Systemic Gaps in Access to Care

Elizabeth Genoway, Richard Bustamante

Introduction:

This project explores the systemic gaps in the United States healthcare system, focusing on how identity, income, age, and disability status can impact a person's ability to receive quality care in a timely fashion. Using the data from the National Health Interview Survey (NHIS) and looking at the time frame 2019 - 2023, we wanted to reveal the "why" behind these unmet and delayed healthcare needs. Our analysis was guided by these 3 questions:

1. Which subgroups experience the highest rates of delayed or unmet care?
2. How do barriers differ by age, sexual orientation, income, and disability?
3. Are there trends over time (2019–2023) in delayed care or health outcomes?

To answer these questions we developed a Metric that allows us to see how much more marginalized groups are affected compared to other demographic groups. We also integrated some research from the KFF and WHO organizations to ensure our findings reflect real-world experiences. Finally we developed a logarithmic regression model that predicts trends in delayed care and health outcomes.

The dataset:

- **Provided by DubsTech: Access_to_Care_Dataset.csv**
  - This data represents the national health estimates for the U.S. population from 2019 - 2024 and is derived from the National Health Interview Survey (NHIS).
- **Additional readings/data**
  - Barriers for sexual orientation: Health and Access to Care and Coverage for Lesbian, Gay, Bisexual, and Transgender (LGBT) Individuals in the U.S. | KFF
  - Barriers for cost (income):Key Facts about the Uninsured Population | KFF
  - Barriers for persons with disabilities:Disability

Question 1 - Which subgroups experience the highest rates of delayed or unmet care?

Metric design: To find the which subgroups have the highest rate of delayed and unmet medical care, our approach was to:

- Separate data that's specific to "Healthcare access and quality"
- Filter out topics that aren't directly related, which included access to prescriptions and having a usual place of care. Also filter the age group "18 to 44" as it's redundant with "18 to 34" but less specific.
- Compute the average estimate for each group and topic combination, and sort from top to bottom. Taking the 5 highest rates for each combination.
- Finally compute the percent change from a baseline average for each of the groups as this is a meaningful metric for how they've been impacted.

```
library("tidyverse")
library("margins")

group_num <- 5
subgroup_avgs <- health_df %>%
  filter(TAXONOMY == "Healthcare access and quality") %>%
  filter(TOPIC != "Has a usual place of care among adults") %>%
  filter(TOPIC != "Did not take medication as prescribed to save money") %>%
  filter(SUBGROUP != "18-44 years") %>%
  group_by(SUBGROUP, TOPIC) %>%
  summarize(avg_estimate = mean(ESTIMATE)) %>%
  arrange(desc(avg_estimate)) %>%
  ungroup()
top_subgroups <- subgroup_avgs %>%
  group_by(TOPIC) %>%
  arrange(desc(avg_estimate)) %>%
  slice(1:group_num) %>%
  ungroup()
```

The average for the total population was computed separately and added here for each topic for comparison.

```
top_subgroups <- top_subgroups %>%
  mutate(total_avg = recode(
    TOPIC,
    "Delayed getting medical care due to cost among adults" = 8.044714,
```

```
    "Did not get needed medical care due to cost" = 7.209051,
    "Did not get needed mental health care due to cost" = 4.961348,
    "Did not take medication as prescribed to save money" = 8.432373,
    "Has a usual place of care among adults" = 87.924838,
    .default = 0
  ))
top_subgroups <- top_subgroups %>%
 mutate(avg_estimate = unlist(avg_estimate)) %>%
 mutate(total_avg = unlist(total_avg)) %>%
 mutate(percent_point_diff = avg_estimate - total_avg) %>%
 mutate(percent_diff = (percent_point_diff / total_avg) * 100)
```

Change the Topic names to shorter versions for visualization, and change the FPL (Federal Poverty Level) to their dollar equivalents to make it easier to understand.

```
top_subgroups <- top_subgroups %>%
 mutate(TOPIC = recode(
    TOPIC,
    "Delayed getting medical care due to cost among adults" = "Delayed Medical Care",
    "Did not get needed medical care due to cost" = "Unmet Medical Care",
    "Did not get needed mental health care due to cost" = "Unmet Mental Health Care",
    "Did not take medication as prescribed to save money" = "Unmet Prescriptions",
    "Has a usual place of care among adults" = "Usual Place of Care",
    .default = TOPIC
  ))%>%
 mutate(SUBGROUP = recode(
    SUBGROUP,
    "<100% FPL" = "Earns <$32k",
    "100% to <200% FPL" = "Earns $32k~$64k",
    .default = SUBGROUP
  ))
```

