Statistics 133 Final Project Report:
The Impact of Affordable Care Act
Group members: Sophie Shang, Claudia Tse, Shang Hao Huang

Introduction

Healthcare system delivers the prevention and intervention system one needs to lead a high-quality and high-efficiency life. In the US, the design of health care system is largely determined by policy makers. Affordable Care Act, also known as Obamacare, aims to improve the accessibility and quality of healthcare, while lowering the costs and uninsured population. Many reports have shown significant impact of Affordable Care Act. Unfortunately, president-elect Donald Trump ordered his first Executive order on repealing Affordable Care Act, which essentially allows healthcare practitioners to reject uninsured patients. Our report essentially aims to understand the impact brought by Affordable Care Act. We first review the original document on Affordable Care Act to understand the structure and specific policies involved. Then, we measure the impact Affordable Care Act has had on the accessibility of care by primarily visualizing the change in insurance coverage starting from 2010 to 2015. Additionally, we measure the change in quality of healthcare through tracking the death rate of infants by state from 2003 to 2014. We also examine the financial health of hospitals by conducting a case study on California hospitals. To understand what is the main factor driving Trump's Executive Order, we visualize attitude data toward ACA in a poll conducted by Kaiser Permanente against participants' political party and income.

To sum up, our research question entails:

- What is the effect of Affordable Care Act on access to and quality of care?
- What is the effect of Affordable Care on hospital financial health?
- Why the Executive Order? How people's attitudes influence Affordable Care Act?

Data Collection/Selection

We used multiple source of data. Please refer to the table below:

Name	Source	Usage/Description
Infant Death Records on CDC WONDER Center for Medicare and Medical	CDC	Used to measure the death rate of infants from 2003-2014
Hospital Profitability	Office of Statewide Health Planning & Development	Used to measure financial health of hospitals/ Hospital profit 2009 -2013
Historical Budget Data	Congressional Budget Office	Used to understand ACA/

		Budget Data and projection
Health Insurance Coverage Status and Type of Coverage, United States	Knoema	Used to compare ACA on health insurance coverage from 2008-2015
Profiles of Affordable Care Act Coverage Expansion Enrollment for Medicaid/CHIP and the Health Insurance Marketplace	Office of the Assistant Secretary for Planning and Evaluation	Used to visualize how ACA is being implemented in the US/Breakdown of insurance coverage 10-1-2013 to 3-31-2014
Health Tracking Poll	Kaiser Permanente	Used to conduct statistical Analysis Attitudes x party & income/ Attitudes towards ACA from 4/10/10 - 4/15/17

Affordable Care Act

To understand what Affordable Care Act entails, we refer back to the original document under Public Law 111-148 and compared the content of this document of a detailed dataset on Affordable Care Care in Year 2014. Here is the breakdown.

Affordable Care Act aims to increase insurance coverage among US citizens and permanent citizens. Thus, under Affordable Care Act, there are health insurance marketplaces that helps and facilitates the purchase of health insurance. There are two types of marketplace: Federally-funded Marketplace (FFM) and State-based Marketplace (SBM) (see Fig 1.1). Many states like California and Massachusetts are in the State-based Marketplace.

Fig: 1.1

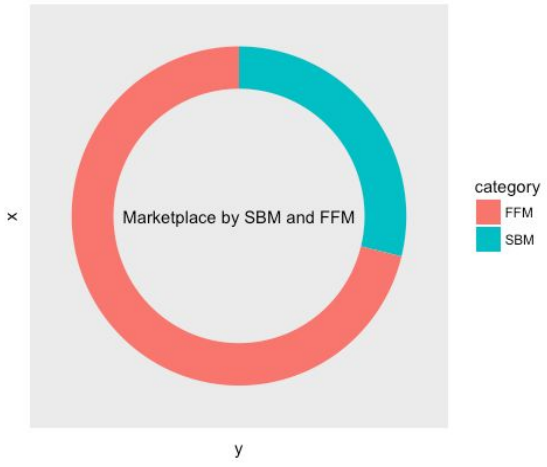
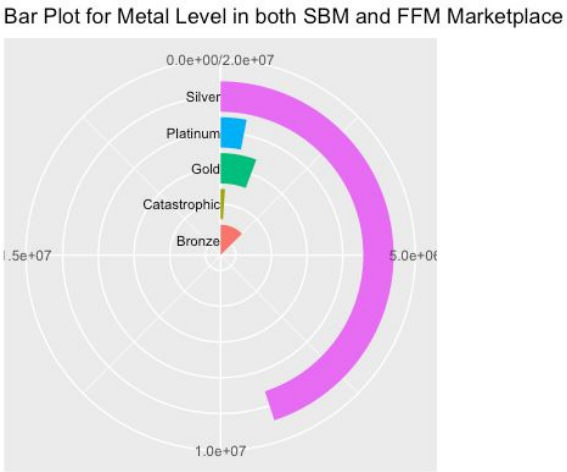


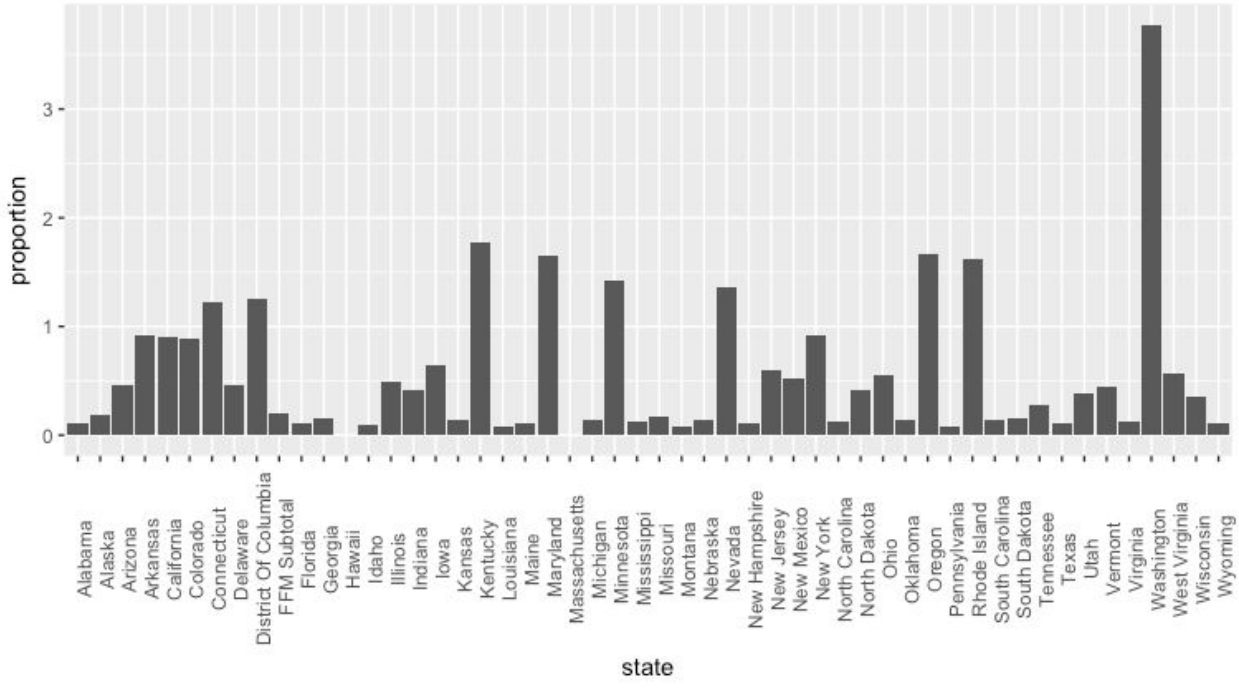
Fig: 1.2



Affordable Care Act also targets the US population based on their income level. With Bronze level targeting the highest income group, the metal level measures how insurance cost is splitted between individuals and insurance companies. Platinum level gives the highest benefit, with insurance company 90% of healthcare care (see detail go to www.healthcare.gov/choose-a-plan/plans-categories/). From our dataset, we can see that the majority of American population is enrolled in Silver level, reflecting a highly populated middle class in the US (see Fig 1.2).

