TITLE TBD

Sheamin Kim, Lomash Sharma, Chris Joon Moy

2025-03-18

```r
# Loading necessary libraries
library(tidyverse)
library(lubridate)
library(gridExtra)
```

Background and Motivation

PASTE HERE

Data Cleaning/Prep

```r
## PRICE DATA CLEANING

vax_df <- read.csv("cdc_vaccine_prices_full.csv")
inflation_df <- read.csv("inflation_cpis.csv")

#standardizing values, getting rid of $
vax_df$Private.Sector.Cost..Dose = gsub("\\$", "", vax_df$Private.Sector.Cost..Dose)
vax_df$CDC.Cost..Dose = gsub("\\$", "", vax_df$CDC.Cost..Dose)

vax_df$Private.Sector.Cost..Dose <- as.numeric(as.character(vax_df$Private.Sector.Cost..Dose))

vax_df$CDC.Cost..Dose <- as.numeric(as.character(vax_df$CDC.Cost..Dose))

vax_df$Date <- as.Date(vax_df$Date)


## Adding inflation data
# extract the year and convert to numeric format
vax_df$year <- as.numeric(format(vax_df$Date, "%Y"))

vax_df = merge(x = vax_df, y = inflation_df, by = "year")
vax_df$CPI <- as.numeric(as.character(vax_df$CPI))
sapply(vax_df, class)

reference_year <- 2009

# Get CPI for the reference year (2009)
reference_cpi <- vax_df$CPI[vax_df$year == reference_year]
```

```r
# Adjust prices for inflation based on the reference CPI
vax_df$adjusted_price <- vax_df$Private.Sector.Cost..Dose * (reference_cpi / vax_df$CPI)
vax_df$adjusted_price_cdc <- vax_df$CDC.Cost..Dose * (reference_cpi / vax_df$CPI)


## RATES DATA CLEANING
df1 <- read.csv("monthly_cumulative.csv")

# Define the correct month order
month_levels <- c("SEP","OCT","NOV","DEC","JAN","FEB","MAR","APR","MAY","JUN","JUL","AUG")

# Ensure month is a factor for proper sorting
df1 <- df1 %>%
  mutate(month = factor(month, levels = month_levels))

# getting new dose numbers
rates_df <- df1 %>%
  arrange(current_season, jurisdiction, age_group_label, month) %>%
  group_by(current_season, jurisdiction, age_group_label) %>%
  mutate(
    new_doses = numerator - lag(numerator, default = NA)
  ) %>%
  ungroup()

overall_pop <- rates_df %>%
  filter(age_group_label == "Overall") %>%
  select(jurisdiction, current_season, population) %>%
  rename(overall_population = population)

rates_df <- rates_df %>%
  left_join(overall_pop, by = c("jurisdiction", "current_season"))

rates_df <- rates_df %>%
  mutate(vax_rate = new_doses / coalesce(population, overall_population))

rates_df <- rates_df %>%
  mutate(start_year = as.integer(substr(current_season, 1, 4)),
         date = as.Date(paste(start_year, month, "01", sep = "-"), format = "%Y-%b-%d"))

df_dedup <- rates_df %>%
  group_by(jurisdiction, age_group_label, current_season, date) %>%
  slice(1) %>%               # Keep only the first row for each group
  ungroup()

# Sort by jurisdiction, age group, season, and date to ensure proper order for calculating new doses
df_dedup <- df_dedup %>%
  arrange(jurisdiction, age_group_label, current_season, date)

# Calculate new doses by comparing the cumulative totals
df_dedup <- df_dedup %>%
  group_by(jurisdiction, age_group_label, current_season) %>%
  mutate(new_doses = numerator - lag(numerator)) %>%
  ungroup() %>%
```

```r
  mutate(new_doses = ifelse(new_doses < 0, 0, new_doses))


## ED VISITS DATA CLEANING
file1 <- "ed_traj.csv"
file2 <- "ed_visits.csv"
df_1 <- read.csv(file1)
df_2 <- read.csv(file2)

# Convert week_end to Date format
df_1$week_end <- as.Date(df_1$week_end, format="%Y-%m-%d")
df_2$week_end <- as.Date(df_2$week_end, format="%Y-%m-%d")

# Clean df1 (Trajectories dataset) - Select relevant columns
df1_clean <- df_1 %>%
  select(week_end, geography, county, percent_visits_influenza) %>%
  filter(!is.na(percent_visits_influenza))
# Clean df2 (Demographics dataset) - Select flu data only
df2_clean <- df_2 %>%
  filter(pathogen == "Influenza") %>%
  select(week_end, geography, percent_visits) %>%
  rename(percent_visits_influenza = percent_visits) %>%
  filter(!is.na(percent_visits_influenza))

# Merge both datasets for better insights
df_combined <- bind_rows(df1_clean, df2_clean)

df_combined$Date <- as.Date(df_combined$week_end)

df_combined$year <- format(df_combined$week_end, "%Y")
df_combined$month <- format(df_combined$week_end, "%m")
df_combined$month_abbr <- month.abb[as.numeric(df_combined$month)]

seasonal <- df_combined %>%
  filter(county == "All") %>%
  group_by(Date) %>%
  summarise(percent_visits_influenza = mean(percent_visits_influenza))

# create year and month columns based on date
seasonal$Date <- as.Date(seasonal$Date)
seasonal$year <- format(seasonal$Date, "%Y")
seasonal$month <- format(seasonal$Date, "%m")
seasonal$month_abbr <- month.abb[as.numeric(seasonal$month)]
```

Datasets

1. Flu vaccination rates

- https://healthdata.gov/dataset/Monthly-Cumulative-Number-and-Percent-of-Persons-W/8y48-wjrp/about_data

The flu vaccination rates dataset, sourced from HealthData.gov and maintained by the CDC, provides monthly cumulative counts and percentages of individuals who have received at least one dose of the influenza vaccine. The data spans multiple flu seasons, from 2019 to 2023, and is categorized by age group and jurisdiction (states, territories, and select cities). The data set is compiled from Immunization Information Systems (IIS), which aggregate vaccine administration data from various public health agencies.

This data set offers insights into vaccination trends over time and across different demographic groups. The cumulative nature of the records ensures that historical data is preserved, allowing for trend analysis. However, the data set has limitations, including variations in data completeness across jurisdictions and differences in state policies regarding vaccine data reporting. The population denominators used for calculating vaccination rates are sourced from the U.S. Census Bureau's 2020 estimates. Standard errors are not provided, as the data includes all vaccinations rather than a sample.

