Prescription Drug Pricing in the United States:

Analyzing the Concrete and Abstract

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Abstract

This paper delves into the intricate dynamics surrounding public spending on prescription drugs and the evolving impact of regulatory legislation over time. Utilizing versatile R packages, particularly the ggplot2 plotting system authored by Hadley Wickham, our methodology takes a departure from minimalist design principles commonly advocated by Edward Tufte. Instead, we embrace a vision that prioritizes extensive customization, achieved through the strategic layering of charts, scales, labels, and other aesthetic elements. Prescription drug prices have drastically increased in the past two decades. Our research finds that consumers get substantial cost savings from implementation of prescription drug pricing policies and government regulations such as the Affordable Care Act and the Inflation Reduction Act. Moreover, our investigation indicates that, despite these legal interventions, drug manufacturers see minimal impact and may even gain increased value by adhering to price constraints. In conclusion our research emphasizes the urgent requirement for policies and regulations to ensure broad access to affordable medications, particularly in light of the consistent growth in demand.

Keywords: R, ggplot2, data visualization, public spending, prescription drugs, regulatory legislation, extensive customization, layered charts, fine-tuned control

I. Introduction

This project focuses on visualizing public spending on prescription drugs and assessing the impact of regulations on affordability and accessibility. Over 131 million people in the US, constituting 66% of adults, depend on prescription drugs, which are crucial for maintaining and improving health; however, the strain of rising drug costs is evident, impacting public healthcare systems and family budgets nationwide, underscoring the urgent need for increased affordability and accessibility. The Assistant Secretary for Planning and Evaluation (ASPE) whose responsibilities encompass policy research, legislation development, and economic analysis estimated $457 billion in prescription drug spending, which accounts for 16.7% of personal health services (U.S. Department of Health and Human Services., 2016). Alongside economic expansion and decline, price control legislation is among the main causal factors for changes in prescription drug pricing. Our research hypothesis explores the measurable impact of prescription drug policies and effect of regulations on the affordability and accessibility of prescriptions.

The philosophy guiding our approach to visualization draws inspiration from Wickham's methodology rather than Tufte's pursuit of simplicity. Our visualization strategy adopts a layered approach to construct meaningful representations of data. Much like peeling back the layers of an onion, we build visualizations through the incorporation of multiple aesthetic elements. Each layer adds depth, allowing for a nuanced understanding of the information at hand. By carefully incorporating various elements, we aim to unveil hidden patterns and relationships, providing a more comprehensive and insightful view.

This stands in contrast to rigid, one-size-fits-all approaches. Customization allows for fine-tuned control over every aspect of a chart, ensuring that the visual representation aligns precisely with the user's needs and preferences. From choosing color palettes that resonate with the user's brand to adjusting the granularity of scales, our approach grants users the freedom to tailor visualizations to their unique requirements. This fosters a sense of ownership and facilitates more effective communication of complex data sets. We also recognize the importance of making data accessible to a wide audience, and thus, we prioritize crafting visuals that are interesting and easily interpreted. By leveraging a combination of engaging design elements, intuitive data representation, and thoughtful storytelling, we strive to make impactful visualizations which convey information accurately and inspire curiosity.

II. Literature Review

Many in the United States rely on prescription drugs to maintain their health. It is estimated that 45.8% of the U.S. population has used at least one prescription drug in the last 30 days (Martin et al. 2019). However, obtaining medications does not always come easily for a significant portion of the population. For example, roughly 12% of adults ages 51-64 diagnosed with diabetes or hypertension have taken less medication than prescribed for the past 2 years because of their medications' high cost. In another study observing adults ages 65+ across multiple U.S. states, more than 20% of participants indicated they had not only skipped doses to afford their medication, but also cut spending on other basic necessities (Health Policy Institute 2002). Healthcare affordability has continued to remain an important issue in the U.S. in the years since this study, as the consequences of inaccessible treatment can potentially lead to negative health outcomes across the country.

Over time, various legislation has been introduced to regulate drug pricing and tackle the issue of prescription affordability. In 2006, the implementation of Medicare Part D, which established prescription drug coverage for senior individuals increased the overall share of spending covered by Medicare and Medicaid to 25% (Congressional Budget Office 2022). Older age groups are thought to have historically paid the highest out-of-pocket costs for medication (Health Policy Institute 2002), so the creation of Medicare Part D, along with further expansions in the Affordable Care Act in 2010 and the Bipartisan Budget Act in 2018, is recognized as a major contributor to an overall increase in prescription drug use in the past decade (Congressional Budget Office 2022). More recently, after various research on the frequency and size of drug price increases, the Inflation Reduction Act has gone into effect to address increases that exceed the current inflation rate and impose requirements on manufacturers to pay rebates to Medicare users (Bosworth et al. 2022).

While we aim to study the impact of how such legislation has affected the affordability of prescriptions over time, it is also important to understand the economic implications for manufacturers from regulations. Regulatory policies across various countries are associated with significant decreases in pharmaceutical revenue (Sood et al. 2008). The economic state of drug manufacturers also plays a hand in the affordability of prescription drugs, so it is important to consider this factor to gain a whole perspective of healthcare spending and pricing.

Research Questions

1. Do prescription drug pricing policies and government regulations have a direct impact on the affordability and accessibility of prescriptions over time?
2. What is the impact of drug pricing policy and government regulation on drug manufacturers?

Research Hypotheses

<u>Primary Hypotheses:</u>

H_0: Prescription drug policies and government regulations have had a measurable impact on affordability and accessibility of prescriptions.

H_{a1}: Prescription drug policies and government regulations have had no measurable impact on affordability and accessibility of prescriptions.

<u>Secondary Hypotheses:</u>

H_{02}: The implementation of new drug pricing policies and regulations has significantly impacted the financial performance of drug manufacturers

H_{a2}: The implementation of new drug pricing policies and regulations had no significant impact on the financial performance of drug manufacturers

III. Data and Methods

We began collecting data utilizing the Centers for Medicare and Medicaid Services (CMS). The CMS stored various prescription drug data and average drug spending on inhalers, insulin, statins, and anti-anaphylactic drugs. We also reviewed data from the Medical Expenditure Panel Survey (MEPS), which provides detailed information on prescribed medicines throughout the U.S. The data extracted from the CMS and MEPS had attributes grouped by year the total spending, total dosage units, claims, beneficiaries, and average spending per dosage weight for hundreds of commonly prescribed drugs, listed alphabetically.

We also gathered data relevant to specific policies affecting the costs of healthcare in the United States. For example, the Inflation Reduction Act (IRA) went into effect in the beginning of 2023 and introduced provisions targeted at individuals on Medicare and drug manufacturers, requiring them to pay a greater rebate to insurers should their prices rise faster than the current inflation rate (Centers for Medicare & Medicaid Services 2023). We wanted to observe the effect of potential savings as a result of this legislation, as reported by the Department of Human Health Services (2023), as well as the economic effect on manufacturers by this legislation; and thus we collected stock price data from Eli Lilly and Company and Novo Nordisk, two well-known manufacturers of diabetes treatment who had to comply with the IRA (Kansteiner 2023). In addition, we wanted to investigate the impact of another important policy, the Affordable Care Act (ACA), which was signed into law in 2010 and aimed to significantly expand healthcare insurance for all Americans. Utilizing data from The Commonwealth Fund (2020), we examined data that covers time periods before and after the passing of the ACA. We also took into account the need to acknowledge differences between individuals that belong to different income groups. For example, Medicaid eligibility is based on a maximum income level that varies by state. Finally, to potentially bring in a comparative perspective, we compared the average out-of-pocket costs of insulin to other developed countries outlined by the U.S. Department of Health and Human Services.

