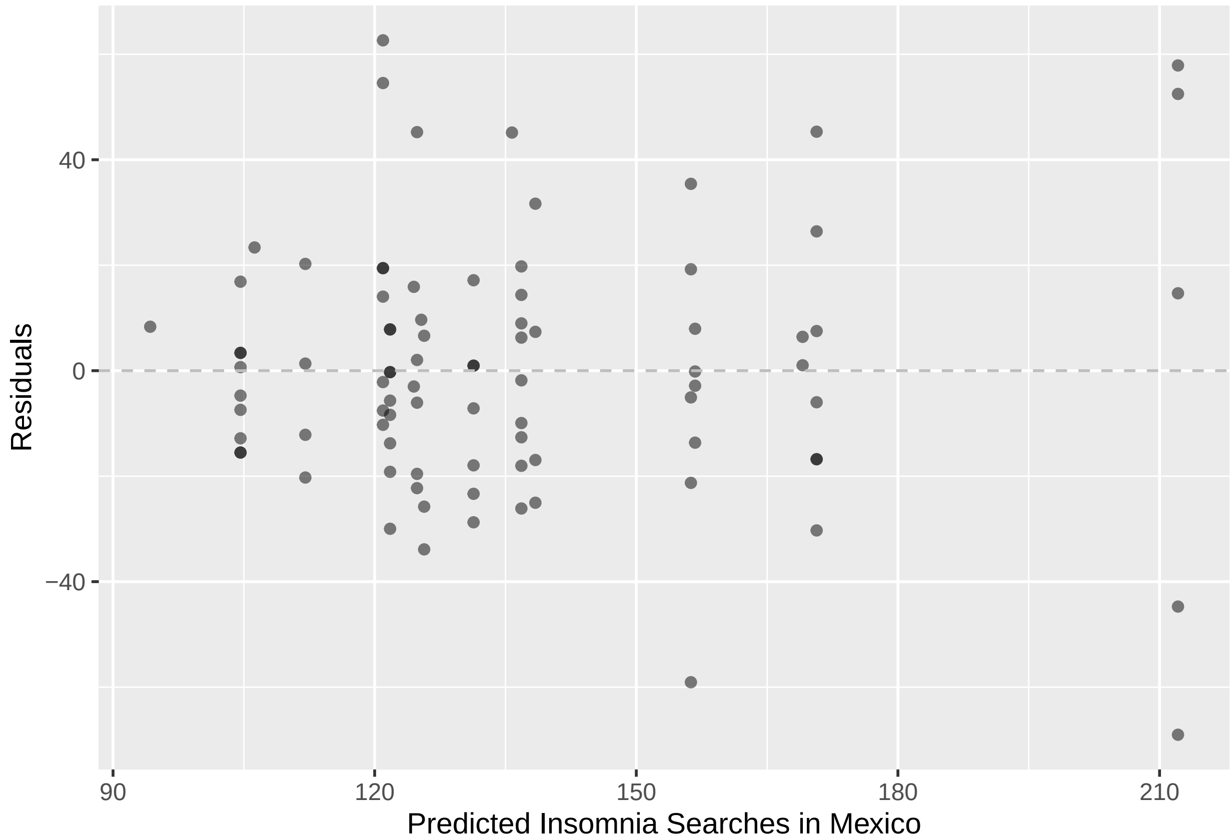

```
Brazil_therapy_aug <- augment(Brazil_relative_therapy_reg$fit)

ggplot(Brazil_therapy_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Therapy Searches in Brazil", y = "Residuals")
```