The table below shows the number of new doses a month across the three available seasons from 2021-2022, 2022-2023, and 2023-2024. Data is aggregated from age ranges and jurisdictions (US states).

```r
## Summary Table
monthly_trends <- rates_df %>%
  group_by(current_season, month) %>%
  summarise(new_doses = sum(new_doses, na.rm = TRUE)) %>%
  arrange(current_season, month)
```

```
## `summarise()` has grouped output by 'current_season'. You can override using
## the `.groups` argument.
```

```r
print(monthly_trends)
```

```
## # A tibble: 33 x 3
## # Groups:   current_season [3]
##    current_season month  new_doses
##    <chr>          <fct>      <dbl>
##  1 2021-22        SEP            0
##  2 2021-22        OCT   1059540168
##  3 2021-22        NOV    564210528
##  4 2021-22        DEC    290056452
##  5 2021-22        JAN    135807960
##  6 2021-22        FEB     64187604
##  7 2021-22        MAR     37405272
##  8 2021-22        APR     14005248
##  9 2021-22        MAY      6891072
## 10 2021-22        JUN      3407448
## # ... with 23 more rows
```

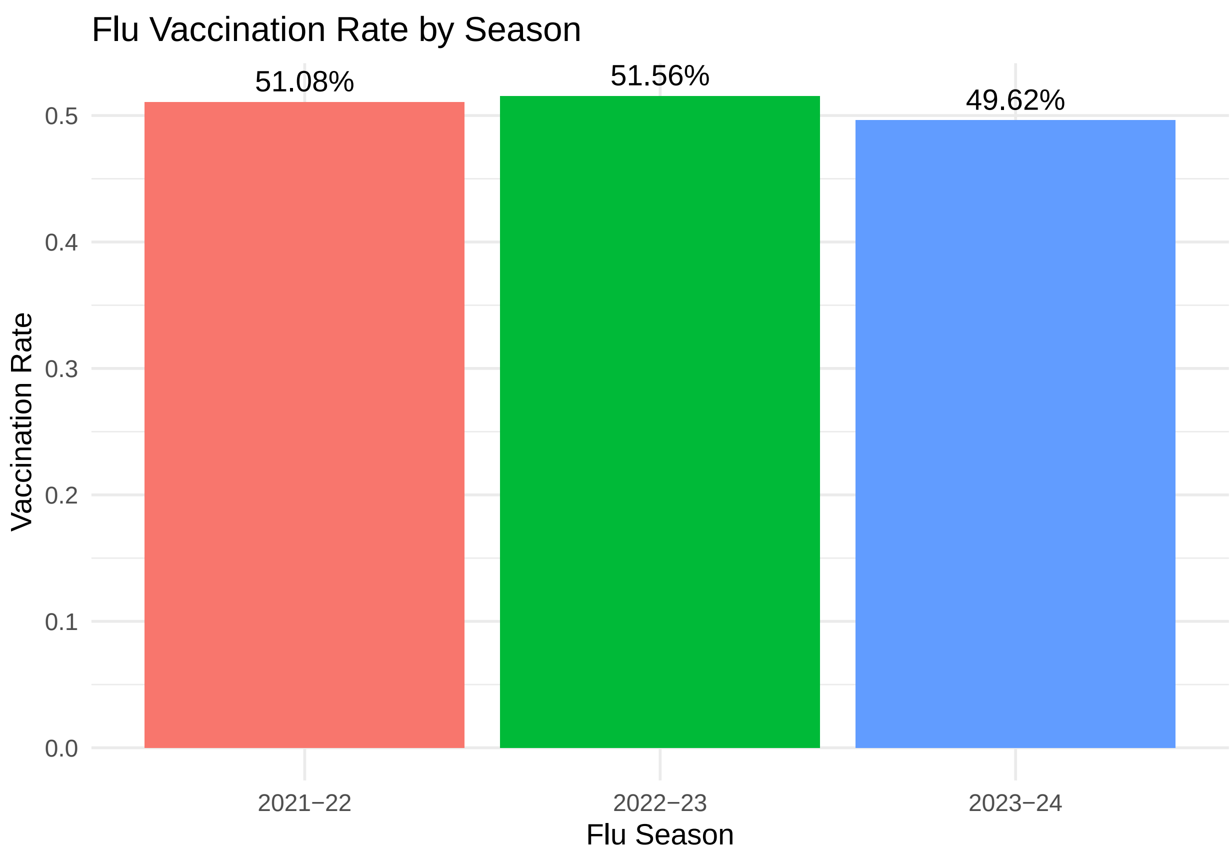
The bar chart below shows the flu vaccination rate for each of the three seasons mentioned before. The rate was calculated by aggregating totals by jurisdiction, season, and age group, then dividing totals by calculated total population (an available data column in the raw data.

```r
## Basic Bar Chart
df_clean <- df1 %>%
  filter(!is.na(numerator)) %>% # Remove rows where numerator is NA
  arrange(jurisdiction, current_season, age_group_label, month) %>% # Sort by jurisdiction, season, and
  group_by(jurisdiction, current_season, age_group_label) %>% # Group by jurisdiction, season, and age
  mutate(monthly_doses = numerator - lag(numerator)) %>% # Subtract previous month from current to get
  ungroup() %>% # Remove the grouping
  filter(!is.na(monthly_doses) & monthly_doses >= 0) # Remove NAs and negative values (in case of any
```

```r
population_per_season_jurisdiction <- df_clean %>%
  filter(age_group_label == "Overall") %>% # Only include rows where age_group_label is "Overall"
  group_by(current_season, jurisdiction) %>%
  summarise(
    unique_population = unique(population), # Get a single unique population value per jurisdiction
    total_doses = sum(monthly_doses, na.rm = TRUE)) %>%
  group_by(current_season) %>%
  summarise(
    total_population = sum(unique_population, na.rm = TRUE), # Sum up the unique population across all j
    total_doses = sum(total_doses, na.rm = TRUE)) %>%
  mutate(vaccination_rate = (total_doses / total_population) * 2.5)
```

```
## `summarise()` has grouped output by 'current_season'. You can override using
## the `.groups` argument.
```

```r
population_per_season_jurisdiction %>%
  ggplot(aes(x = current_season, y = vaccination_rate, fill = current_season)) +
  geom_col() +
  geom_text(aes(label = scales::percent(vaccination_rate)), vjust = -0.5, size = 4) +
  labs(title = "Flu Vaccination Rate by Season",
       x = "Flu Season",
       y = "Vaccination Rate") +
  theme_minimal() +
  theme(legend.position = "none")
```



2. Flu vaccination expenditure

- https://www.cdc.gov/vaccines-for-children/php/awardees/current-cdc-vaccine-price-list.html
- https://www.cdc.gov/vaccines/programs/vfc/awardees/vaccine-management/price-list/archive.html

The flu vaccination expenditure dataset is derived from CDC's Vaccine Price Lists, which detail both public-sector contract prices and private-sector prices for influenza vaccines. The dataset includes pricing information for pediatric and adult flu vaccines, with historical records dating back to 2001. The primary source for current vaccine prices is the CDC's publicly available vaccine price list, while archived prices are stored separately.