Affordable Care Act also includes two special packages for employees and families with children. To be more specific, Medicaid provides health care insurance towards children, women and disabled population from low income families. Meanwhile, Children's Health Insurance Program (CHIP) provides health care coverage to children up to age 19. Those being covered by CHIP are usually children coming from families with relatively high income that don't qualify for Medicaid. Thus, with CHIP and Medicaid combined, women, children and disabled population are being properly covered. We calculate the proportion of people being covered by CHIP and Medicaid to the total amount of people being covered under Affordable Care Act (see Fig 1.3). This figure reflects only a small proportion of people is covered by CHIP and Medicaid.

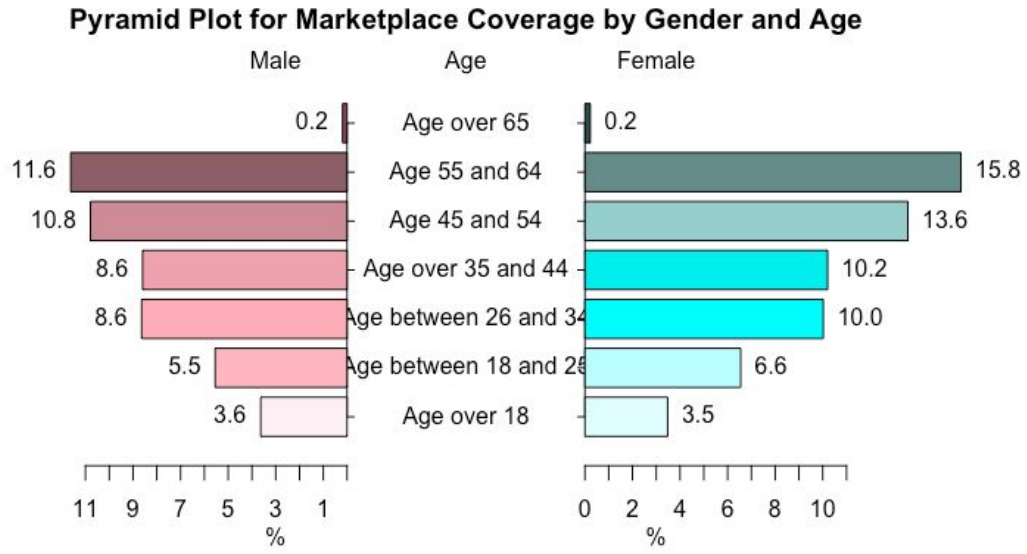
Fig 1.3



We then breakdown the data to see the demographics of population covered by Affordable Care Act. Overall, there are more females than males enrolled in Affordable Care Act. This pattern is being observed across all age group. With the majority of the workforce (between Age 18 and

Age 65) being covered by Affordable Care Act, we think this policy is, to some extent, efficient and effective (see Fig 1.4). Further analysis confirms our initial impression of the data.

Fig 1.4

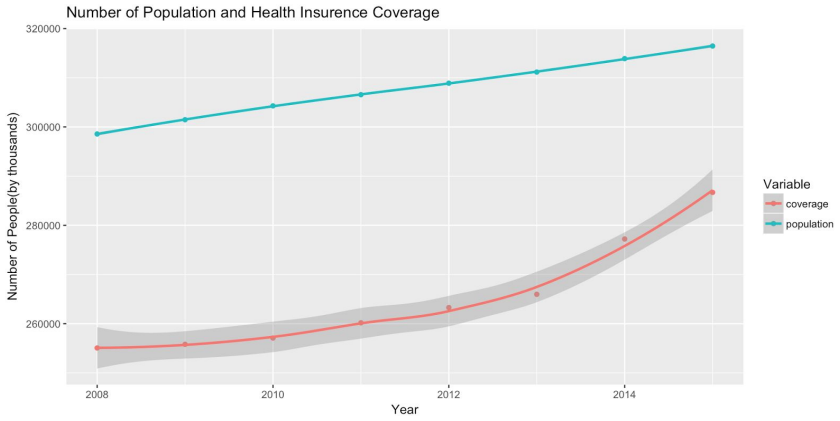


Data Visualization and Analysis

- ❖ What is the effect of Affordable Care Act on access to care?

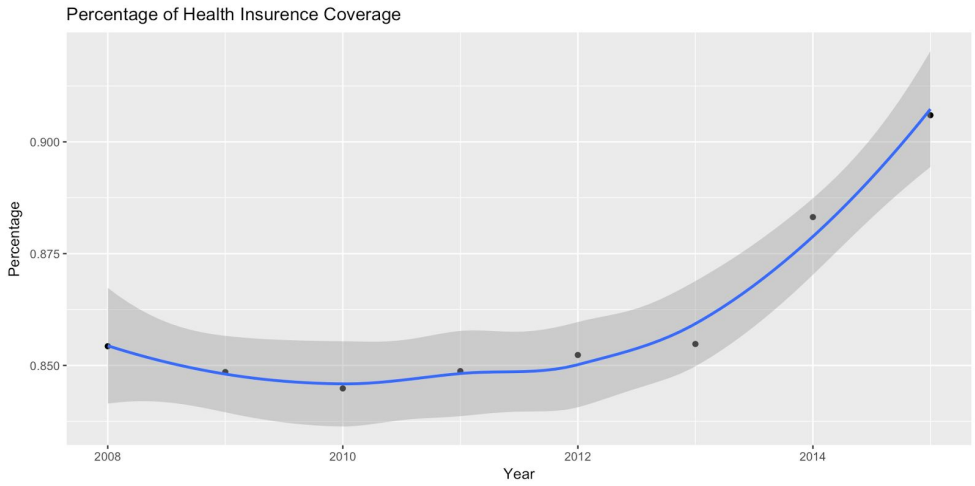
We used data that shows the number of people in the United States with health insurance coverage to analyze how the Affordable Care Act affects health insurance coverage of the overall population. By inspecting the number of people with coverage in the years before and after the Affordable Care Act, which was passed in 2009), we will be able to analyze the impact Affordable Care Act has had on the accessibility of care to the overall population. The population data, specifically the data on each state's coverage and population size, was essential in analyzing the change of rate in the number of people with coverage over the years.

Fig 1.5



We decide to use a line graph for the number of coverage and population in the Unites States. (Fid 1.5) Although we can see a clear growth in the red coverage line after year 2011, we need to take the effect of growing population(indicate as blue line). So we decide to make the "percentage of Health Insurance Coverage instead as shown in Fig 1.6.