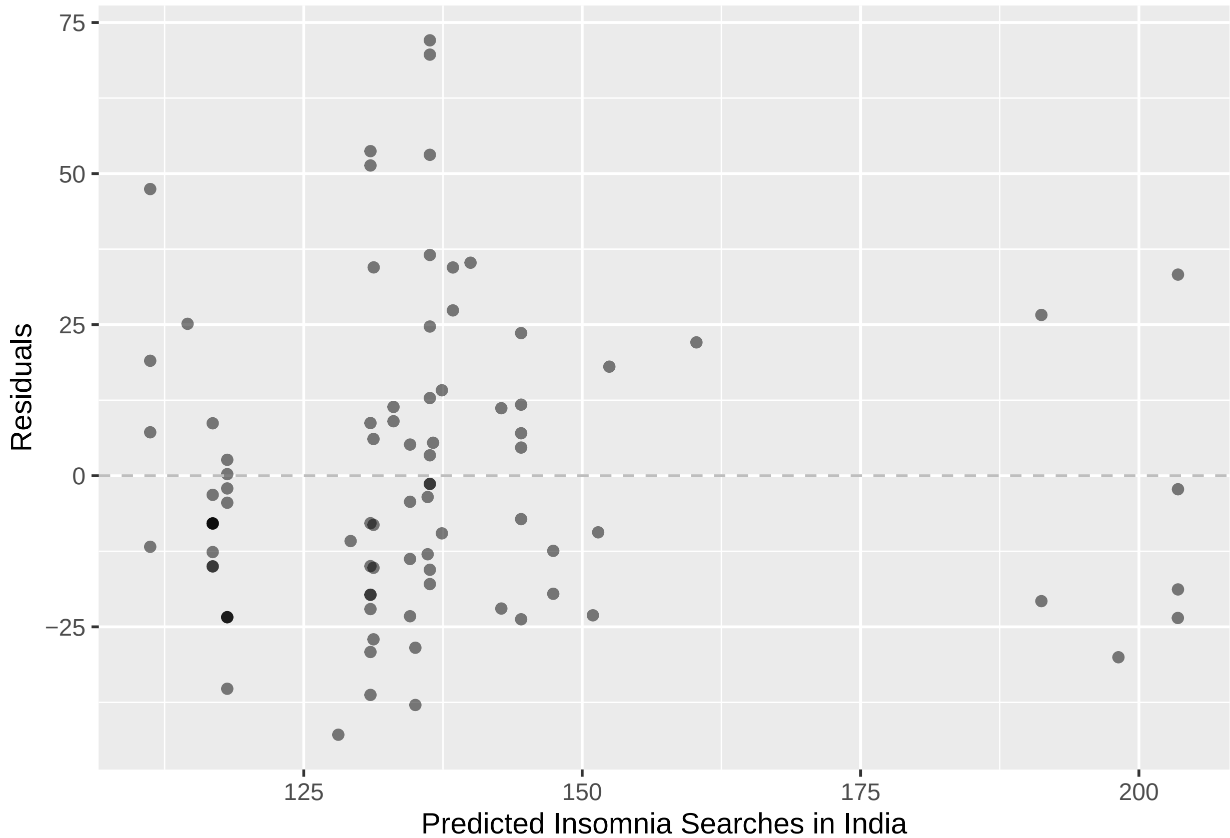

```
Mexico_dep_aug <- augment(Mexico_dep_reg$fit)

ggplot(Mexico_dep_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Depression Searches in Mexico", y = "Residuals")
```




```
Mexico_insomnia_aug <- augment(Mexico_relative_insomnia_reg$fit)

ggplot(Mexico_insomnia_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Insomnia Searches in Mexico", y = "Residuals")
```




```
India_insomnia_aug <- augment(India_relative_insomnia_reg$fit)

ggplot(India_insomnia_aug, mapping = aes(x = .fitted, y = .resid)) +
  geom_point(alpha = 0.5) +
  geom_hline(yintercept = 0, color = "gray", lty = "dashed") +
  labs(x = "Predicted Insomnia Searches in India", y = "Residuals")
```



The residual plots above were created to understand any concern over the linear regression models applied to the data. Residual plots were only created for models that showed significant findings, as these are the data sets the rest of the interpretation will primarily focus on.

None of the residual plots have a clear pattern. Although some of the residual plots are concentrated on one side of the plot, there is still no discernible pattern in the variation, indicating that the models are appropriate for the data.

References

Centers for Disease Control and Prevention. (2021). Coping with stress. Centers for Disease Control and Prevention. Retrieved October 11, 2021, from (https://www.cdc.gov/mentalhealth/stress-coping/cope-with-stress/index.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fdaily-life-coping%2Fmanaging-stress-anxiety.html).

Our World in Data. Cumulative confirmed covid-19 cases and deaths. Our World in Data. (n.d.). Retrieved October 11, 2021, from (https://ourworldindata.org/grapher/cumulative-deaths-and-cases-covid-19).