Once data was gathered and cleaned in an excel format, we proceeded to create and visualize the data in the respective categories, utilizing various R packages. To visualize the impact of prescription drug policy and regulation we employed R packages of the following: Plotly, Ggplot, RColorBrewer, and Quantmod. We utilized a variety of visualizations, such as line graphs, bar graphs, and interactive charts, to enhance the visual appeal of our data. These visual representations not only provided clarity but also allowed for customization of scales, contributing to a more engaging and informative presentation.

Code Samples

The code samples below utilize Plotly to create line graphs for select statins and inhalers, respectively, and show the trend of average prices on the market.

Image 1: *Figure 1*: Average Spending Per Dosage Unit: Statins

```
library(readr)
library(readxl)
library(plotly)
df <- read_csv("https://raw.githubusercontent.com/sharonjepkosgei/sharonjepkosgei.github.io/main/df_revised.csv")

df$`Brand Name` <- as.factor(df$`Brand Name`)
df$`Generic Name` <- as.factor(df$`Generic Name`)
df$Manufacturers <- as.integer(df$Manufacturers)
df$Year <- as.integer(df$Year)
df$`Total Spending` <- as.numeric(df$`Total Spending`)
df$`Total Dosage Units`<- as.numeric(df$`Total Dosage Units`)
df$`Total Claims` <- as.numeric(df$`Total Claims`)
df$`Total Beneficiaries` <- as.numeric(df$`Total Beneficiaries`)
df$`Average Spending Per Dosage Unit (Weighted)` <- as.numeric(df$`Average Spending Per Dosage Unit (Weighted)`)
df$`Average Spending Per Claim`<- as.numeric(df$`Average Spending Per Claim`)
df$`Average Spending Per Beneficiary` <- as.numeric(df$`Average Spending Per Beneficiary`)

brandspec <- c("Crestor", "Lipitor", "Zocor")

newdf <- df[df$'Brand Name' %in% brandspec, ]

# Assuming 'newdf' is your filtered dataset
# You may need to replace the column names with the actual column names in your dataset

#colors assigned
brandcolors <- c("Zocor" = "orchid", "Crestor" = "springgreen4", "Lipitor" = "navy")

line_plot <- plot_ly(newdf, x = ~Year, y = ~`Average Spending Per Dosage Unit (Weighted)`, color = ~`Brand Name`,
colors = brandcolors, type = 'scatter', mode = 'lines+markers') %>%
  layout(title = 'Average Spending Per Dosage Unit (2012-2021)', font = list(family = 'Ubuntu', color = 'gray7', size
= 16),
         xaxis = list(title = '',  font = list(family = 'Ubuntu', size = 12, color = 'gray7')),
         yaxis = list(title = 'Price per dose (USD)', font = list(family = 'Ubuntu', size = 14, color = 'gray7')),
         margin = list(l = 75, r = 50, b = 75, t = 50),
         plot_bgcolor = 'ivory1'
  )
```

Image 2: R Code Inhalers

```
library(readr)
library(readxl)
library(plotly)
df <- read_csv("https://raw.githubusercontent.com/sharonjepkosgei/sharonjepkosgei.github.io/main/df_revised.csv")

df$`Brand Name` <- as.factor(df$`Brand Name`)
df$`Generic Name` <- as.factor(df$`Generic Name`)
df$Manufacturers <- as.integer(df$Manufacturers)
df$Year <- as.integer(df$Year)
df$`Total Spending` <- as.numeric(df$`Total Spending`)
df$`Total Dosage Units`<- as.numeric(df$`Total Dosage Units`)
df$`Total Claims` <- as.numeric(df$`Total Claims`)
df$`Total Beneficiaries` <- as.numeric(df$`Total Beneficiaries`)
df$`Average Spending Per Dosage Unit (Weighted)` <- as.numeric(df$`Average Spending Per Dosage Unit (Weighted)`)
df$`Average Spending Per Claim`<- as.numeric(df$`Average Spending Per Claim`)
df$`Average Spending Per Beneficiary` <- as.numeric(df$`Average Spending Per Beneficiary`)


brandspec <- c("Proair HFA", "Proventil HFA")

newdf <- df[df$'Brand Name' %in% brandspec, ]

# Assuming 'newdf' is your filtered dataset
# You may need to replace the column names with the actual column names in your dataset

#colors assigned
brandcolors <- c("Proair HFA" = "cadetblue1", "Proventil HFA" = "orchid4")

line_plot <- plot_ly(newdf, x = ~Year, y = ~`Average Spending Per Dosage Unit (Weighted)`, color = ~`Brand Name`,
colors = brandcolors, type = 'scatter', mode = 'lines+markers') %>%
  layout(title = 'Average Spending Per Dosage Unit (2012-2021)', font = list(family = 'Gill Sans', color = 'gray7',
size = 16),
         xaxis = list(title = '',  font = list(family = 'Gill Sans', size = 12, color = 'gray7')),
         yaxis = list(title = 'Price per dose (USD)', font = list(family = 'Gill Sans', size = 14, color = 'gray7')),
         margin = list(l = 75, r = 50, b = 75, t = 50),
         plot_bgcolor = 'ivory1'
  )
```

The code sample below utilizes Plotly to create a line graph showing the dosage price of insulin brands Apidura, Humalog, and Lantus over a time period of 9 years.

Image 3: R Code Insulin

```
library(readr)
library(readxl)
library(plotly)
df <- read_csv("https://raw.githubusercontent.com/sharonjepkosgei/sharonjepkosgei.github.io/main/df_revised.csv")

df$`Brand Name` <- as.factor(df$`Brand Name`)
df$`Generic Name` <- as.factor(df$`Generic Name`)
df$Manufacturers <- as.integer(df$Manufacturers)
df$Year <- as.integer(df$Year)
df$`Total Spending` <- as.numeric(df$`Total Spending`)
df$`Total Dosage Units`<- as.numeric(df$`Total Dosage Units`)
df$`Total Claims` <- as.numeric(df$`Total Claims`)
df$`Total Beneficiaries` <- as.numeric(df$`Total Beneficiaries`)
df$`Average Spending Per Dosage Unit (Weighted)` <- as.numeric(df$`Average Spending Per Dosage Unit (Weighted)`)
df$`Average Spending Per Claim`<- as.numeric(df$`Average Spending Per Claim`)
df$`Average Spending Per Beneficiary` <- as.numeric(df$`Average Spending Per Beneficiary`)

brandspec <- c("Apidra", "Humalog", "Lantus")

newdf <- df[df$'Brand Name' %in% brandspec, ]

# Assuming 'newdf' is your filtered dataset
# You may need to replace the column names with the actual column names in your dataset

#colors assigned
brandcolors <- c("Apidra" = "orchid", "Lantus" = "springgreen4", "Humalog" = "navy")


line_plot <- plot_ly(newdf, x = ~Year, y = ~`Average Spending Per Dosage Unit (Weighted)`, color = ~`Brand Name`,
colors = brandcolors, type = 'scatter', mode = 'lines+markers') %>%
  layout(title = 'Average Spending Per Dosage Unit (2012-2021)', font = list(family = 'Ubuntu', color = 'gray7', size
= 16),
         xaxis = list(title = '',  font = list(family = 'Ubuntu', size = 12, color = 'gray7')),
         yaxis = list(title = 'Price per dose (USD)', font = list(family = 'Ubuntu', size = 14, color = 'gray7')),
         margin = list(l = 75, r = 50, b = 75, t = 50),
         plot_bgcolor = 'ivory1'
  )
```

The code sample below utilizes ggplot2, RColorBrewer, and Plotly to map estimated out-of-pocket savings by state if the Inflation Reduction Act had been in effect in 2020.