Fig 1.6



In Fig 1.6 we can see that the growth rate increase dramatically after the year 2011, the year Affordable Care Act pass. Now we want to see if it is actually the difference of Affordable Care Act so we are going to compare states approve and disapprove the Act

Fig 1.7

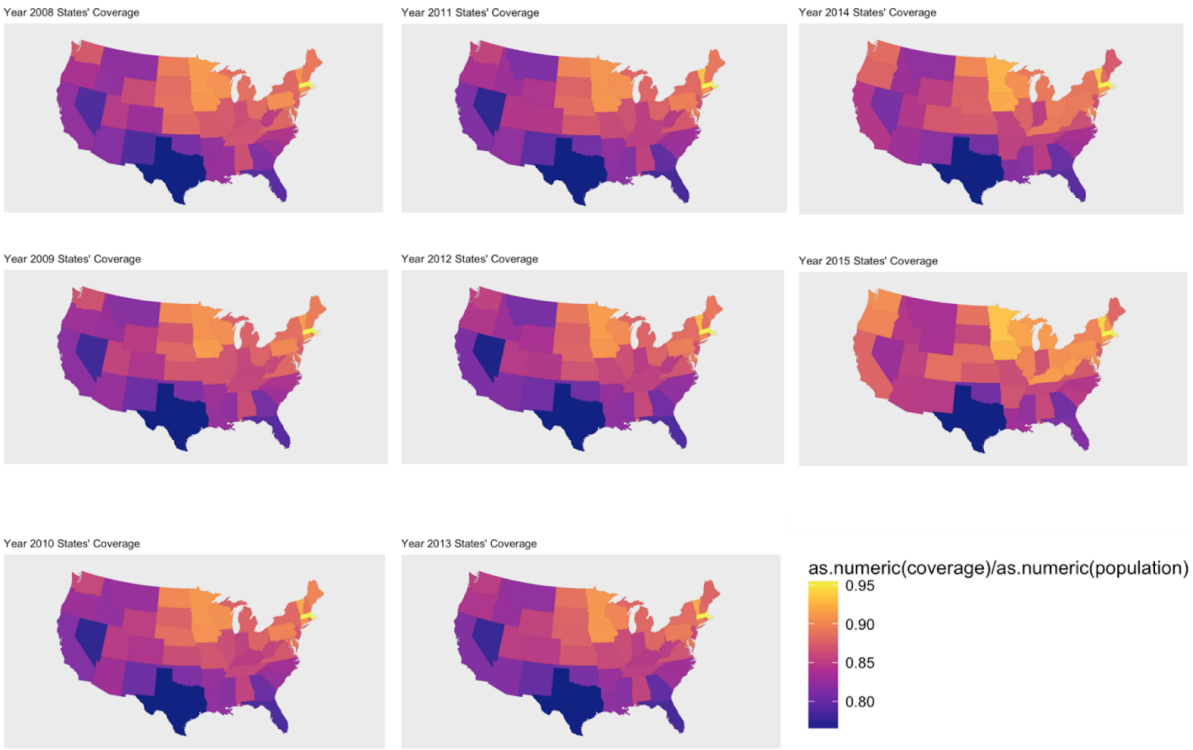
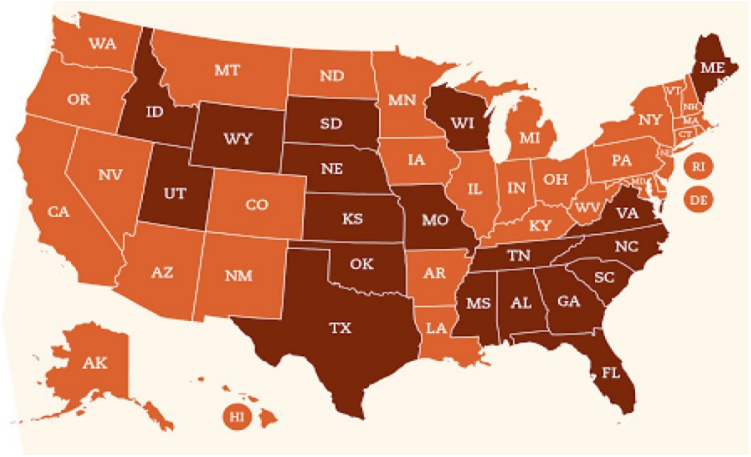


Fig 1.8

This is graph of states that pass ACA.(Lighter orange passed)



Although the Affordable Care Act is a bill that was crafted by the United States House of Representatives, it's not officially the law. There are certain states that do not approve of the bill and thus have not expanded it. To give a clearer, broader look on the effects of Affordable Care Act, we've separated the states that have and haven't expanded Medicaid and used the latter as our control group. We compare the growth rate of coverage for the overall population of states that have expanded Medicaid and those that haven't (see Fig 1.7).

From the interacting graph we can see that the states that passed the Affordable Care Act turns from purple to orange. And the states that does not approve mostly stay at the similar color.

- What is the effect of Affordable Care Act on quality of care?

The health of infants is a good indicator of the quality of care in hospitals and the care accessible to the general public. This is due to the fragile state of health of an infant; the health of an infant at this lifestage is highly dependent on factors outside of its control such as the health of its parents (in particular its mother) and the care it receives in the womb and during its most vital development stages. We made line graphs showing the death rate of infants per year for each state. We separated these states into two groups: the states that have expanded Medicaid and those that haven't. Additionally, we made line graphs showing the number of births in states that have and haven't expanded Medicaid.