The dataset includes details such as vaccine brand names, National Drug Codes (NDCs), packaging information, CDC cost per dose, private sector cost per dose, contract end dates, and manufacturers. This data allows for an analysis of pricing trends over time, identifying fluctuations in vaccine costs and potential disparities between public and private sector pricing.

Obtaining historical data was attempted with web scraping or API access, as the archived prices are distributed across multiple web pages. When this proved not possible given the archived status of all pages, data was manually extracted from four time points in every year (one point per season, drawing mostly from months January or February, March or April or May, July or August, and September and October).

The summary table below summarizes the product data across all the given years (2009 to 2025), giving the number of products, average, minimum and maximum price for both private sector prices and CDC prices.

```r
## Summary Table
summary_table <- vax_df %>%
  group_by(year) %>%
  summarise(
    num_products = n(),
    avg_cdc_price = mean(CDC.Cost..Dose, na.rm = TRUE),
    avg_private_price = mean(Private.Sector.Cost..Dose, na.rm = TRUE),
    avg_adj_cdc_price = mean(adjusted_price_cdc, na.rm = TRUE),
    avg_adj_private_price = mean(adjusted_price, na.rm = TRUE),
    min_private_price = min(Private.Sector.Cost..Dose, na.rm = TRUE),
    max_private_price = max(Private.Sector.Cost..Dose, na.rm = TRUE),
  )

print(summary_table)
```

```
## # A tibble: 16 x 8
##     year num_products avg_cdc_price avg_private_price avg_adj_cdc_price
##    <dbl>        <int>         <dbl>             <dbl>             <dbl>
##  1  2009           32          7.99              11.2              7.99
##  2  2010           32          9.78              11.9              9.62
##  3  2011           37         10.5               12.2              9.99
##  4  2012           39          9.23              12.2              8.63
##  5  2013           43          8.77              12.8              8.08
##  6  2014           32          9.14              13.8              8.28
##  7  2015           44         10.5               16.0              9.49
##  8  2016           35         11.8               17.9             10.6
##  9  2017           32         12.2               17.6             10.6
## 10  2018           26         12.4               17.6             10.6
## 11  2019           27         12.8               18.1             10.7
## 12  2020           31         13.4               19.5             11.1
```

```
## 13  2021            32        13.9              19.8            11.0
## 14  2022            32        14.5              20.4            10.7
## 15  2023            32        15.1              21.2            10.7
## 16  2024            24        15.8              23.1            10.8
## # ... with 3 more variables: avg_adj_private_price <dbl>,
## #   min_private_price <dbl>, max_private_price <dbl>
```

3. Flu emergency department visit rates

- https://healthdata.gov/dataset/NSSP-Emergency-Department-Visit-Trajectories-by-St/hr4c-e7p6/about_data
- https://healthdata.gov/dataset/NSSP-Emergency-Department-Visits-COVID-19-Flu-RSV-/vfw5-fbqw/about_data

The flu emergency department (ED) visit rates dataset is sourced from the National Syndromic Surveillance Program (NSSP) and published on HealthData.gov. This dataset provides the percentage of emergency department visits that are attributed to influenza, alongside data for other respiratory illnesses such as COVID-19 and RSV. The dataset spans from 2022 to 2025 and is updated weekly.

The data set is available in two formats:

- **NSSP Emergency Department Visit Trajectories by State and Sub-State Regions**: This data set reports the percentage of ED visits for flu at both state and sub-state (Health Service Area) levels. It also includes trend classifications (increasing, decreasing, or stable) based on statistical models.
- **NSSP Emergency Department Visits by Demographic Category**: This dataset categorizes ED visits for influenza by demographic variables such as age, sex, and race/ethnicity. It provides insights into disparities in flu-related ED visits across different population groups.

The data is collected from health facilities participating in the NSSP and is intended to track trends over time.

The table below gives a summarized preliminary geographical analysis, showing the top ten states in percent of emergency department visits due to influenza.

```r
# Create yearly summary table (limit to top 10 states)
summary_table <- df_combined %>%
  mutate(year = year(week_end)) %>%
  group_by(year, geography) %>%
  summarize(avg_percent_influenza = mean(percent_visits_influenza, na.rm = TRUE), .groups = "drop") %>%
  arrange(desc(avg_percent_influenza)) %>%
  group_by(year) %>%
  slice_max(order_by = avg_percent_influenza, n = 10) # Keep only the top 10 states

print(summary_table)
```

```
## # A tibble: 40 x 3
## # Groups:   year [4]
##     year geography      avg_percent_influenza
##    <dbl> <chr>                          <dbl>
##  1  2022 Mississippi                     5.66
##  2  2022 New Mexico                      5.23
```

```
## 3  2022 Alabama                             5.22
## 4  2022 Kentucky                            4.99
## 5  2022 North Carolina                      4.93
## 6  2022 Indiana                             4.92
## 7  2022 Virginia                            4.85
## 8  2022 South Carolina                      4.74
## 9  2022 Texas                               4.61
## 10 2022 West Virginia                       4.44
## # ... with 30 more rows
```

Methods

Individual Analysis: Vaccination Rates

- To analyze vaccination rates across different seasons, new dose values and rate values were computed from the raw data. An Analysis of Variance (ANOVA) was conducted to determine if there were statistically significant differences in vaccination rates across the various seasons. ANOVA was chosen as it allows for the comparison of means across multiple groups, in this case, different vaccination seasons. The null hypothesis for this test was that there is no significant difference in vaccination rates across the seasons, while the alternative hypothesis was that at least one season's vaccination rate differed significantly from the others.