Image 4: R Code Inflation Reduction Act

```
# Read shapefile
download.file(
  "https://github.com/abiburns/abiburns.github.io/raw/main/states.zip",
  zip_path <- tempfile(fileext = ".zip")
)
unzip(zip_path, exdir = tempdir())
setwd(tempdir())
states <- st_read("states.shp")

# Read csv
url = "https://raw.githubusercontent.com/abiburns/abiburns.github.io/main/InflationReducationAct.csv"
mapData <- read_csv(url)

# Merge attribute
map <- merge(states, mapData, by.x = "STATE_NAME", by.y = "State Name")

# Plot states with graduated colors representing annual savings
choropleth <- (
  ggplot(data = map,
         aes(fill = `Average Annual Out-of-Pocket Savings Per Enrollee ($)`)) +
    labs(fill = "Average Annual Out-of-Pocket \nSavings Per Enrollee ($)") +
    theme(plot.title = element_text(hjust = 0.5),
          panel.grid.major = element_blank(),
          panel.grid.minor = element_blank(),
          axis.title.x=element_blank(),
          axis.text.x=element_blank(),
          axis.ticks.x=element_blank(),
          axis.title.y=element_blank(),
          axis.text.y=element_blank(),
          axis.ticks.y=element_blank()
    ) +
    geom_sf() +
    geom_sf_text(aes(label = `STATE_ABBR`), size = 3) +
    coord_sf(xlim = c(-165, -70), ylim=c(21,62)) +
    scale_fill_gradientn(colours = brewer.pal(5, "Greens"),
                         labels = c("$300", "$400","$500","$600","$700", "$800")
                         ) +
    ggtitle("Inflation Reduction Act: Major Savings for Americans Who Use Insulin") +
    guides(fill = FALSE)
)
```

Image 6: R Code Inflation Reduction Act

```r
# Read shapefile
download.file(
  "https://github.com/abiburns/abiburns.github.io/raw/main/states.zip",
  zip_path <- tempfile(fileext = ".zip")
)
unzip(zip_path, exdir = tempdir())
setwd(tempdir())
states <- st_read("states.shp")

# Read csv
url = "https://raw.githubusercontent.com/abiburns/abiburns.github.io/main/InflationReducationAct.csv"
mapData <- read_csv(url)

# Merge attribute
map <- merge(states, mapData, by.x = "STATE_NAME", by.y = "State Name")

# Plot states with graduated colors representing annual savings
choropleth <- (
  ggplot(data = map,
         aes(fill = `Average Annual Out-of-Pocket Savings Per Enrollee ($)`)) +
    labs(fill = "Average Annual Out-of-Pocket \nSavings Per Enrollee ($)") +
    theme(plot.title = element_text(hjust = 0.5),
          panel.grid.major = element_blank(),
          panel.grid.minor = element_blank(),
          axis.title.x=element_blank(),
          axis.text.x=element_blank(),
          axis.ticks.x=element_blank(),
          axis.title.y=element_blank(),
          axis.text.y=element_blank(),
          axis.ticks.y=element_blank()
    ) +
    geom_sf() +
    geom_sf_text(aes(label = `STATE_ABBR`), size = 3) +
    coord_sf(xlim = c(-165, -70), ylim=c(21,62)) +
    scale_fill_gradientn(colours = brewer.pal(5, "Greens"),
                         labels = c("$300", "$400","$500","$600","$700", "$800")
                         ) +
    ggtitle("Inflation Reduction Act: Major Savings for Americans Who Use Insulin") +
    guides(fill = FALSE)
)
```

The code sample below utilizes Tidyverse to create a bar chart of affordability challenges among diabetic patients grouped by income as a percentage of the federal poverty level and stacked to depict three different time periods between 2007 and 2017.

Image 6: R Code Affordability

```r
# Read the data
afford_data <- read.csv("https://raw.githubusercontent.com/sharonjepkosgei/sharonjepkosgei.github.io/main/afford.csv")
library(tidyverse)

# Data reshaping
afford_data_long <- afford_data %>%
  pivot_longer(cols = starts_with("X"), names_to = "Year", values_to = "Value")

# Remove "X" from the Year column
afford_data_long$Year <- gsub("X", "", afford_data_long$Year)

# Replace underscores with hyphens in the Year column
afford_data_long$Year <- gsub("_", "-", afford_data_long$Year)

# Reorder the levels of Year
afford_data_long$Year <- factor(afford_data_long$Year, levels = c("2014-2017", "2010-2013", "2007-2009"))

# Create a stacked bar chart
ggplot(afford_data_long, aes(x = Column1, y = Value, fill = Year)) +
  geom_bar(stat = "identity") +
  labs(title = "Diabetic People With Difficulty Affording Prescriptions",
       x = "Income as percentage of federal poverty level (FPL)",
       y = "Percent") +
  scale_fill_brewer(palette = "Paired") +
  theme_minimal() +
  theme(
    legend.position = c(0.9, 0.8),
    plot.title = element_text(face = "bold", size = 14, hjust = 0.5),
    axis.text.x = element_text(face = "bold", size = 10, angle = 60, hjust = 0.5, vjust = 0.6),
    axis.text.y = element_text(size = 12),
    axis.title.x = element_text(size = 14),
    axis.title.y = element_text(size = 14)
  )
```

The code samples below utilize Plotly and Quantmod to create animated interactive charts for stock price of Ely Lily and Novo Nordisk and show their movement after capping the market price of insulin.

Image 7: R Code Ely Lily Stock Price

```r
getSymbols("LLY",src='yahoo')

df <- data.frame(Date=index(LLY),coredata(LLY))
df <- tail(df, 365)
df$ID <- seq.int(nrow(df))

accumulate_by <- function(dat, var) {
  var <- lazyeval::f_eval(var, dat)
  lvls <- plotly:::getLevels(var)
  dats <- lapply(seq_along(lvls), function(x) {
    cbind(dat[var %in% lvls[seq(1, x)], ], frame = lvls[[x]])
  })
  dplyr::bind_rows(dats)
}

df <- df %>% accumulate_by(~ID)
fig <- df %>% plot_ly(
  x = ~ID,
  y = ~LLY.Close,
  frame = ~frame,
  type = 'scatter',
  mode = 'lines',
  fill = 'tozeroy',
  fillcolor='lightblue',
  line = list(color = 'navy'),
  text = ~paste("Day: ", ID, "<br>Close: $", LLY.Close),
  hoverinfo = 'text'
)
fig <- fig %>% layout(
  title = "Ely Lilly Stock Price in the Past Year",
  yaxis = list(
    title = "Closing Price", font = list(size = 16, family = "Ubuntu"), tickfont = list(size = 16, family = "Ubuntu"),
    range = c(0,700),
    zeroline = F,
```

Image 8: R Code Novo Nordisk Stock Price

```r
library(plotly)
library(quantmod)

getSymbols("NVO",src='yahoo')

df <- data.frame(Date=index(NVO),coredata(NVO))
df <- tail(df, 365)
df$ID <- seq.int(nrow(df))

accumulate_by <- function(dat, var) {
  var <- lazyeval::f_eval(var, dat)
  lvls <- plotly:::getLevels(var)
  dats <- lapply(seq_along(lvls), function(x) {
    cbind(dat[var %in% lvls[seq(1, x)], ], frame = lvls[[x]])
  })
  dplyr::bind_rows(dats)
}

df <- df %>% accumulate_by(~ID)
fig <- df %>% plot_ly(
  x = ~ID,
  y = ~NVO.Close,
  frame = ~frame,
  type = 'scatter',
  mode = 'lines',
  fill = 'tozeroy',
  fillcolor='lightblue',
  line = list(color = 'navy'),
  text = ~paste("Day: ", ID, "<br>Close: $", NVO.Close),
  hoverinfo = 'text'
)
fig <- fig %>% layout(
  title = "Novo Nordisk Stock Price in the Past Year", font = list(size = 12, weight = "bold"),
  yaxis = list(
    title = "Closing Price", font = list(size = 16), tickfont = list(size = 16),
    range = c(0,150),
    zeroline = F,
    tickprefix = "$"
```

The code sample below utilizes Tidyverse and Plotly to create a bar chart of income grouped by percentage of the federal poverty level and by four different levels of insurance coverage.