Fig 1.9

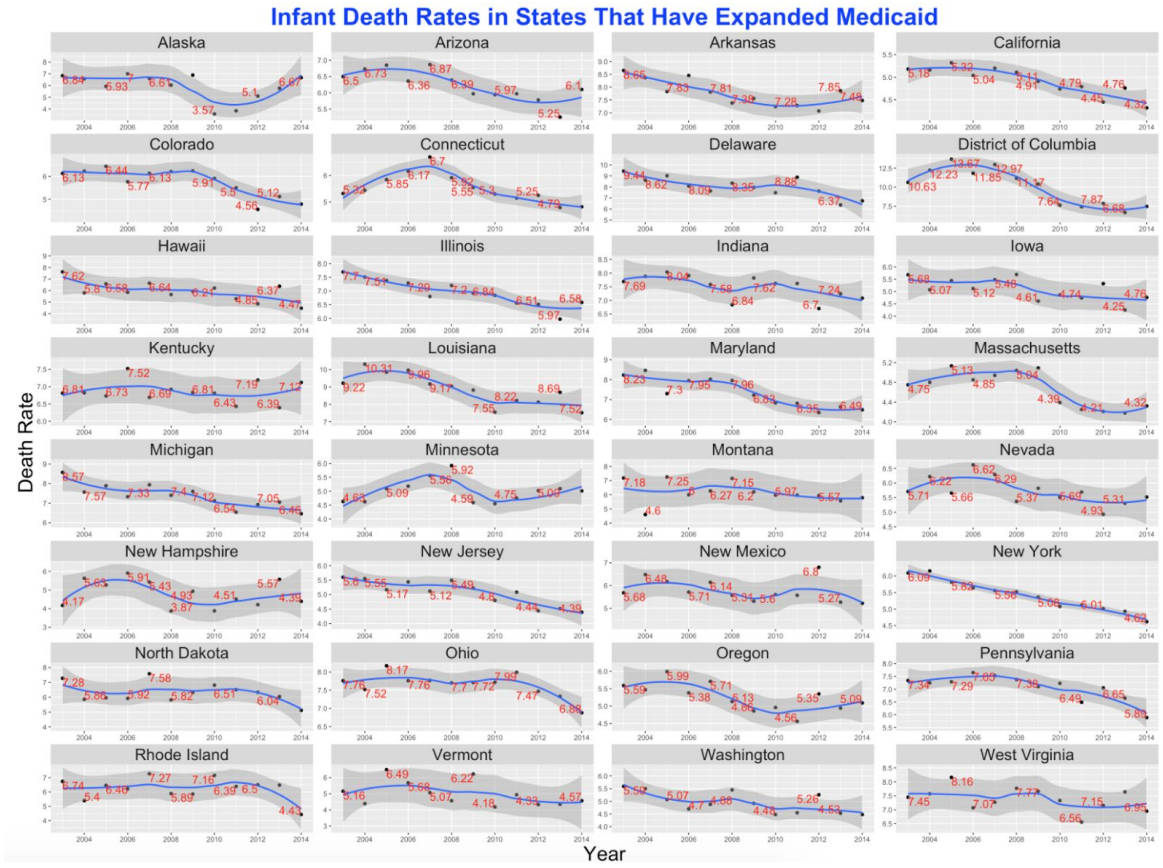
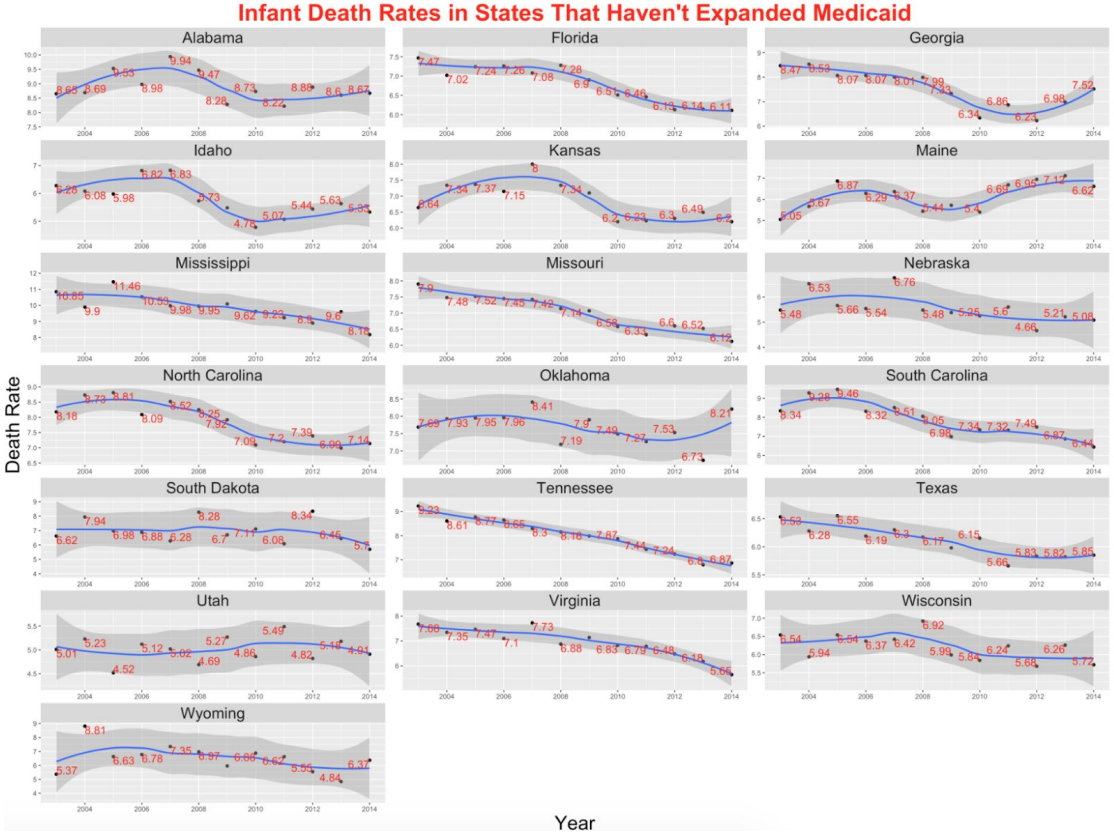


Fig 1.10



From Fig 1.9 and Fig 1.10, we can see that there is not much

difference in death rate for states approve medicare expansion and states disapprove medicare expansion. The Death rate for most of the states dropping.