Emergency Department (ED) Visits

- To examine trends in emergency department visits over the years, an ANOVA was also performed. This test was selected to assess whether there were statistically significant differences in the mean number of ED visits across the years included in the dataset. The null hypothesis assumed that there was no significant variation in ED visits from year to year, while the alternative hypothesis suggested that at least one year group's mean had a significantly different number of ED visits.

Price Data

- To determine if there was a significant change in vaccine prices over time, a linear regression analysis was performed. Linear regression was chosen to model the relationship between time (years) and vaccine prices, allowing us to assess the slope of the trend and determine if price changes over time were statistically significant. The null hypothesis was that there was no significant change in prices over time, while the alternative hypothesis was that prices did change significantly.

Relationship Analysis: Vaccination Rates vs. ED Visits

- An attempt was made to perform a correlation analysis to examine the relationship between vaccination rates and ED visits. However, due to insufficient data points, a reliable correlation could not be established. Correlation analysis would have been used to determine if there was a linear relationship between vaccination rates and ED visits, with the intent of seeing if higher vaccination rates correlated with lower ED visits.

Vaccination Rates vs. Price Data

- To analyze the relationship between vaccination rates and price data, the total amount spent on vaccines each year was computed by multiplying the number of doses administered by the price per dose. An ANOVA was then conducted to determine if there were statistically significant differences in the total amount spent on vaccines across the years. This test was chosen to assess if changes in spending over time were significant. The null hypothesis was that there was no significant difference in the total amount spent each year, while the alternative hypothesis was that at least one year shows a significant difference in the total amount spent on vaccines.

Overall Visual Analysis

- Throughout the analysis, visual analysis was utilized with preliminary plots to explore the data and identify potential trends. Some of these preliminary plots are not included here for the sake of relevancy and conciseness, but they were instrumental in guiding the selection of appropriate statistical tests and interpreting the results.

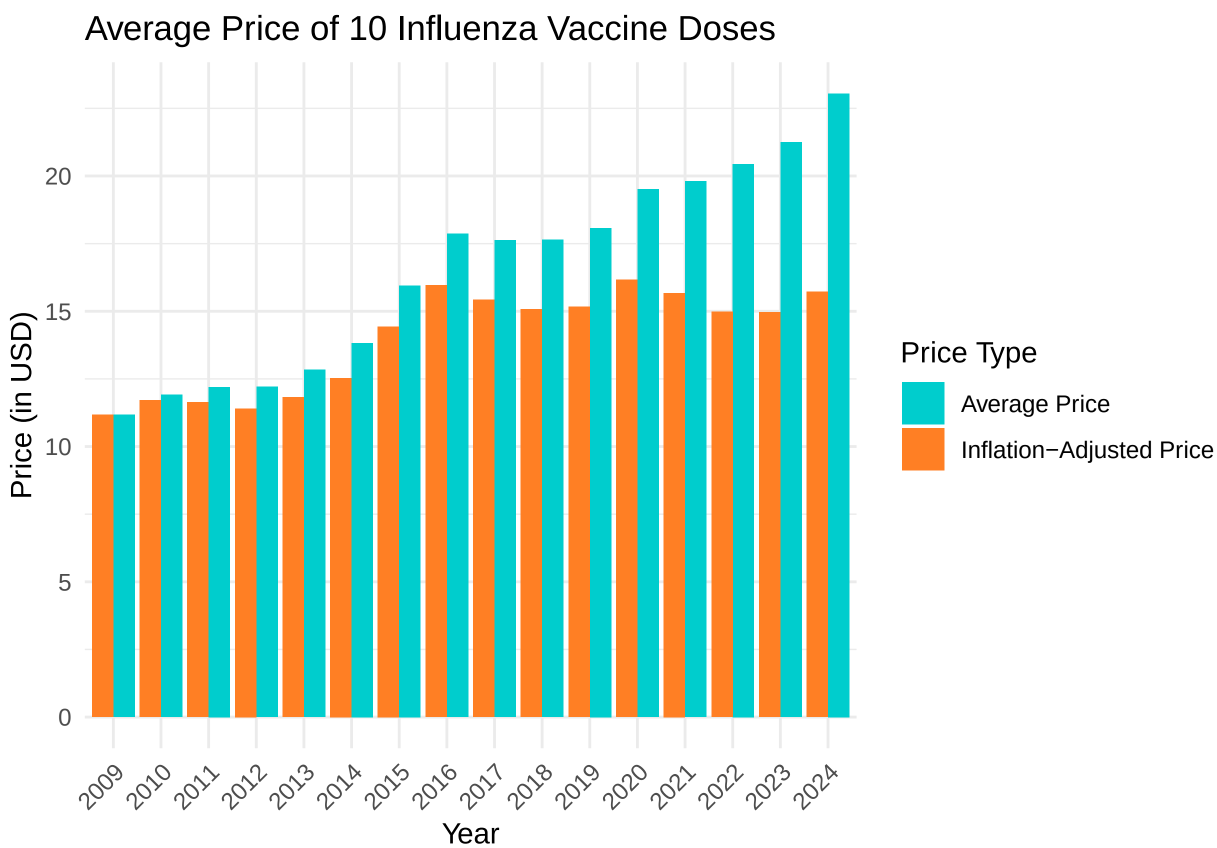
Results

Individual Analysis

Price Data

```r
plot_1 <- vax_df %>%
  group_by(year) %>%
  summarise(average_price = mean(Private.Sector.Cost..Dose),
            average_adjust_price = mean(adjusted_price)) %>%
  pivot_longer(cols = c("average_price", "average_adjust_price"),
               names_to = "price_type",
               values_to = "price") %>%
  ggplot(aes(x=factor(year), y=price, fill=price_type)) +
  geom_col(position="dodge") +
  theme(axis.text.x = element_text(angle = 90)) +
  scale_x_discrete(labels = 2009:2025, breaks = 2009:2025) +
  labs(title = "Average Price of 10 Influenza Vaccine Doses",
       x = "Year",
       y = "Price (in USD)",
       fill = "Price Type") +
  theme_minimal() +
  scale_fill_manual(values = c("average_price" = "cyan3",
                               "average_adjust_price" = "chocolate1"),
                    labels = c("average_price" = "Average Price",
                               "average_adjust_price" = "Inflation-Adjusted Price")) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

print(plot_1)
```



Here we have a barplot over time

Bar plot of average private sector costs of flu vaccines for every year (n= 6-8), price adjusted for inflation with reference year of 2009