Image 5: R Code Impact of Insurance

```
library(tidyverse)
library(plotly)

# Read the data
insurance <- read.csv("https://raw.githubusercontent.com/sharonjepkosgei/sharonjepkosgei.github.io/main/data_files/aff
ord2.csv")


# Create a Plotly plot
plt3 <- plot_ly(insurance, x = ~col1, y = ~values, type = 'bar', color = ~insurance_status, colors = 'Paired', text =
~paste("status: ", insurance_status, "<br>Percent: ", values, "%")) %>%
  layout(title = "Percentage of Diabetic People Reporting Affordability Problems", font = list(size = 12, color =
'black', family = 'Arial', weight = 'bold'),
         xaxis = list(title = "Income as a percentage of federal poverty level (FPL)", font = list(size = 14),
tickfont = list(size = 16)),
         yaxis = list(title = "Percent", font = list(size = 14), tickfont = list(size = 16)),
         legend = list(x = 0.9, y = 0.8),
         hovermode = "closest",
         barmode = "group",
         legend = list(x = 0.6, y = 0.9,font = list(size = 16)),
         showlegend = TRUE)
```

IV. Results

Prescription Drug Pricing Over Time

Statins

The visual representation of average spending per dosage of popular statin brands from 2012 to 2021 reveals a compelling narrative in the realm of prescription drug costs. Among the commonly used medications Crestor, Lipitor, and Zocor, it is evident that prices have experienced a significant upward trend over the past decade. Notably, Lipitor stands out as the highest-priced medication, reaching up to $14 per dose, while Zocor emerges as the most affordable option at $7 per dose. *Figure 1* below reveals the stark contrast in pricing, which underscores the considerable financial impact on individuals and healthcare systems, prompting a closer examination of the factors influencing the soaring costs of essential medications.

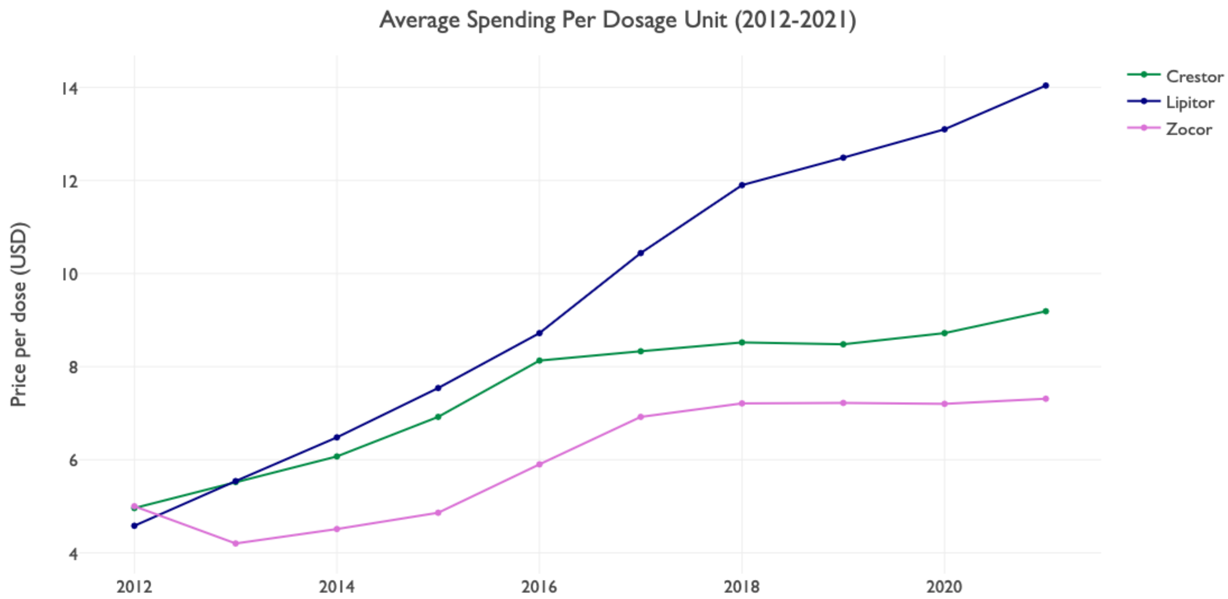

Figure 1: Average Spending Per Dosage Unit: Statins

Inhalers

The visual representation below of average spending per dosage units from 2012 to 2021 on Inhalers, reveals a compelling narrative in the realm of prescription drug costs. Among the commonly used medications, Proair and Proventil it's evident that the prices have experienced a significant upward trend over the past decade. Notably in *Figure 2*, Proventil HFA stands out as the highest-priced medication, reaching up to $11.23 per dose, while Proair emerges as the most affordable option at $7.50 per dose.