Change subgroup to a factor so it appears as a category, and set the order so the order of bars and legend are consistent.

```
top_subgroups$SUBGROUP <- factor(top_subgroups$SUBGROUP, levels = c(
    "Bisexual",
    "Gay or Lesbian",
    "Living with a partner",
    "Earns <$32k",
    "Earns $32k~$64k",
    "18-34 years",
    "With disability"
  ))
```

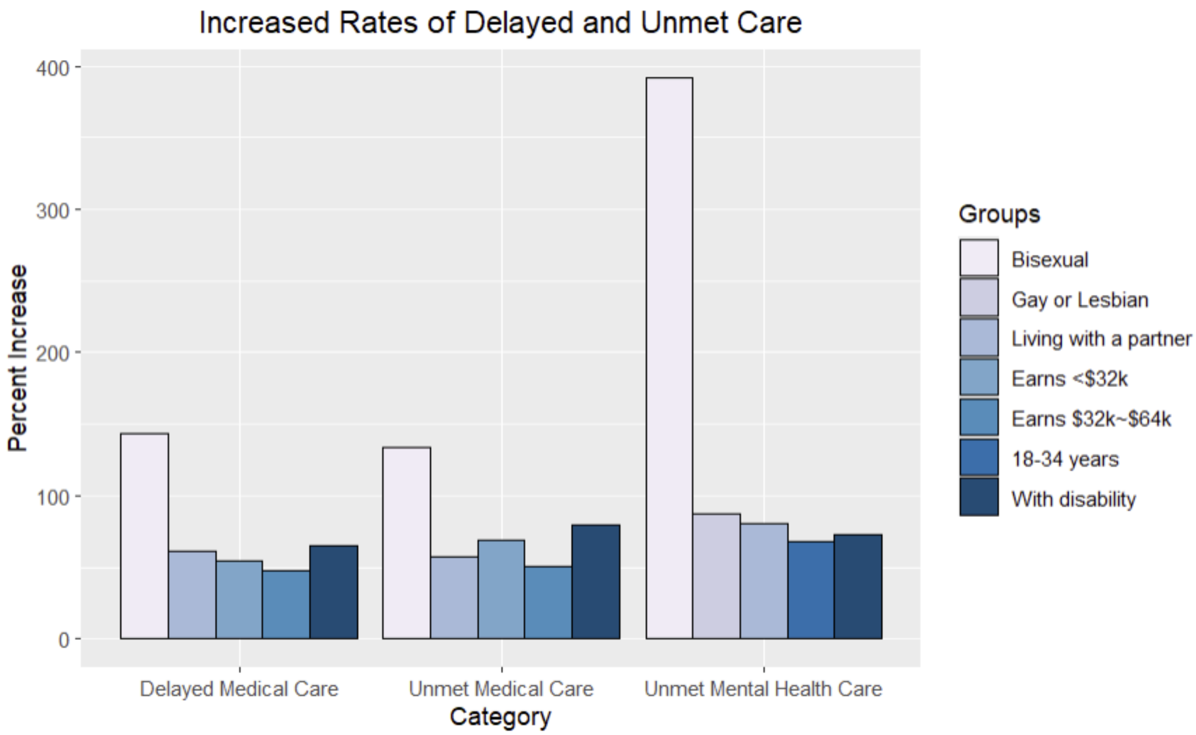
Do the same for the subgroups to set the order they appear in the visualization.

```
top_subgroups$TOPIC <- factor(top_subgroups$TOPIC, levels = c(
    "Delayed Medical Care",
    "Unmet Medical Care",
    "Unmet Mental Health Care",
    "Unmet Prescriptions",
    "Usual Place of Care"
))
```

- **Visualizations information:**
    - **Add plots, charts, any visualization we have in this section**

Finally create a barchart plot, use a "Purple to Blue" color scheme.

```
top_subgroups %>%
  ggplot(aes(y = percent_diff, x = TOPIC, fill=SUBGROUP)) +
  geom_bar(stat = "identity", position = position_dodge(), col="black") +
  labs(
    x = "Category",
    y = "Percent Increase",
    title = "Increased Rates of Delayed and Unmet Care",
    fill = "Groups"
  ) +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_fill_brewer(palette = "PuBu")
```



Conclusion:

Based on this analysis it is clear that healthcare access is not equal amongst everyone. We can see that the Bisexual subgroup experiences a larger disparity compared to any other demographic in this dataset. We can see that sexual orientation and disability status are strong indicators of unmet mental health and medical care and quality.