Fig 1.11

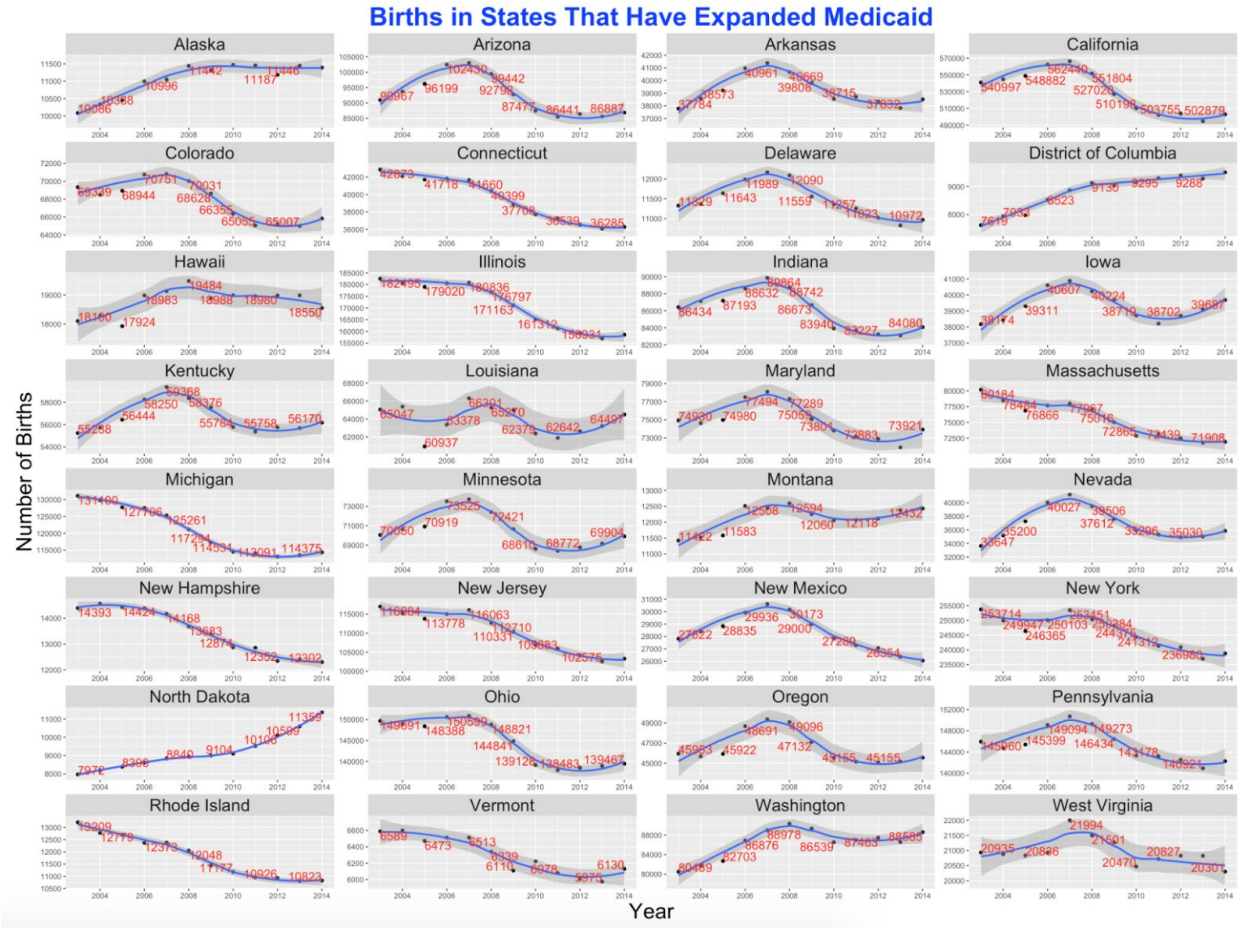
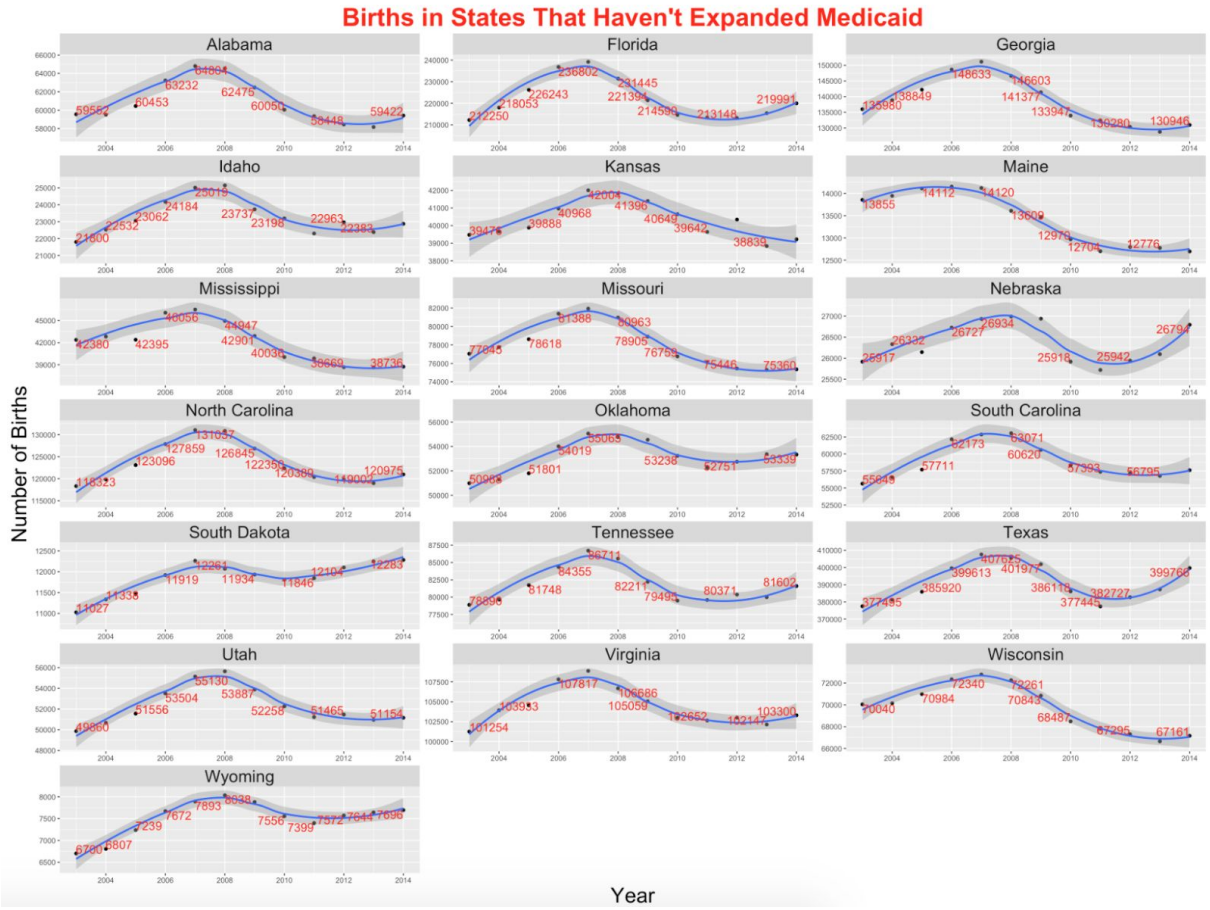


Fig. 1.12



From Fig 1.11 and Fig 1.12, we can see that there is not much difference in birth rate for states approve medicare expansion and states disapprove medicare expansion. The birth rate for most of the states are rising after year 2012.

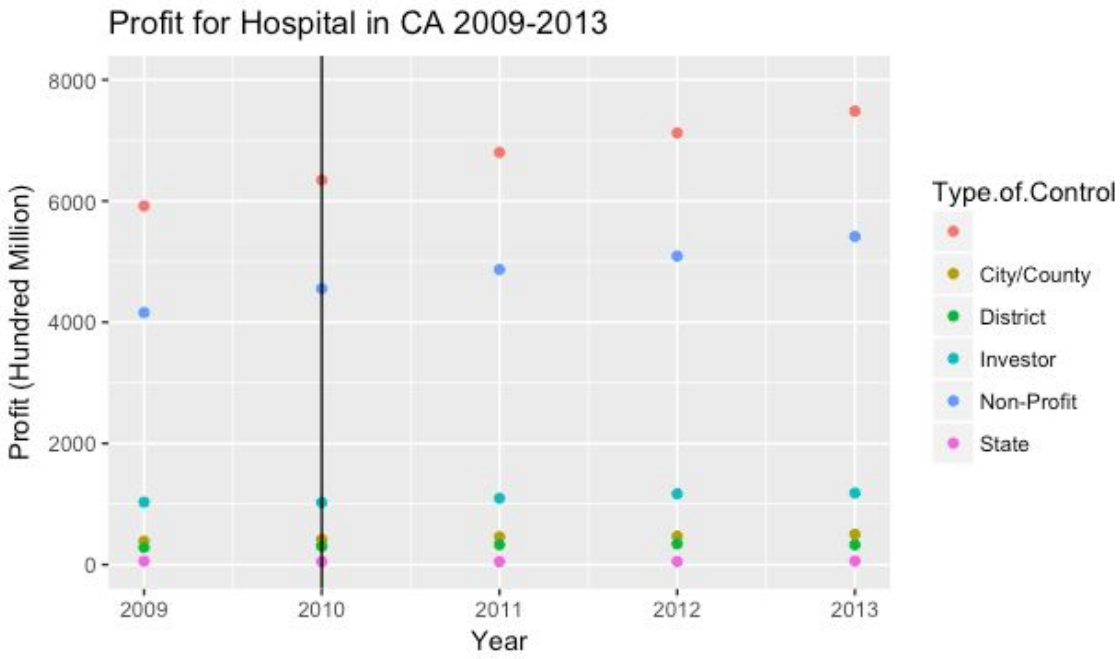
From the two observation for the death rate and birth rate, we can see that although the health insurance coverage is different in states that approve the Affordable Care Act and that does not, the quality of medical care is not being affected.

- ❖ What is the effect of Affordable Care on hospital financial health?

We then decided to look at some claims made by press and policy advisors that Affordable Care Act may bankrupt hospitals. To check the validity of this statement, we found did a case study on hospitals in California. We look at hospitals at California, excluding Kaiser hospitals, state mental hospitals, psychiatric health facilities, and hospitals with mainly long-term care patients. These exclusions applied mainly to align with the reimbursement policy under Affordable Care Act, which exclude private hospitals and mental hospitals. The net profit is a result of Deductions from revenue, net patient revenue, net operations (Operating Revenue less Operating Expense), and net income for public hospitals. We then visualize our dataset by Year

and Profit. We further categorized the hospitals by source of funding to show if Affordable Care Act adversely impacted any type of hospitals. The vertical line shows the start date of Affordable Care Act. We observe that hospital profit increases steadily over the years for all types of hospitals. We were overwhelmed by the fact that nonprofit hospitals receive the most amount of profit, consistently. Going back to the dataset, we discovered that there are substantially more non profit hospitals than any other types of hospitals, resulting in an overall larger sum of profit (see Fig 2.1).