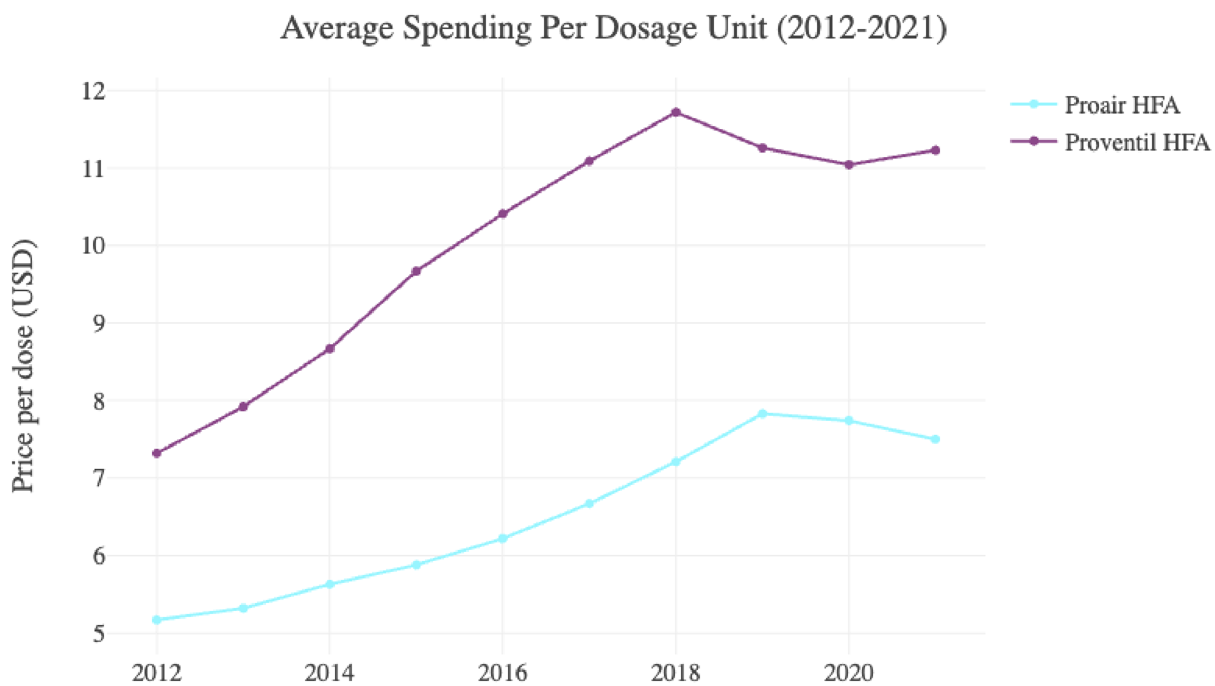

Figure 2: Average Spending Per Dosage Unit: Inhalers

Insulin

This visual representation in *figure 3* on average spending per dosage unit for Insulin drugs 2012-2021 examines the most common drugs in today's market: Apidra, Humalog, and Lantus Pharmaceuticals companies have steadily increased the list prices on insulin over the past decades. In 2012 the cost for Apidra was $9.84, it then significantly rose throughout the years with the cost in 2021 being $28.13. We see the same trend for Humalog and Lantus, with Lantus standing out being the highest priced medication in 2021 at $28.32 and Humalog emerging as the more affordable option in 2021 at $26.76. *Figure 3* shows the significant upward trend from January 2014 to April 2019 with a 54% spike on insulin. In the following year we saw a 10.6% drop from January 2020 to July 2021 during a period of economic decline.

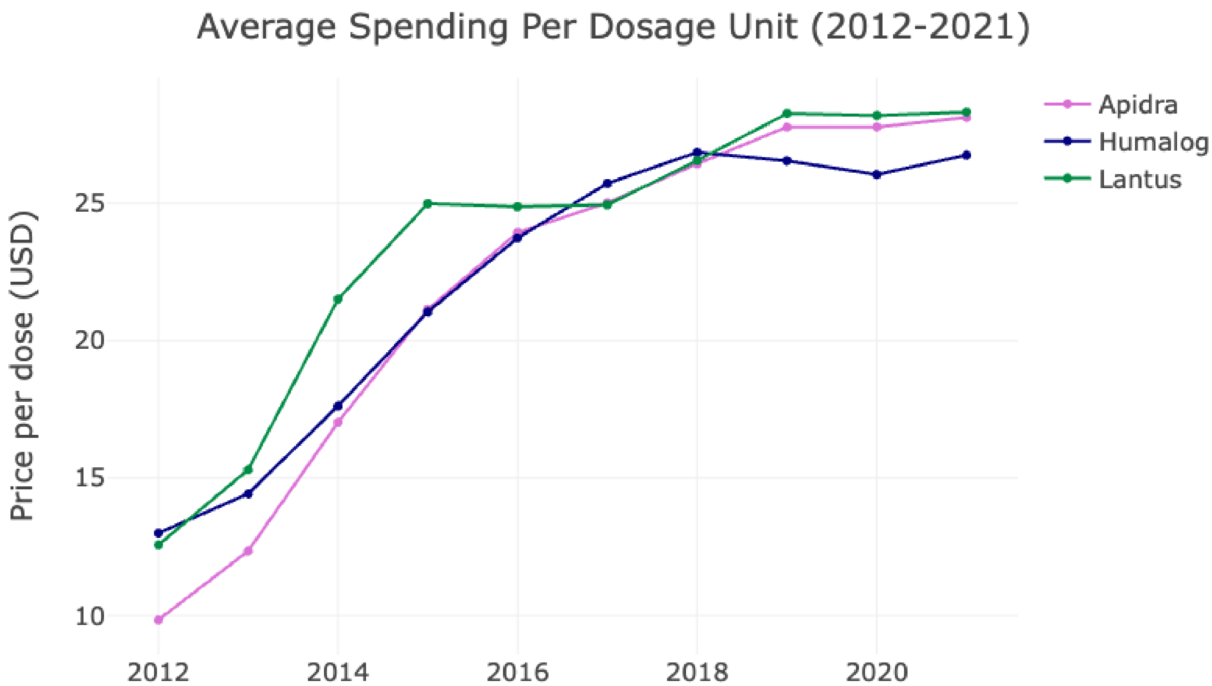

Figure 3: Average Spending Per Dosage Unit: Insulin

Case Study: Diabetic Prescription

Using the example of diabetes prescription the following section describes:

1. Findings on the trend of insulin pricing
2. Impact of insulin drug regulation on consumers
3. Impact on insulin drug regulations on corporations,
4. Impact of insurance on access and affordability of diabetes prescriptions.

Diabetic Prescription Usage Over Time

The graph in *figure 4* illustrates the usage trends of two types of diabetic medications - insulin and insulin and pills from 2000 to 2021. In the year 2000, insulin usage was 2.5 million, while insulin and pills were 1.4 million. The overall trend in both categories exhibits fluctuations, characterized by periods of decline followed by subsequent increases in medication usage. Notably, by 2021, the usage of insulin and pills reached 4.4 million, surpassing insulin alone, which stood at 3.2 million. But a notable trend is the drastic drop in 2018, where there was a drop in diabetes medication use. What could have caused such a drop in use? Research does not reveal any decrease in diabetes prevalence.

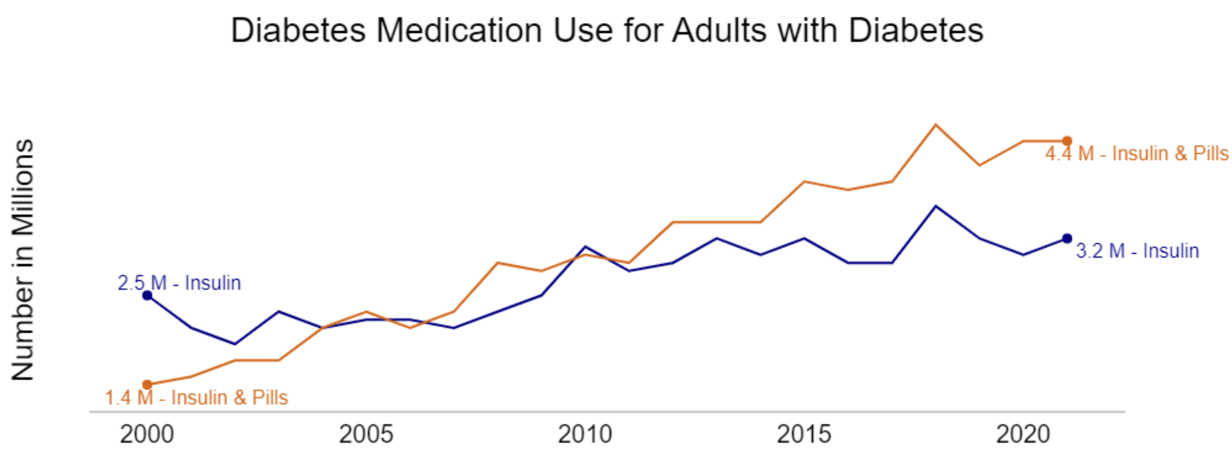

Figure 4: Diabetic Medication use for Adults with Diabetes

Comparing Price with Other Developed Countries: 2018

Our research found a possible explanation for the drastic drop in diabetes medication use in 2018. Statistics show that in 2018, the average price of one vial for insulin cost $98.70 in the United States. This is 10 times the average price per vial than Japan, which had the second highest cost compared to other select developed countries. It is important to note that Type I requires about one to three vials of insulin per month. Type II diabetes patients, unlike their Type I counterparts, don't require regular insulin use. However, when needed, they typically administer larger quantities per dose compared to Type I patients. With the average price at about $100 in 2018, many patients would have either skipped or rationed their medications due to affordability problems. This could be one explanation for the drop in insulin use in 2018.