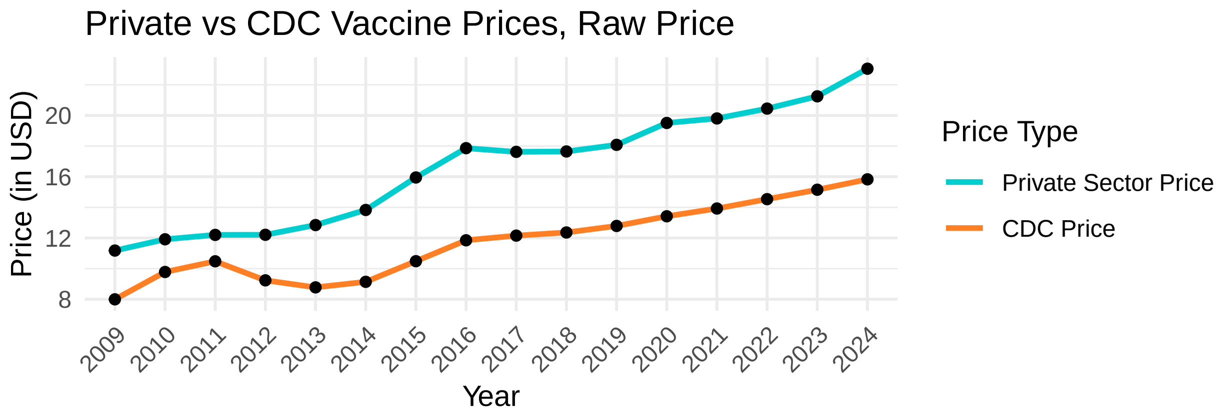
Here is a bar plot of averaged private sector costs of 6 to 8 flu vaccine products for every year from 2009 to 2025. The blue bars are the given prices and the red bars are adjusted for inflation with a reference year of 2009 using yearly CPIs. While the cost goes up every year (looking at the blue bars), when adjusted for inflation we see that the cost stays pretty constant after increasing until 2017.

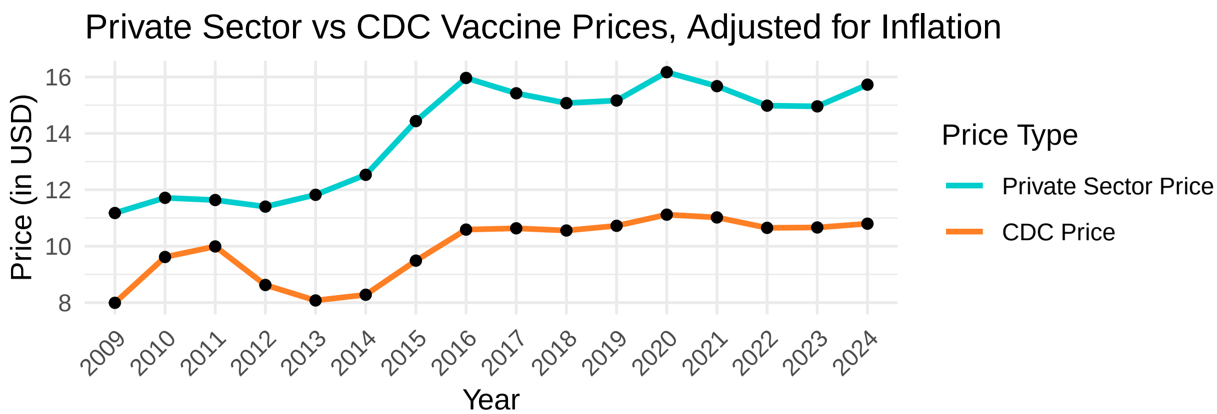
```
adj_private_cdc_comparison_plot <- vax_df %>%
  group_by(year) %>%
  summarise(average_priv_price = mean(adjusted_price),
            average_cdc_price = mean(adjusted_price_cdc)) %>%
  pivot_longer(cols = c("average_priv_price", "average_cdc_price"),
               names_to = "price_type",
               values_to = "price") %>%
  ggplot(aes(x=factor(year), y=price, group=price_type)) +
  geom_line(aes(color=price_type), size = 1) +
    geom_point() +
  labs(
    title = "Private Sector vs CDC Vaccine Prices, Adjusted for Inflation",
    x = "Year",
    y = "Price (in USD)",
    color = "Price Type"
  ) +
  scale_color_manual(
```

```r
    values = c("average_priv_price" = "cyan3",
               "average_cdc_price" = "chocolate1"),
    labels = c("average_priv_price" = "Private Sector Price",
               "average_cdc_price" = "CDC Price")  # Custom legend labels
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))


private_cdc_comparison_plot <- vax_df %>%
  group_by(year) %>%
  summarise(average_priv_price = mean(Private.Sector.Cost..Dose),
            average_cdc_price = mean(CDC.Cost..Dose)) %>%
  pivot_longer(cols = c("average_priv_price", "average_cdc_price"),
               names_to = "price_type",
               values_to = "price") %>%
  ggplot(aes(x=factor(year), y=price, group=price_type)) +
  geom_line(aes(color=price_type), size = 1) +
  geom_point() +
  labs(
    title = "Private vs CDC Vaccine Prices, Raw Price",
    x = "Year",
    y = "Price (in USD)",
    color = "Price Type"
  ) +
  scale_color_manual(
    values = c("average_priv_price" = "cyan3",
               "average_cdc_price" = "chocolate1"),
    labels = c("average_priv_price" = "Private Sector Price",
               "average_cdc_price" = "CDC Price")
  ) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))


print(grid.arrange(private_cdc_comparison_plot, adj_private_cdc_comparison_plot))
```






```
## TableGrob (2 x 1) "arrange": 2 grobs
##   z     cells    name           grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (2-2,1-1) arrange gtable[layout]
```

Here we have similar plots as the one before, but visualized as two line graphs- on top we have the raw/given average prices of vaccine products over time for both the private and public sector whereas on the bottom we have the prices adjusted for inflation with a reference year of 2009. There are four points averaged for every year. For the graph on top we can see that the the prices are generally higher and increase faster as well. But once adjusted for inflation we see less of an increase, especially more so with the public sector/CDC price. This indicates that when adjusted for inflation, vaccine product prices don't necessarily fluctuate very heavily, and this trend is even strong with public sector costs.