Question 2 - How do barriers differ by age, sexual orientation, income, and disability?

Access to healthcare and quality care are fundamental human needs; however, from our data, we can see that medical needs are not met equally. By measuring the Percent Increase in unmet needs relative to the national average, we identified five subgroups facing the most significant barriers: the LGBTQ+ community, persons with disabilities, lower-income earners (<$64K), individuals living with a partner, and the 18-34 age group.

The most significant outlier is the Bisexual subgroup, which exhibits the highest percent increase in unmet mental healthcare needs in the entire dataset. This disparity highlights a critical failure in equitable access for specific identities. Many LGBTQ+ individuals face discrimination and “poor treatment from healthcare providers,” which creates a dangerous cycle of avoidance. This treatment often stems from a "knowledge gap" where providers are not trained to address the specific health needs of this demographic.

Similarly, persons with disabilities face systemic exclusion, and many encounter inaccessible health facilities or medical equipment not designed for their bodies. Some providers might also not have the necessary disability-specific training.

Lastly, the “high cost of insurance” is cited as the primary reason individuals lack coverage. This financial barrier creates a measurable trend of delayed and unmet care for both low-income earners and our 18 - 34 age group. People earning less than $64K appear to have to choose between medical insurance and basic lifestyle needs. The 18 - 34 age group might have high rates of delayed care due to the high cost of insurance plans. Many people in this category may be students, off their parents' insurance, or simply can’t afford the high premiums.

Question 3 - Are there trends over time (2019–2023) in delayed care or health outcomes?

Metric design: Create a logarithmicregression model to predict the overall change in access to healthcare, as issues with access will never be zero, this is a better model than a linear one. The approach to this metric was to:

- Separate data that's specific to "Healthcare access and quality" and a specific topic, either unmet needs or delayed medical care.
- Filter only for years between 2019-2023, for the purposes of modeling treat 2019 as year 0.
- Then use glm() with family set to quasibinomial(link = "logit") to build a logarithmicregression model and run the data.
- Create a data frame with the year and predicted values, and return it for the model for use in graphs and summary.

```
log_regression_topic <- function (topic) {
  glm_health_df <- health_df %>%
    filter(TAXONOMY == "Healthcare access and quality") %>%
    filter(TOPIC == topic) %>%
    filter(TIME_PERIOD >2018 & TIME_PERIOD <2024) %>%
    mutate(TIME_PERIOD = TIME_PERIOD - 2019)
  m <- glm(ESTIMATE/100 ~ TIME_PERIOD, family = quasibinomial(link = "logit"),
data=glm_health_df)

  years <- 0:6
  b0 <- coef(m)["(Intercept)"]
  b1 <- coef(m)["TIME_PERIOD"]
  p_hat <- 1/(1 + exp(-(b0 + b1*years))) * 100

  predicted_estimate <- data.frame(year = years, p_hat = p_hat)
  return(list(model = m, predicted_estimate = predicted_estimate))
}
```

Use the function to get the logarithmicregression model for delayed care.