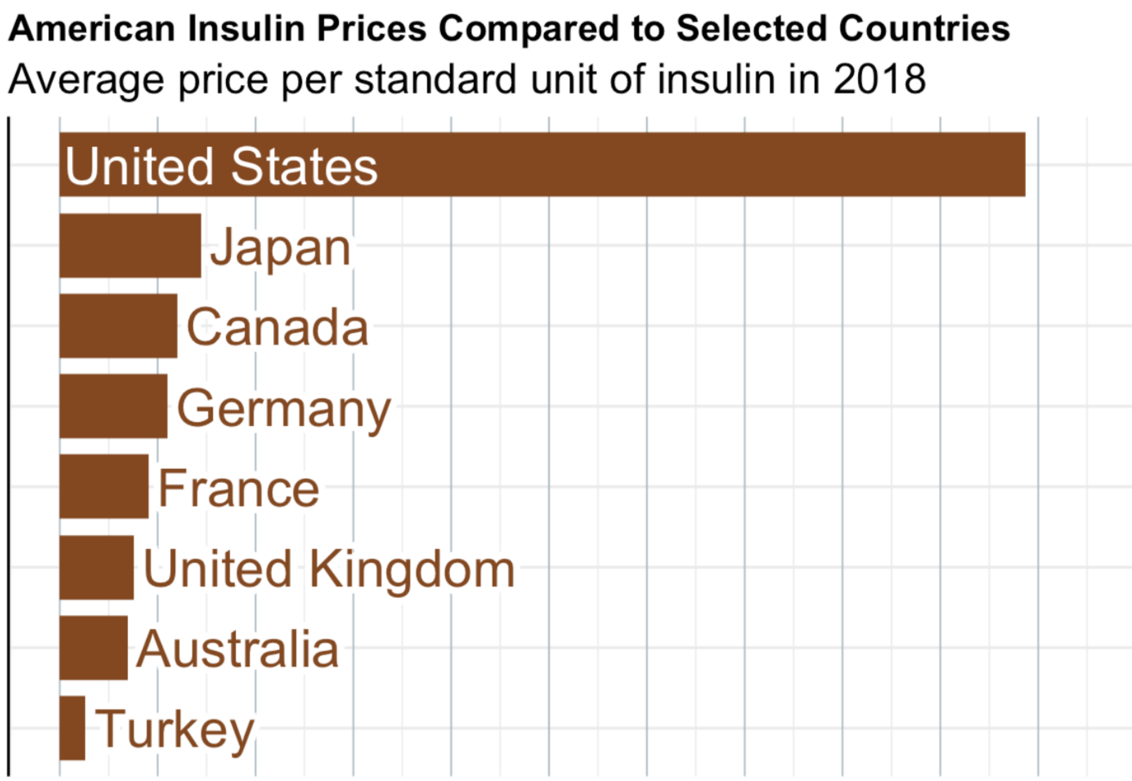

Figure 5: American Insulin Prices Compared to Selected Countries

Inflation Reduction Act

As drug prices surge, the U.S. government implements policies to curb the impact of rising prescription costs. One of the recent and vital regulations was the Inflation Reduction Act. It went into effect in January of 2023. According to the act, patients covered by Medicare under Part D plan have a $35 out-of-pocket monthly cap for insulin. Moreover, IRA provides higher rebates, even exceeding 100% of a drug's price, in cases when manufacturers have raised list prices sharply over time triggering large best price discounts. Again, under the IRA, manufacturers will face penalties in Medicare for raising list prices faster than inflation

Impact of Legislation: Consumers

Next, we investigate the impact of the Inflation Reduction Acton consumers. We found data reporting that were the Inflation Reduction Act in place by 2020, the total savings to beneficiaries would have been $734 million in Part D and $27 million in Part B, with an average annual savings of $500 for Medicare beneficiaries. The states with the most people on Medicare projected to benefit from the new IRA insulin cap policy are Texas (114,000 beneficiaries), California (108,000 beneficiaries), and Florida (90,000). Meanwhile, the states with the highest average annual out-of-pocket savings per person would be North Dakota ($805), Iowa ($725), and South Dakota ($725). It should be noted that these states have relatively low populations, which may have increased the amount of average savings.

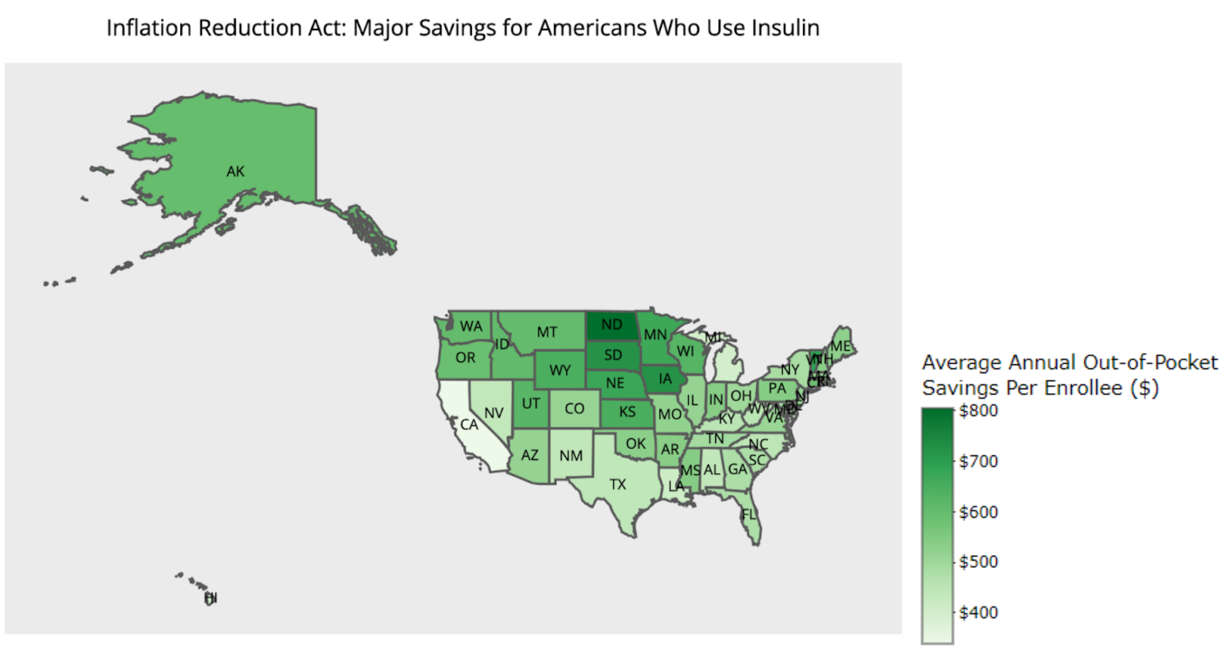

Figure 6: Map of Savings for Americans from IRA by State

Impact of Legislation: Corporations (Ely Lilly)

We also wanted to observe how various corporations integral to the development of diabetes treatment were affected by the introduction of the Inflation Reduction Act. *Figure 7* shows how stock prices of Eli Lilly Company have changed from June 2022 to November 2023, documenting prices from before and after the company's announcement regarding their slash in insulin prices (roughly occuring around Day 125). As one can see, the stock prices are increasing in a positive trend from Day 180 to the end of the time period; furthermore, a sharp increase in stock prices occurs just a few days after Eli Lilly and Company's announcement. From this data, it appears that the slashed prices of insulin treatments did not affect the corporation negatively; rather, price of reduction of insulin is associated with an increase in stake in the company.