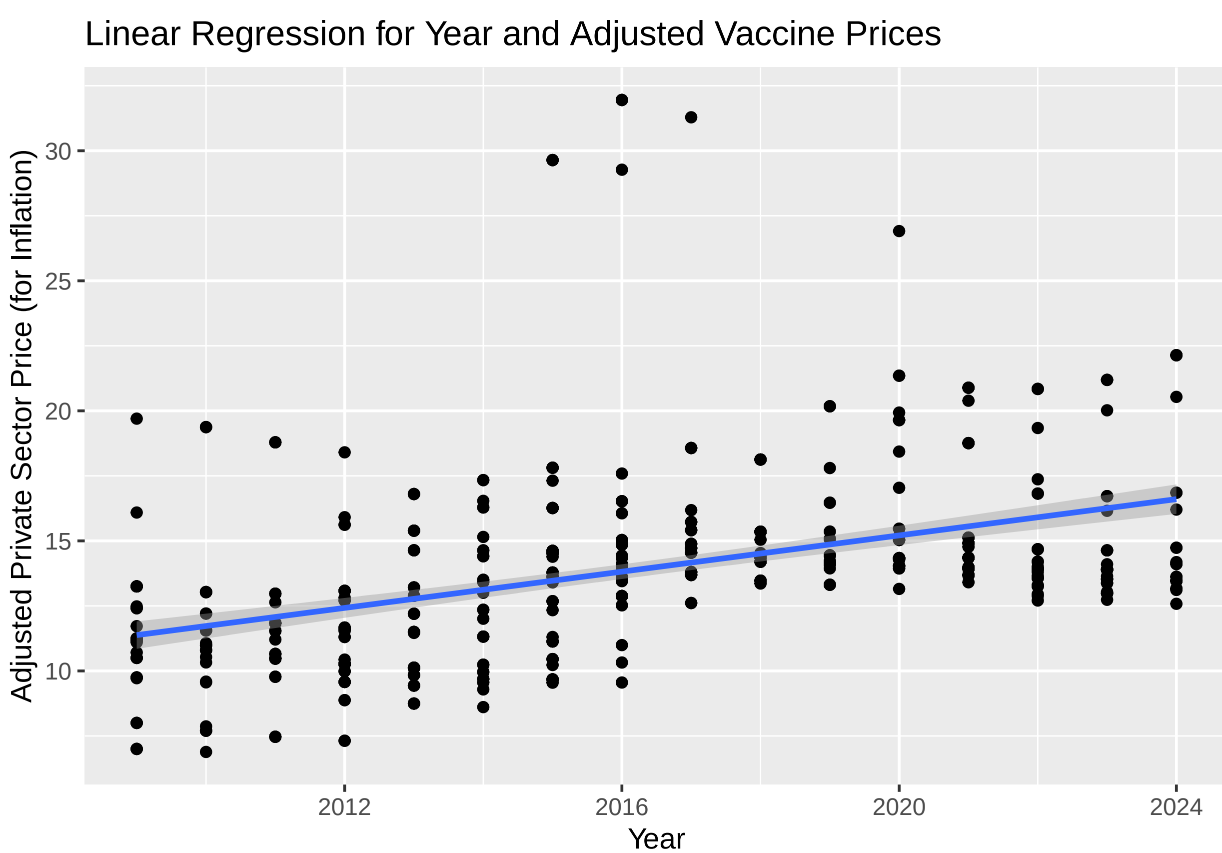
```
# linear regression model
model <- lm(adjusted_price ~ year, data = vax_df)
print(summary(model))
```

```
##
## Call:
## lm(formula = adjusted_price ~ year, data = vax_df)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.1079 -2.0896 -0.6466  1.0323 18.1349
##
```

```
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -688.58851   64.19093  -10.73   <2e-16 ***
## year           0.34842    0.03184   10.94   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.301 on 528 degrees of freedom
## Multiple R-squared:  0.1849, Adjusted R-squared:  0.1833
## F-statistic: 119.8 on 1 and 528 DF,  p-value: < 2.2e-16
```

```
ggplot(vax_df, aes(x = year, y = adjusted_price)) +
  geom_point() +
  geom_smooth(method = "lm") +
  labs(title = "Linear Regression for Year and Adjusted Vaccine Prices",
       x = "Year",
       y = "Adjusted Private Sector Price (for Inflation)")
```

```
## `geom_smooth()` using formula 'y ~ x'
```



EXPLAIN PLOT HERE

is there a correlation between year and vaccine price

So to further understand the trend, I created a linear regression model to see whether or not prices have a statistically significant trend over time. Since the p-value is **very small (9.19e-06)** and marked ***, this relationship is **highly statistically significant** — there **is evidence** that adjusted prices trend upwards over time, even accounting for inflation. Using the year and adjusted prices, I came out with a R-squared value of around .14, which means that year explains about 14.1% of the variation in adjusted prices. So, while there **is a significant upward trend**, this means that **year alone doesn't explain most of the variation** — other factors (like vaccine type, manufacturer, etc.) probably matter a lot too.

here we can see a low positive relationship, as confirmed by the low R squared value

```
test <- t.test(vax_df$Private.Sector.Cost..Dose, vax_df$CDC.Cost..Dose,
               alternative = "greater")
test
```

```
##
##  Welch Two Sample t-test
##
## data:  vax_df$Private.Sector.Cost..Dose and vax_df$CDC.Cost..Dose
## t = 17.525, df = 943.6, p-value < 2.2e-16
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  4.302051      Inf
## sample estimates:
## mean of x mean of y
##  16.27383  11.52568
```

Here we used a one-tail t-test because we're comparing the two groups with a specified direction. In this case, the test compares:

- `vax_df$Private.Sector.Cost..Dose` → The private sector cost per vaccine dose.
- `vax_df$CDC.Cost..Dose` → The CDC (public sector) cost per vaccine dose.

Null Hypothesis: There is no difference or the private sector cost is less than or equal to the CDC (public sector) cost.