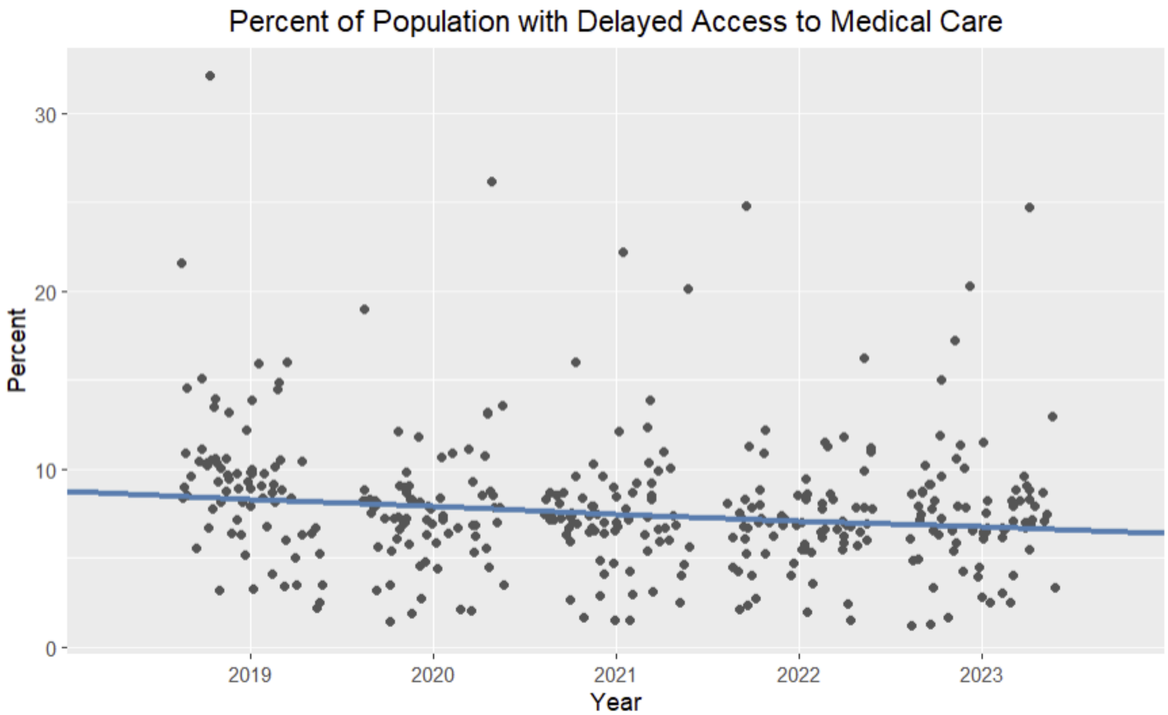
```
result <- log_regression_topic(
  "Delayed getting medical care due to cost among adults")
```

Build the plot with the predicted trend line added.

```
health_df %>%
  filter(TAXONOMY == "Healthcare access and quality") %>%
  filter(TOPIC == "Delayed getting medical care due to cost among adults") %>%
  filter(TIME_PERIOD >2018 & TIME_PERIOD <2024) %>%
  ggplot(aes(factor(TIME_PERIOD),ESTIMATE)) +
  geom_jitter(color="#555") +
  geom_line(size=1.2,data = result$predicted_estimate, aes(year, p_hat), col = "steelblue") +
  labs(
    x = "Year",
    y = "Percent",
    title = "Percent of Population with Delayed Access to Medical Care",
  ) +
  theme(plot.title = element_text(hjust = 0.5))
```

Use margins to interpret the results, seeing a 0.41 percentage point decrease each year (p=0.0027)

```
margins(result$model) %>% summary()
```



Use the function above to get the logarithmic regression model for unmet medical needs.

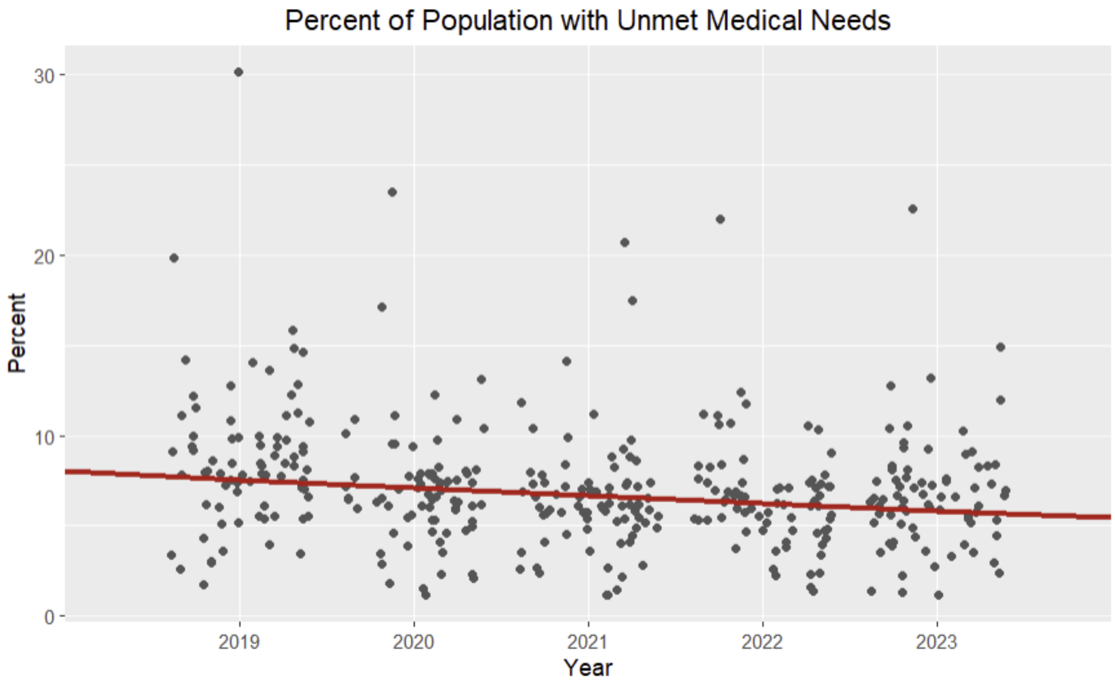
```
result <- log_regression_topic(
  "Did not get needed medical care due to cost")
```