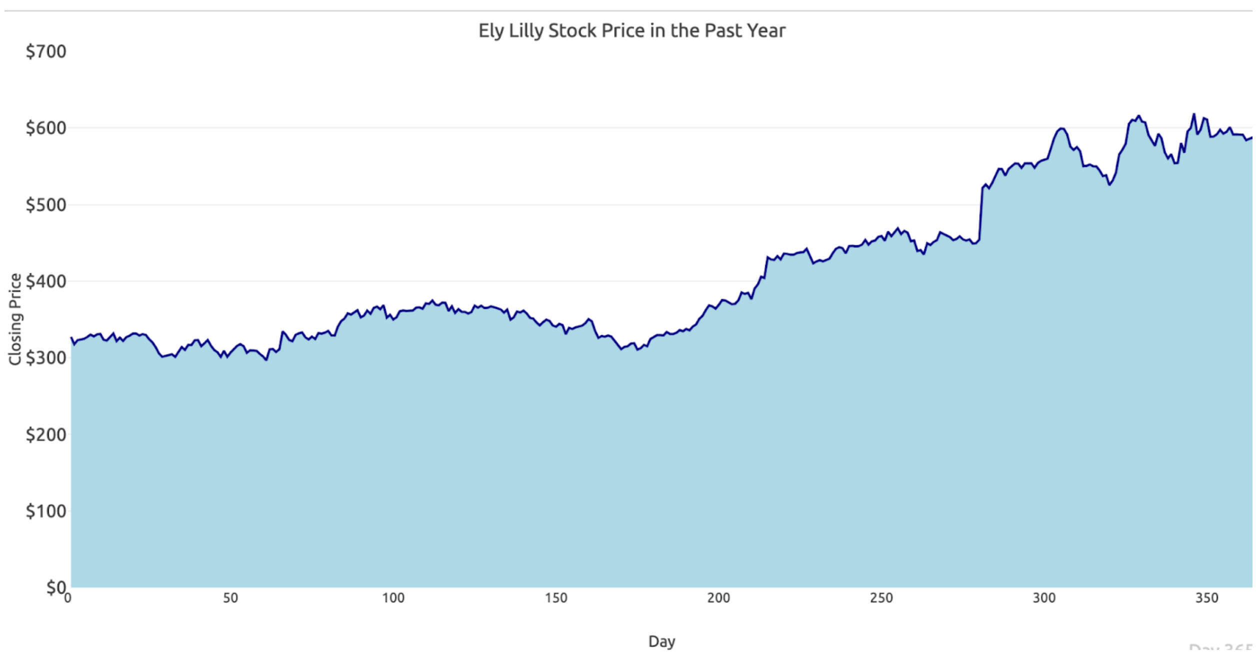

Figure 7: Graph of Eli Lilly Stock Price from June 2022 to November 2023

Impact of Legislation: Corporations (Novo Nordisk)

Similarly, Novo Nordisk, another highly influential insulin manufacturer, has had overall increasing stock prices from June 2022 to November 2023, with a generally increasing trend in prices from the time it announced insulin costs were being significantly decreased (around day 125).

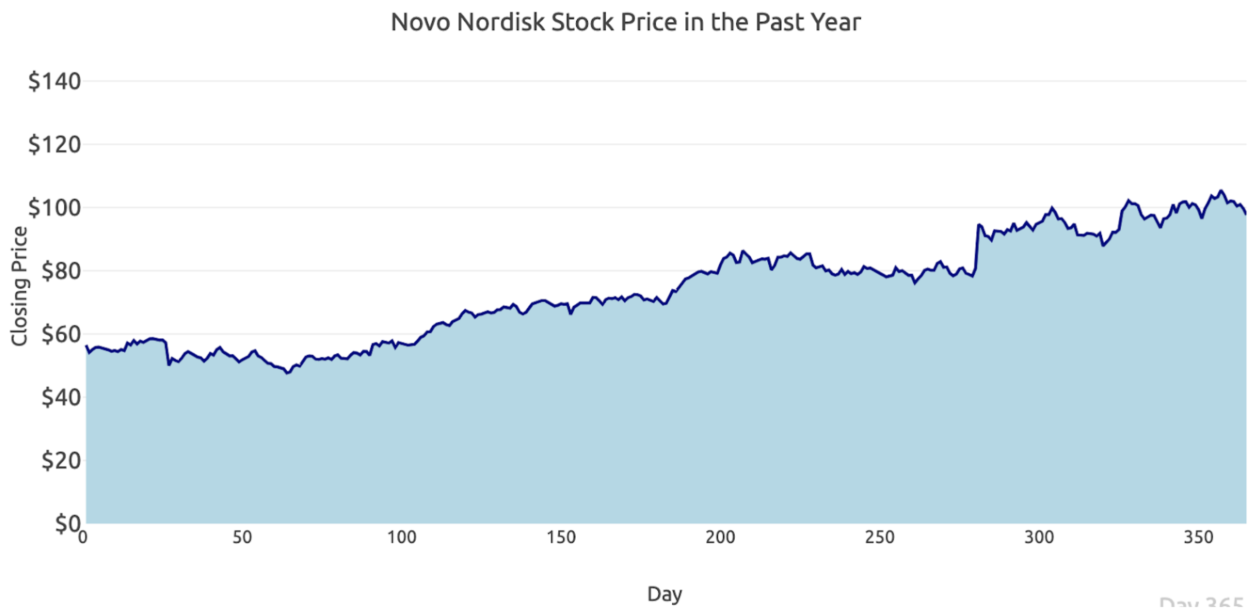

Figure 8: Graph of Novo Nordisk Stock Prices from June 2022 to November 2023

Affordable Care Act

The Affordable Care Act is a health reform that went into effect in March of 2010. It aimed to significantly expand healthcare insurance for all Americans. It is another regulation that we can use to explore the impact of government regulations on prescription drug affordability. In *figure 9* shows the percentage of diabetic persons who have difficulty affording prescriptions across different time periods (2007-2009, 2010-2013, 2014-2017). There is a clear decrease in the overall percentage of diabetic persons who have affordability problems over time. This is most evident for people with an income 200-499% of the federal poverty level. For individuals with an income 199% or less of the Federal Poverty Level a decrease in affordability problems occurs a little bit later, with only a decrease observed between 2010-2013 and 2014-2017. In contrast, individuals with an income at least 500% greater than the federal poverty level did not see much change. In general, coverage expansions from ACA reduced the share of those with diabetes in each income group who reported difficulty affording prescription drugs.