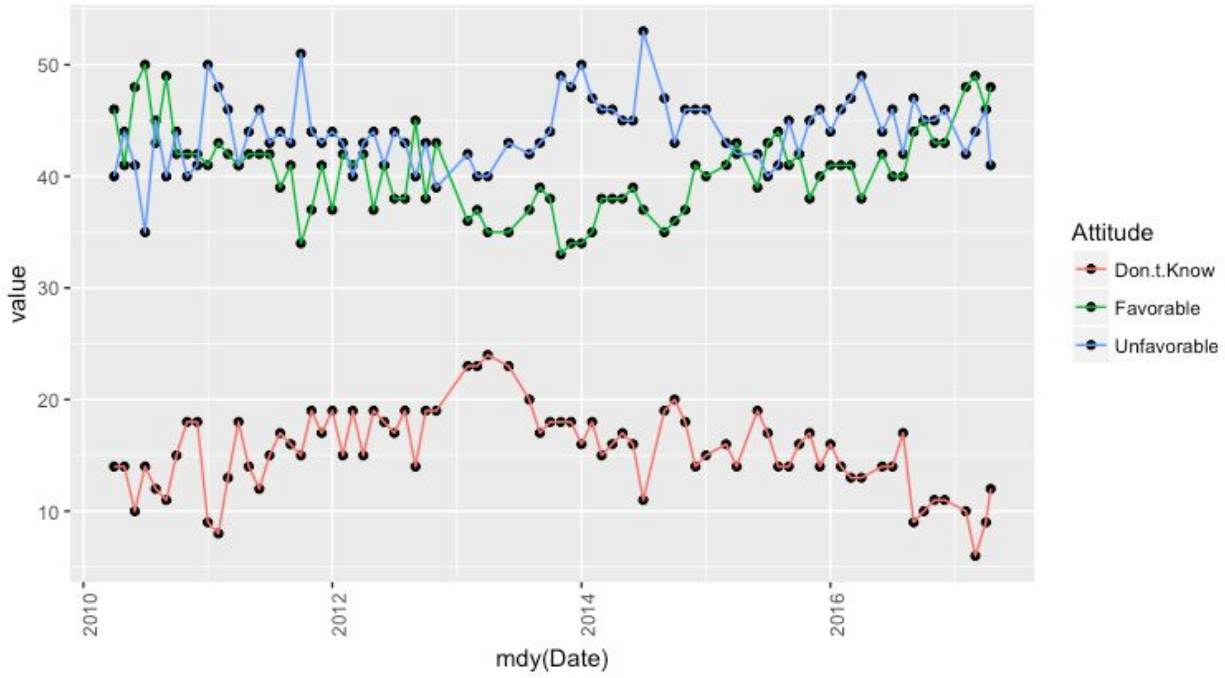
Fig 2.1



- Why the Executive Order? What factors influence people's attitudes towards Affordable Care Act?

From the previous two sections, we can see that Affordable Care Act have been truly effective: improving access to care and quality of care. Yet, many people still appauld Trump's Executive order and his recent act on repeal Affordable Care Act. Thus, we decided to look at people's attitude towards Affordable Care Act. Here is a percentage breakdown of attitudes towards Affordable Care Act (Don't know, Favored, Unfavored). From Fig 3.1, we can see some fluctuation of attitudes towards Affordable Care Care across the years. From 2011 to 2017, the amount of people that are ignorant of Affordable Care Act drops. Yet, there is no obvious trend for the other two attitudes, suggesting the controversial nature of Affordable Care Act.

Fig 3.1



Conclusion

There are many outside factors such as financial changes and advances in technology that would also have an impact on the data used in this project. In acknowledgement of this fact, we drew upon multiple data sources to allow us to better analyze the data and come to more accurate conclusions of this phenomenon. To be more specific, we drew upon data that would have also been affected by the Affordable Care Act, such as death rate, birthday, ect. Obviously though, we cannot account for all factors but the data that we used has allowed us to gain a big picture on the areas of life that are affected by Affordable Care Act.

All in all, we conclude that

- There is increase in access to care, with Federally-funded Marketplace the most effective one.
- There is improve in quality of care, regardless of it is Federally-funded or State-based.
- In our case study on California, we did find influence of Affordable Care Act on the financial health of hospitals.
- People's attitudes towards Affordable Care Act is mixed, revealing its controversial nature.

Citation

Oberlander, Jonathan (1 June 2010). "Long Time Coming: Why Health Reform Finally Passed". *Health Affairs*. **29** (6): 1112–1116. doi:10.1377/hlthaff.2010.0447

https://www.usatoday.com/story/news/politics/2013/11/07/fact-check-medicaid-rand-paul-bankrupt-hospitals/3469017/