Build the plot with the predicted trend line added.

```
health_df %>%
  filter(TAXONOMY == "Healthcare access and quality") %>%
  filter(TOPIC == "Did not get needed medical care due to cost") %>%
  filter(TIME_PERIOD >2018 & TIME_PERIOD <2024) %>%
  ggplot(aes(factor(TIME_PERIOD),ESTIMATE)) +
  geom_jitter(color="#555") +
  geom_line(size=1.2,data = result$predicted_estimate, aes(year, p_hat), col = "#b11") +
  labs(
    x = "Year",
    y = "Percent",
    title = "Percent of Population with Unmet Medical Needs",
  ) +
  theme(plot.title = element_text(hjust = 0.5))
```

Use margins to interpret the results, seeing a 0.46 percentage point decrease each year (p=0.0002)

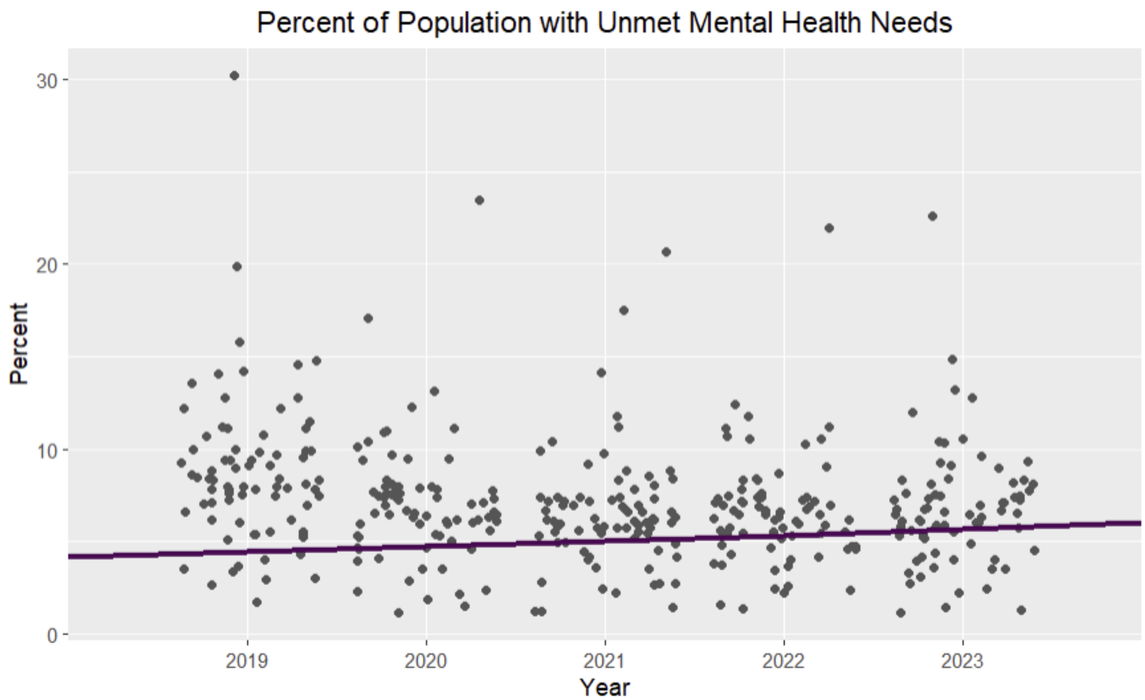
```
margins(result$model) %>% summary()
```



Use the function above to get the logarithmic regression model for unmet mental health care.