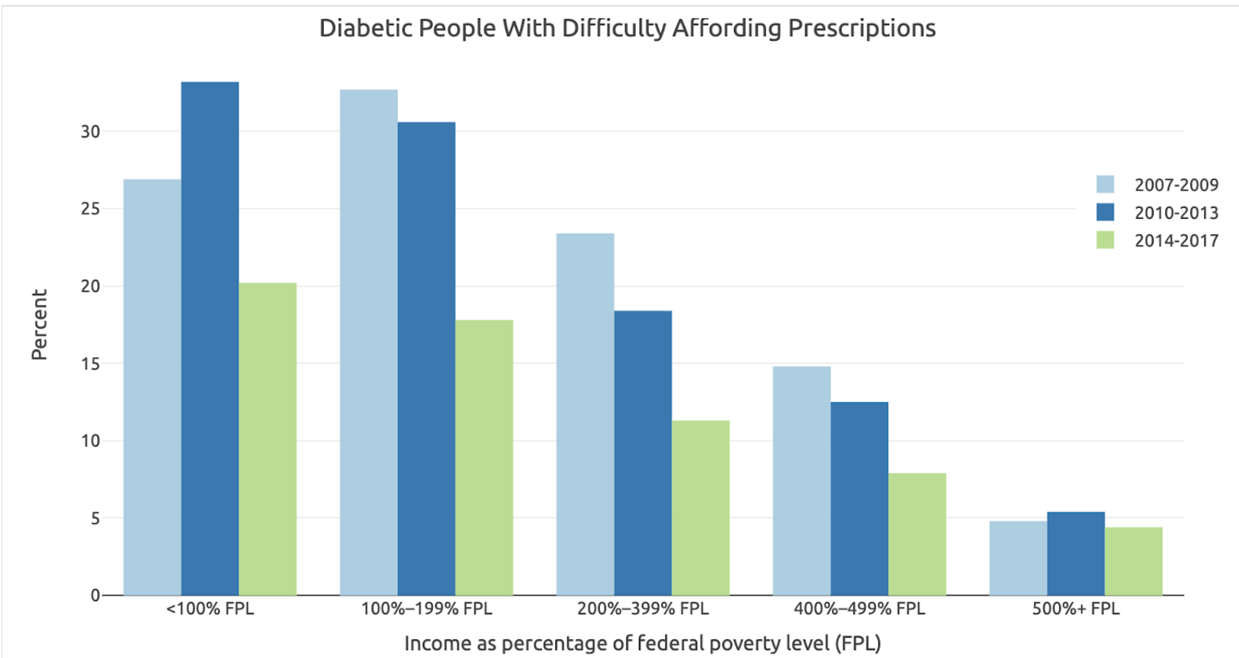

Figure 9: Chart of Patients with Affordability Problems by Year

Impact of Insurance

The Affordable Care Act reveals the significance of coverage for people using various prescription drugs. Our last visualization explores the impact of insurance on prescription drug affordability. It depicts the percentage of diabetic people reporting affordability problems, separated by income as a percentage of the federal poverty level (FPL) and types of insurance coverage (Medicaid, private insurance with high deductibles, private insurance with low/medium deductibles, uninsured). According to *figure 10*, all uninsured groups for each income level reported a higher percentage of affordability problems than any other group across income levels. Within each income group, private insurance holders with high deductibles reported more affordability problems than those with low deductibles. Finally, groups of Medicaid users separated by income reported a similar number or less affordability problems compared to private insurance holders with low/medium deductibles. Overall, the graph demonstrates that while affordability problems seem to increase with income, the presence of insurance is also associated with a smaller likelihood of experiencing affordability issues.

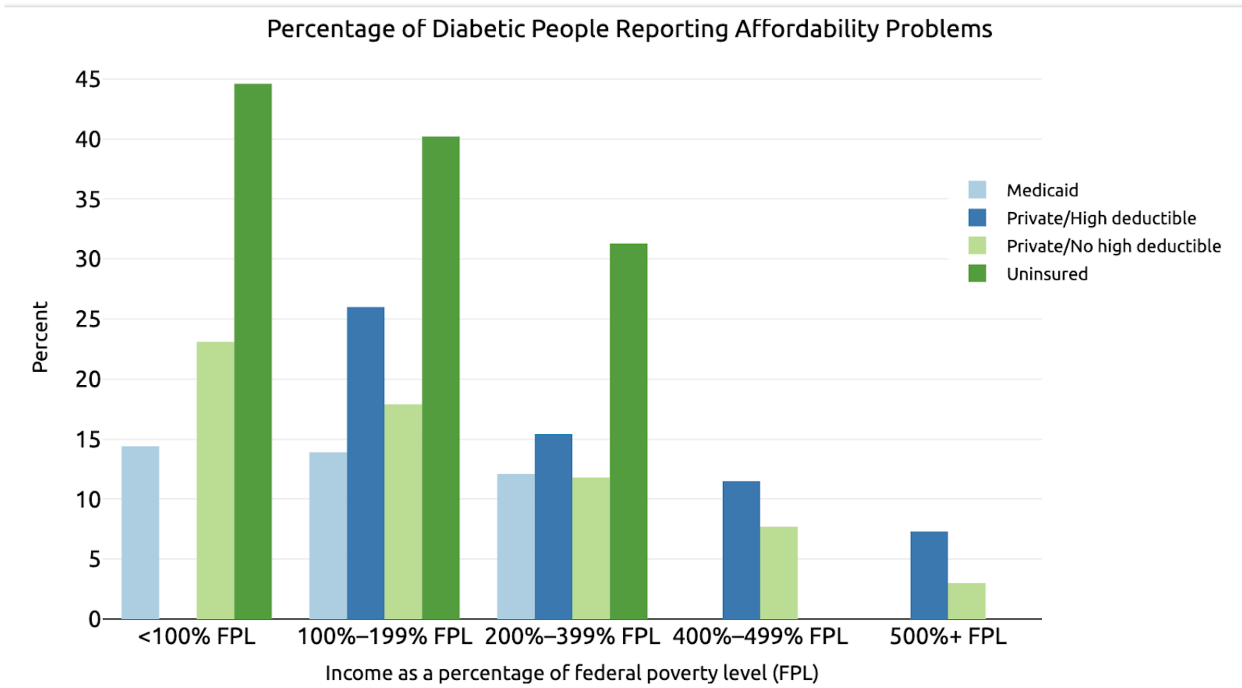

Figure 10: Chart of People Reporting Affordability Problems by Type of Coverage

V. Conclusions

Through the last decade or so, there has been an overall increase in usage of various prescriptions in the United States, most noticeably in insulin treatments. Similarly, prescription prices have increased over the years, especially evident when observing positive trends by dosage unit, and are much more expensive when compared to other countries with similarly developed healthcare systems. We believe that this data indicates the need for policies and regulations to ensure that affordable medications can be of reach across the country, even if demand for these prescriptions continues to rise.

There is evidence that existing laws have allowed for people to comfortably access prescriptions despite these price increases. There was an overall decrease in reported affordability problems among diabetic individuals across all income groups in the years following the introduction of the Affordable Care Act, which was integral in lowering prescription prices and expanding Medicaid coverage. Notably, this decrease occurred while insulin prescriptions were rising, suggesting that the presence of insurance can protect individuals from rising out-of-pocket costs. The later introduction of the Inflation Reduction Act put a $35-monthly cap on insulin prices for Medicare users and included provisions to target manufacturers should they impose disproportionate price increases. Our investigation showcases how even with the IRA in place, drug manufacturers are not significantly affected, and may in fact, become slightly more valuable as they comply with price prescriptions. As a result, such corporations may be deterred from going against these restrictions, all while individuals benefit from increased savings on treatment.

Overall, we propose that the affordability of insulin and other common prescription drugs are most greatly affected by the availability and form of coverage one has against high out-of-pocket costs. However, it is important to understand that in the present day, various states within the U.S. significantly differ in regard to these factors, and further investigation on how these state policies affect healthcare is needed to observe a more complete state of prescription affordability in the country. Our group advocates for the expansion of programs such as Medicare and Medicaid, among other laws, to protect individuals from drug and treatment price increases.

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