The t-value of **17.525** is very large, indicating a substantial difference between the private and CDC costs. Additionally, the p-value is very small **(< 2.2e-16)**, indicating strong evidence against the null hypothesis, leading us to **reject the null hypothesis** and conclude that the private sector cost is **significantly higher** than the CDC cost. Because the test is one-sided, testing whether the private sector cost is significantly greater than the CDC cost and the data supports the alternative hypothesis, we can confirm that the private sector cost is indeed higher. The difference in means is about 4.74, indicating that the average private sector cost is about $4.74 higher than the CDC cost

Vaccination Rates

```
anova_result <- aov(numerator ~ as.factor(current_season), data = df_clean)
summary(anova_result)
```

```
##                              Df    Sum Sq   Mean Sq F value  Pr(>F)
## as.factor(current_season)     2 6.356e+12 3.178e+12   4.917 0.00733 **
## Residuals                 15382 9.941e+15 6.462e+11
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Null Hypothesis: No difference in vaccine doses across seasons.

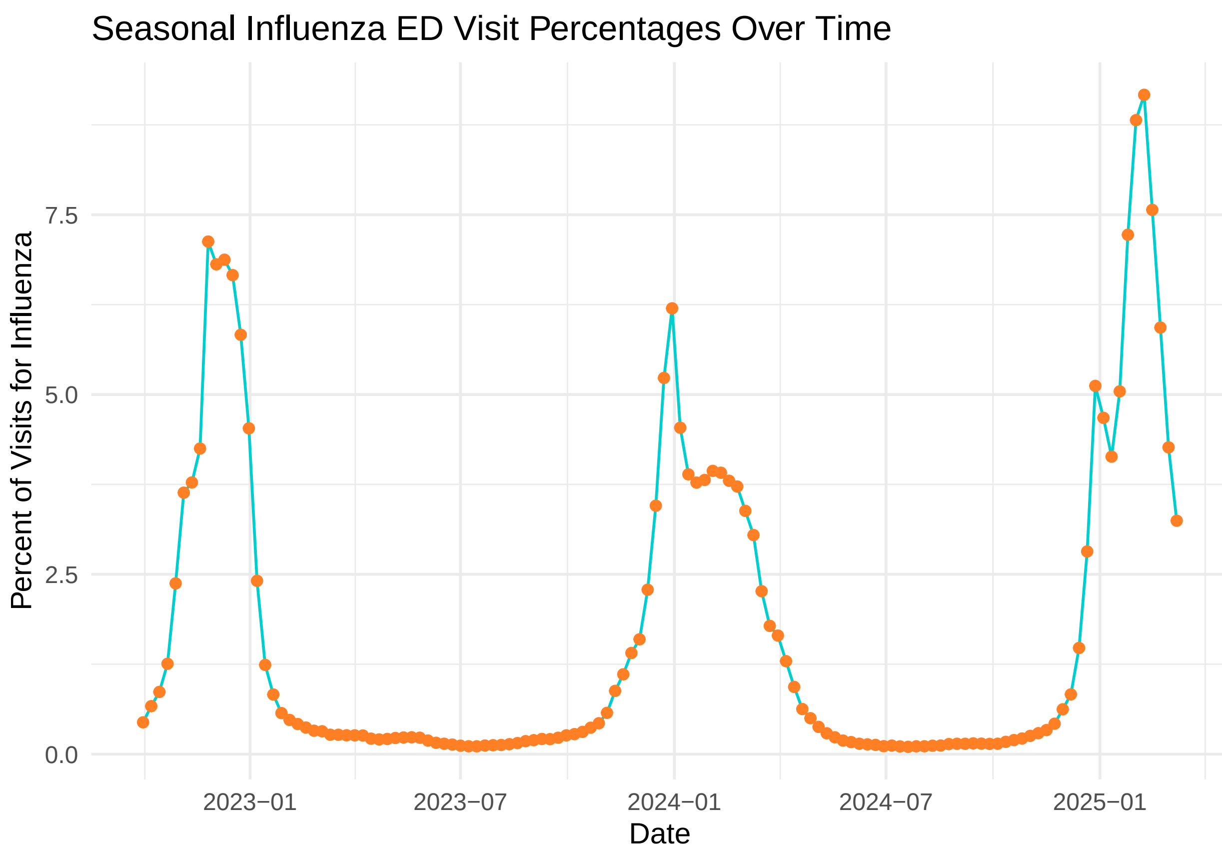
Here we are using an ANOVA test because we are comparing the number of vaccine doses across multiple seasons/years. The **p-value is 0.00733** which is less than .05, indicating a statistically significant difference in the means of doses across the different seasons and a rejection of the null hypothesis. However, the F-value of 4.917 suggests that the between-group variability is roughly 5 times larger than the within-group variability, implying that **season has a moderate influence of number of doses** and that most of variation is due to other factors rather than season alone.

Emergency Department Visits

```r
df_for_plot <- df_combined %>%
  group_by(Date) %>%
  summarise(value = mean(percent_visits_influenza))

plot_time <- ggplot(data = df_for_plot) +
  geom_line(aes(x = Date, y = value), color = "cyan3") +
  geom_point(aes(x = Date, y = value), color = "chocolate1") +
  labs(
    title = "Seasonal Influenza ED Visit Percentages Over Time",
    x = "Date",
    y = "Percent of Visits for Influenza"
  ) +
  theme_minimal()

plot_time # n = 128 values
```



EXPLAIN PLOT HERE

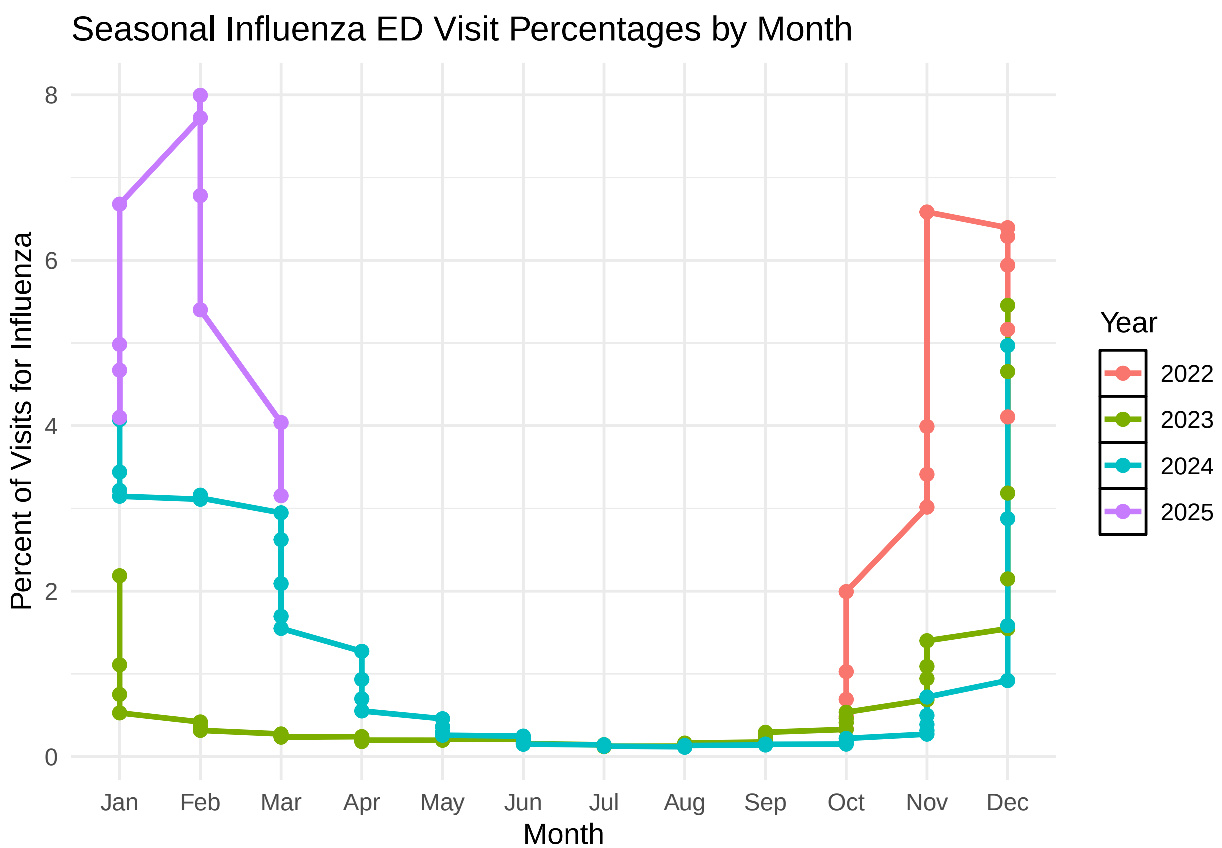
```r
# getting how many points per year
point_counts <- seasonal %>%
  group_by(year) %>%
  summarise(n = n())