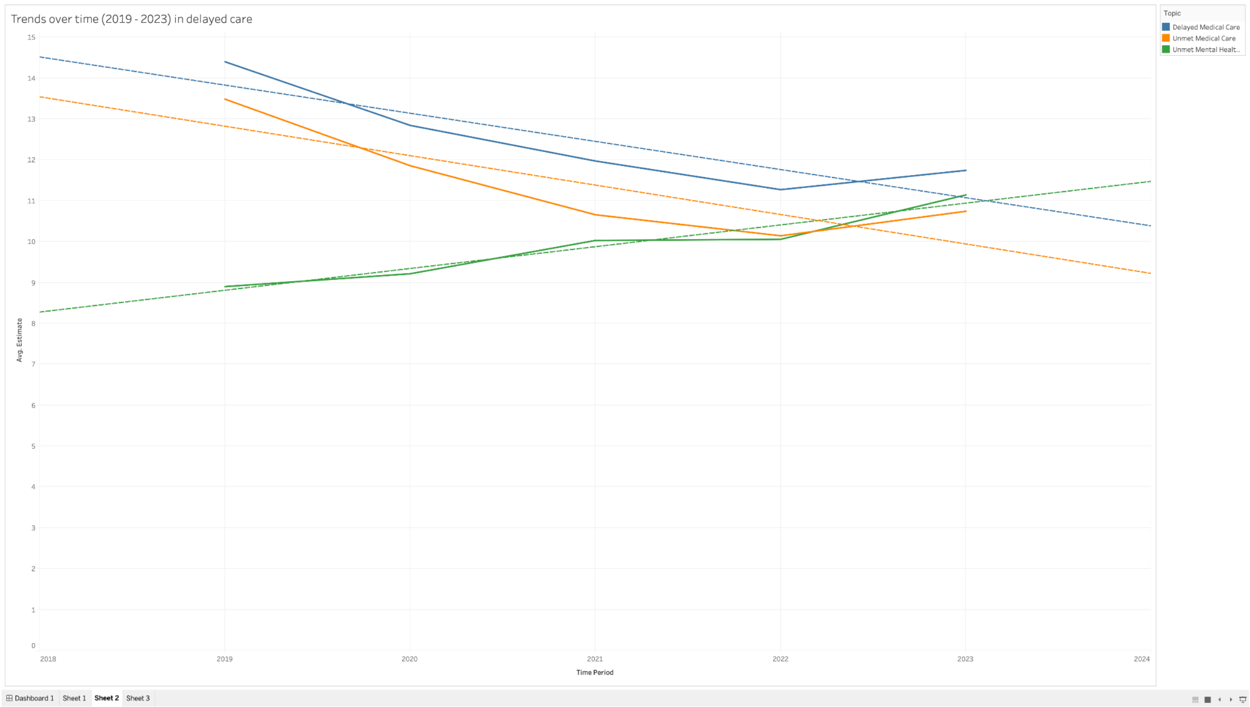
```
result <- log_regression_topic(
  "Did not get needed mental health care due to cost")

health_df %>%
  filter(TAXONOMY == "Healthcare access and quality") %>%
  filter(TOPIC == "Did not get needed medical care due to cost") %>%
  filter(TIME_PERIOD >2018 & TIME_PERIOD <2024) %>%
  ggplot(aes(factor(TIME_PERIOD),ESTIMATE)) +
  geom_jitter(color="#555") +
  geom_line(size=1.2,data = result$predicted_estimate, aes(year, p_hat), col = "#505") +
  labs(
    x = "Year",
```

```
  y = "Percent",
  title = "Percent of Population with Unmet Mental Health Needs",
 ) +
 theme(plot.title = element_text(hjust = 0.5))
```



Use margins to interpret the results, seeing a 0.29 percentage point increase each year (p=0.0086)

```
margins(result$model) %>% summary()
```



Conclusion: Yearly trends show a contrast in how patients are able to get access to care. While steady progress is being made in access to physical care for the overall population, access to mental health is becoming more difficult. The model shows these trends are highly statistically significant and likely to continue in future years.