Appendix

```{r include=FALSE}
library(DataComputing)
library(tidyr)
library(dplyr)
library(ggplot2)
library(ggthemes)
library(ggmap)
library(XML)
library(viridis)
```
```{r fig.width=10,fig.height=5, message=FALSE, warning=FALSE, echo=FALSE}
totalcoverage = read.csv("~/Desktop/total-coverage.csv")

 a= totalcoverage %>%
                    select(State.Name, Variable, X2008, X2009,X2010,X2011, X2012,X2013,X2014,X2015) %>%
   filter(State.Name== "United States")


 a = a %>%
                                gather(key= year, value = number, X2008,X2009,X2010,X2011,X2012,X2013,X2014,X2015)
Narrow = a %>%
                     mutate(Variable=ifelse(Variable=="KN.VV1","population","coverage"), year=gsub("X","",a$year))

ggplot(Narrow,aes(x=as.numeric(year),y=as.numeric(number),col=Variable))+geom_point()+geom_smooth()+labs(title="Number of Population and Health Insurence Coverage",x="Year",y="Number of People(by thousands)")


expand= Narrow %>%
   spread(key= Variable, value=number)

ggplot(expand,aes(x=as.numeric(year),y=as.numeric(coverage/population)))+geom_point()+geom_smooth()+labs(title="Percentage of Health Insurence Coverage",x="Year",y="Percentage")
```

```
coverage = read.csv("~/Desktop/coverage.csv")

 a= coverage %>%
                    select(State.Name, Variable, X2008, X2009,X2010,X2011,
X2012,X2013,X2014,X2015)

 a = a %>%
                                gather(key= year, value = number,
X2008,X2009,X2010,X2011,X2012,X2013,X2014,X2015)
statecoverage = a %>%
                     mutate(Variable=ifelse(Variable=="KN.VV1","population","coverage"),
year=gsub("X","",a$year)) %>%
   spread(key= Variable, value=number)

statecoverage= filter(statecoverage,State.Name!="")
statecoverage = statecoverage %>%  mutate(State.Name =tolower(State.Name))

ditch_the_axes <- theme(
  axis.text = element_blank(),
  axis.line = element_blank(),
  axis.ticks = element_blank(),
  panel.border = element_blank(),
  panel.grid = element_blank(),
  axis.title = element_blank()
  )

us <- map_data("state")

gg <- ggplot()
gg <- gg + geom_map(data=us, map=us,aes(x=long, y=lat, map_id=region))



#2008 graph
statecoverage2008 = filter(statecoverage,year==2008)

gg2008 <- gg + geom_map(data=statecoverage2008, map=us,
                                      aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name,legend.title="hi"))
```

```
gg2008 <- gg2008 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2008 <- gg2008 + labs(x=NULL, y=NULL)
gg2008 <- gg2008 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2008 <- gg2008 + ditch_the_axes + labs(title ="Year 2008 States' Coverage")
gg2008

#2009 graph
statecoverage2009 = filter(statecoverage,year==2009)
gg2009 <- gg + geom_map(data=statecoverage2009, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2009 <- gg2009 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2009 <- gg2009 + labs(x=NULL, y=NULL)
gg2009 <- gg2009 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2009 <- gg2009 + ditch_the_axes+ labs(title ="Year 2009 States' Coverage")
gg2009

#2010 graph
statecoverage2010 = filter(statecoverage,year==2010)
gg2010 <- gg + geom_map(data=statecoverage2010, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2010 <- gg2010 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2010 <- gg2010 + labs(x=NULL, y=NULL)
gg2010 <- gg2010 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2010 <- gg2010 + ditch_the_axes+ labs(title ="Year 2010 States' Coverage")
gg2010

#2011 graph
statecoverage2011 = filter(statecoverage,year==2011)
gg2011 <- gg + geom_map(data=statecoverage2011, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2011 <- gg2011 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2011 <- gg2011 + labs(x=NULL, y=NULL)
gg2011 <- gg2011 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2011 <- gg2011 + ditch_the_axes+ labs(title ="Year 2011 States' Coverage")
```

```
gg2011

#2012 graph
statecoverage2012 = filter(statecoverage,year==2012)
gg2012 <- gg + geom_map(data=statecoverage2012, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2012 <- gg2012 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2012 <- gg2012 + labs(x=NULL, y=NULL)
gg2012 <- gg2012 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2012 <- gg2012 + ditch_the_axes+ labs(title ="Year 2012 States' Coverage")
gg2012

#2013 graph
statecoverage2013 = filter(statecoverage,year==2013)
gg2013 <- gg + geom_map(data=statecoverage2013, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2013 <- gg2013 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2013 <- gg2013 + labs(x=NULL, y=NULL)
gg2013 <- gg2013 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2013 <- gg2013 + ditch_the_axes+ labs(title ="Year 2013 States' Coverage")
gg2013

#2014 graph
statecoverage2014 = filter(statecoverage,year==2014)
gg2014 <- gg + geom_map(data=statecoverage2014, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2014 <- gg2014 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2014 <- gg2014 + labs(x=NULL, y=NULL)
gg2014 <- gg2014 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2014 <- gg2014 + ditch_the_axes+ labs(title ="Year 2014 States' Coverage")
gg2014


#2015 graph
statecoverage2015 = filter(statecoverage,year==2015)
```

```
gg2015 <- gg + geom_map(data=statecoverage2015, map=us,
                                        aes(fill=as.numeric(coverage)/as.numeric(population),
map_id=State.Name))

gg2015 <- gg2015 + scale_fill_viridis(option="plasma",begin = 0, end = 1)
gg2015 <- gg2015 + labs(x=NULL, y=NULL)
gg2015 <- gg2015 + coord_map("albers", lat0 = 39, lat1 = 45)
gg2015 <- gg2015 + ditch_the_axes + labs(title ="Year 2015 States' Coverage")
gg2015
```
```{r include=FALSE}
# Don't delete this chunk if you are using the DataComputing package
library(DataComputing)
library(ggplot2)
library(dplyr)
library(tidyr)
library(scales)
```
<!-- Don't edit the material above this line -->

```{r include=FALSE}
infantRecords2003                                                                    <-
read.csv("~/Desktop/Linked-Birth-Infant-Death-Records-2003-2006.csv")
infantRecords2014                                                                    <-
read.csv("~/Desktop/Linked-Birth-Infant-Death-Records-2007-2014.csv")
```

```{r include=FALSE}
infantRecords2003$Notes <- NULL
colnames(infantRecords2003)[2] <- "Year"
totalDeathsBirths2003 <- infantRecords2003 %>%
  na.omit() %>%
  mutate(Death.Rate = as.numeric(Death.Rate))
```

```{r include=FALSE}
infantRecords2014$Notes <- NULL
colnames(infantRecords2014)[2] <- "Year"
totalDeathsBirths2014 <- infantRecords2014 %>%
  na.omit() %>%
  mutate(Death.Rate = as.numeric(Death.Rate))
```

```

```{r include=FALSE}
totalRecords <- totalDeathsBirths2003%>% full_join(totalDeathsBirths2014)
totalRecordsWith <- totalRecords %>%
    filter(!State %in% c("Alabama", "Florida", "Georgia", "Idaho", "Kansas", "Maine", "Mississippi", "Missouri", "Nebraska", "North Carolina", "Oklahoma", "South Carolina", "South Dakota", "Tennessee", "Texas", "Utah", "Virginia", "Wisconsin", "Wyoming"))

totalRecordsWithout <- totalRecords %>%
    filter(State %in% c("Alabama", "Florida", "Georgia", "Idaho", "Kansas", "Maine", "Mississippi", "Missouri", "Nebraska", "North Carolina", "Oklahoma", "South Carolina", "South Dakota", "Tennessee", "Texas", "Utah", "Virginia", "Wisconsin", "Wyoming"))
```

```{r fig.width=20, fig.height=15, message=FALSE, warning=FALSE, echo=FALSE}
deaths_with_plot <- totalRecordsWith %>%
  ggplot(aes(x=Year, y=Death.Rate, label=Death.Rate)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~State, ncol=4, scales="free") +
  scale_x_continuous(breaks= pretty_breaks()) +
   labs(title="Infant Death Rates in States That Have Expanded Medicaid", y="Death Rate") +
         geom_text(aes(label=Death.Rate), vjust="inward", hjust="inward", size=5, check_overlap = TRUE, color="red") +
  theme(plot.title=element_text(size=30, color = "blue", face="bold", hjust = 0.5),
        axis.title.x=element_text(size=25),
        axis.title.y=element_text(size=25),
        strip.text = element_text(size=20), )
deaths_with_plot
```