print(point_counts)
```

```
## # A tibble: 4 x 2
##   year      n
##   <chr> <int>
## 1 2022     14
## 2 2023     52
## 3 2024     52
## 4 2025     10
```

```r
ggplot(seasonal, aes(x = factor(month_abbr, levels = c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul",
  geom_line(size=1) +
  geom_point(size=2) +
  labs(
    title = "Seasonal Influenza ED Visit Percentages by Month",
    x = "Month",
    y = "Percent of Visits for Influenza",
    color = "Year"  # Legend title
  ) +
```

```r
  theme_minimal() +
  theme(
    legend.key = element_rect(fill = "white", color = "black")
  )
```



plot explanation

```r
anova_result <- aov(percent_visits_influenza ~ as.factor(year), data = df_combined)
summary(anova_result) # Print ANOVA test result
```

```
##                      Df  Sum Sq Mean Sq F value Pr(>F)
## as.factor(year)       3  733391  244464   39752 <2e-16 ***
## Residuals        294524 1811259       6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Null Hypothesis: No difference in ED visit rates between years

Here we are using an ANOVA test because we are comparing the rates of ED visits due to influenza across multiple years. The **p-value is <2e-16**, indicating a strong statistically significant difference in the means of ED visit rates across the different years and leading us to reject the null hypothesis.

Relationship Analysis

Vaccination Rates and Emergency Department Visits

```
df_for_cop <- df_dedup %>%
  group_by(date) %>%
  summarise(plot_col = sum(new_doses, na.rm = TRUE))

merged = merge(df_for_cop, seasonal, by.x="date", by.y="Date")
print(merged)
```

```
##         date plot_col percent_visits_influenza year month month_abbr
## 1 2022-10-01 90963003                0.3352941 2022    10        Oct
## 2 2023-07-01        0                0.1425490 2023    07        Jul
```

```
# cor.test(merged$plot_col, merged$percent_visits_influenza, method = "pearson")
```

Here we attempt to run a correlation analysis (and hopefully down the line a linear regression model) between vaccination rates and emergency department visits to establish whether or not there was a relationship between the two variables. However, due to the structure of our datasets, we were unable to merge enough data for a correlation test to be run- as you can see, the merged dataset only returns two rows. This is because of the different timing of our two datasets- vaccination rates were based on monthly cumulative totals while ED visit rates were collected weekly. Additionally, there were only two years that had overlapping data. While we are unable to prove a statistically significant relationship here, we hope to use this preliminary analysis and data visualizations to inform statistical tests down the line.

Vaccination Rates and Vaccine Product Prices

```
all_totals <- df_dedup %>%
  group_by(date) %>%
  summarise(total_doses = sum(new_doses, na.rm = TRUE))

all_totals$year <- format(all_totals$date, "%Y")

all_totals$doses_div_ten <- (all_totals$total_doses) / 10

yr_totals <- all_totals %>%
  group_by(year) %>%
  summarise(total_doses = sum(total_doses))


price_table <- vax_df %>%
  group_by(year) %>%
  summarise(cost = mean(adjusted_price))

price_table$cost_per_dose <- (price_table$cost) / 10

price_yr_totals <- merge(x = yr_totals, y = price_table, by = "year")

price_yr_totals$money_spent <- price_yr_totals$total_doses * price_yr_totals$cost_per_dose
```

```r
print(price_yr_totals)
```

```
##   year total_doses     cost cost_per_dose money_spent
## 1 2021   219844791 15.67542      1.567542   344615912
## 2 2022   224176457 14.98390      1.498390   335903771
## 3 2023   208979305 14.95873      1.495873   312606423
```

Through some various calculations, we aimed to get an estimate on how much money is spent a year on vaccinations based on number of doses and vaccine product data. We found that both the total doses and money spent decreases from 2021 to 2023- however, so does the average cost per dose. Without more statistical analysis, we're unable to clearly say which has the biggest effect, but through this table we can see a general downwards trend. We can also use this table for statistical testing below.

```r
anova_result <- aov(money_spent ~ as.factor(year), data = price_yr_totals)
summary(anova_result)
```

```
##                 Df    Sum Sq   Mean Sq
## as.factor(year)  2 5.478e+14 2.739e+14
```

Here we attempt to run an ANOVA test to see whether or not there is a statistically significant difference in the amount of money spent on vaccinations based on vaccination product prices over the three years (the null hypothesis being that there is no difference between the years). However due to the aggregation of the data, we are unable to generate a p-value making. While we could attempt to run this test on unaggregated data, due to the way the cumulative totals are calculated it is difficult to get an aggregate with the right number of values for both without doubting the accuracy of totals. So at this time we can neither reject nor accept the null hypothesis.

Discussion

text here