```{r fig.width=20, fig.height=15, message=FALSE, warning=FALSE, echo=FALSE}
deaths_without_plot <- totalRecordsWithout %>%
  ggplot(aes(x=Year, y=Death.Rate, label=Death.Rate)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~State, ncol=3, scales="free") +
  scale_x_continuous(breaks= pretty_breaks()) +
```
```

```
  labs(title="Infant Death Rates in States That Haven't Expanded Medicaid", y="Death Rate") +
        geom_text(aes(label=Death.Rate), vjust="inward", hjust="inward", size=5, check_overlap = TRUE, color="red") +
  theme(plot.title=element_text(size=30, color = "red", face="bold", hjust = 0.5),
        axis.title.x=element_text(size=25),
        axis.title.y=element_text(size=25),
        strip.text = element_text(size=20))
deaths_without_plot
```

```{r fig.width=20, fig.height=15, message=FALSE, warning=FALSE, echo=FALSE}
births_with_plot <- totalRecordsWith %>%
  ggplot(aes(x=Year, y=Births, label=Births)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~State, ncol=4, scales="free") +
  scale_x_continuous(breaks= pretty_breaks()) +
  labs(title="Births in States That Have Expanded Medicaid", y="Number of Births") +
   geom_text(aes(label=Births), vjust="inward", hjust="inward", size=5, check_overlap = TRUE, color="red") +
  theme(plot.title=element_text(size=30, color = "blue", face="bold", hjust = 0.5),
        axis.title.x=element_text(size=25),
        axis.title.y=element_text(size=25),
        strip.text = element_text(size=20))
births_with_plot
```

```{r fig.width=20, fig.height=15, message=FALSE, warning=FALSE, echo=FALSE}
births_without_plot <- totalRecordsWithout %>%
  ggplot(aes(x=Year, y=Births, label=Births)) +
  geom_point() +
  geom_smooth() +
  facet_wrap(~State, ncol=3, scales="free") +
  scale_x_continuous(breaks= pretty_breaks()) +
  labs(title="Births in States That Haven't Expanded Medicaid", y="Number of Births") +
   geom_text(aes(label=Births), vjust="inward", hjust="inward", size=5, check_overlap = TRUE, color="red") +
  theme(plot.title=element_text(size=30, color = "red", face="bold", hjust = 0.5),
        axis.title.x=element_text(size=25),
        axis.title.y=element_text(size=25),
```

```
      strip.text = element_text(size=20))
births_without_plot
```
```{r include=FALSE}
library(DataComputing)
library (XML)
library(dplyr)
library (tidyr)
library(ggplot2)
library(plotrix)
library(plyr)
library(lubridate)
library(likert)
library(ggthemes)
library(viridis)
```
```{r}
data_set <- read.csv(file = "~/Desktop/data set.csv")
names(data_set)

### metal level circular bar plot ###
a <- sum(data_set['Bronze'])
b <- sum(data_set['Silver'])
c <- sum(data_set['Gold'])
d <- sum(data_set['Platinum'], na.rm = TRUE)
e <- sum(data_set['Catastrophic'])

metal_level = data.frame(group =c('Bronze', 'Silver', 'Gold', 'Platinum', 'Catastrophic'),
                         value = c(a, b, c, d, e))
bar <- ggplot(metal_level, aes(x = group, y = value, fill=group))+geom_bar(width = 0.85,
stat="identity")+coord_polar(theta = "y") +xlab("") + ylab("") +ylim(c(0,20000000))
bar <- bar + ggtitle("Bar Plot for Metal Level in both SBM and FFM Marketplace")
bar <- bar + geom_text(data = metal_level, hjust = 1, size = 3, aes(x = group, y = 0,
label = group))
bar <- bar + theme(legend.position = "none" , axis.text.y = element_blank() , axis.ticks =
element_blank())

### Age Level Bar Plot ###
fe_18<-sum(data_set["Female.below.18"], na.rm = TRUE)
fe_18_25<-sum(data_set['Female18.25'], na.rm = TRUE)
fe_26_34<-sum(data_set['Female.26.34'], na.rm = TRUE)
```

```
fe_35_44<-sum(data_set['Female.35.44'], na.rm = TRUE)
fe_45_55<-sum(data_set['Female.45.55'], na.rm = TRUE)
fe_55_64<-sum(data_set['Female.55.64'], na.rm = TRUE)
fe_64<-sum(data_set['Female.over.65'], na.rm = TRUE)

m_18<-sum(data_set["Male.below.18"], na.rm = TRUE)
m_18_25<-sum(data_set['Male18.25'], na.rm = TRUE)
m_26_34<-sum(data_set['Male.26.34'], na.rm = TRUE)
m_35_44<-sum(data_set['Male.35.44'], na.rm = TRUE)
m_45_55<-sum(data_set['Male.45.55'], na.rm = TRUE)
m_55_64<-sum(data_set['Male.55.64'], na.rm = TRUE)
m_64<-sum(data_set['Male.over.65'], na.rm = TRUE)

#xy.pop<-c(fe_18, fe_18_25, fe_26_34, fe_35_44, fe_45_55, fe_55_64, fe_64)
#xx.pop<-c(m_18, m_18_25, m_26_34, m_35_44, m_45_55, m_55_64, m_64)
xx.pop<-c(3.47832, 6.55026, 10.02370, 10.20536, 13.58190, 15.81246, .22765)
xy.pop<-c(3.63176, 5.54770, 8.63940, 8.59850, 10.79076, 11.62240, .18887)
agelabels<-c('Age over 18', 'Age between 18 and 25', 'Age between 26 and 34',
          'Age over 35 and 44', 'Age 45 and 54', 'Age 55 and 64', 'Age over 65')

#mcol<-color.gradient(c(0,0,0.5,1),c(0,0,0.5,1),c(1,1,0.5,1),7)
#fcol<-color.gradient(c(1,1,0.5,1),c(0.5,0.5,0.5,1),c(0.5,0.5,0.5,1),7)
mcol<-c("#FFF0F5", "#FFB6C1", "#FFAEB9", "#EEA2AD", "#CD8C95", "#8B5F65",
'#8B475D')
fcol<-c("#E0FFFF", "#BBFFFF", "#00FFFF", "#00EEEE", "#96CDCD", "#668B8B",
"#2F4F4F")

par(mar=pyramid.plot(xy.pop,xx.pop,labels=agelabels,
                          main="Pyramid Plot for Marketplace Coverage by Gender and
Age",lxcol=mcol,rxcol=fcol,
                gap=5,show.values=TRUE))
data_set %>%
  group_by(MarketType) %>%
  summarise(no_rows = length(MarketType))
dat = data.frame(count=c(15, 37), category=c("SBM", "FFM"))

# Add addition columns, needed for drawing with geom_rect.
dat$fraction = dat$count / sum(dat$count)
dat = dat[order(dat$fraction), ]
dat$ymax = cumsum(dat$fraction)
dat$ymin = c(0, head(dat$ymax, n=-1))
```

```
# Make the plot
p1 = ggplot(dat, aes(fill=category, ymax=ymax, ymin=ymin, xmax=4, xmin=3)) +
  geom_rect() +
  coord_polar(theta="y") +
  xlim(c(0, 4)) +
  theme(panel.grid=element_blank()) +
  theme(axis.text=element_blank()) +
  theme(axis.ticks=element_blank()) +
  annotate("text", x = 0, y = 0, label = "Marketplace by SBM and FFM") +
  labs(title="")
p1

# Medicade & CHIP
proportion <- data_set["Medicaid.CHIP"]/data_set["TotalEligible"]
state <- data_set['StateName']
CHIP_Medi <- data.frame(proportion, state = state)
colnames(CHIP_Medi) <- c("proportion", "state")
prop_plot <- ggplot(data=CHIP_Medi, aes(x=state, y=proportion)) +
  geom_bar(stat="identity") +
  theme(axis.text.x=element_text(angle=90))
```
```{r}
# Health Poll
tracking <- read.csv('~/Desktop/Health.csv')
names(tracking)
bar <- tracking %>%
  select(Date, Favorable, Unfavorable, Don.t.Know) %>%
  gather (key = Attitude, value, Favorable, Unfavorable, Don.t.Know)
ggplot(bar, aes(x=Date, y=value, fill = Attitude)) + geom_bar(stat="identity") +
theme(axis.text.x=element_text(angle=90))

# Attitudes towards ACA against Age, Party, Income
regression<-tracking %>%
        select(Democrat_Favorable, Democrat_Unfavorable, Democrat_Don.t.Know,
Independent_Favorable, Independent_Unfavorable, Independent_Don.t.know,
Republican_Don.t.know, Republican_Unfavorable, Republican_Don.t.know)%>%
      gather(key = Party, Attitude, Democrat_Favorable, Democrat_Unfavorable,
Democrat_Don.t.Know, Independent_Favorable, Independent_Unfavorable,
Independent_Don.t.know, Republican_Don.t.know, Republican_Unfavorable,
Republican_Don.t.know)
```

```
model <- lm(Attitude~Party, data=regression)
summary(model)
```