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Finding Trends in Big City Health Issues with Data Visualization

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Abstract

In recent years, data visualization has become one of the most effective tools to understand and identify unseen features of the large datasets available. An open source data set available for health issues for big cities across the United States was obtained. There are numerous indicators presented in the dataset including Demographics, Chronic Health Diseases, Social and Economic Factors, Food Safety, Mortality Rates, Cancer and Life Expectancy Rates. The dataset encompassed myriad of demographics as well as specific data for a number of US cities. The data was explored in different methods in Data points in terms of the demographic data available. These data visualizations could be used to understand and identify trends for providing improvement in vital areas of public health issues faced by these populated centers. The project employed R studio software. Multiple data visualization was created and discussed in detail.

Keywords: Big Data, Data Visualization, Healthcare Issues, R programming, Cancer Mortality, Demographics, Heart Disease

Introduction

There has been increasing interest in utilizing big data sets to review, understand and observe trends in healthcare industry. The amount of data collected now has been expanded to bigger populations to assist big data in making smart epidemiological and informatics decisions. The ever-increasing application of digitalization within day - to - day living and as part of our healthcare systems – with the resultant data generation – presents the opportunity to better define the populations exposed to medicines, and their benefits and harm in real world settings. (Mueller, 2019, Tideman 2019)

Today, we are facing a situation wherein we are flooded with tons of data from every aspect of our life such as social activities, science, work, health, etc. In a way, we can compare the present situation to a data deluge. The technological advances have helped us in generating more and more data, even to a level where it has become unmanageable with currently available technologies. This has led to the creation of the term ‘big data’ to describe data that is large and unmanageable. In order to meet our present and future social needs, we need to develop new strategies to organize this data and derive meaningful information. One such special social need is healthcare. Like every other industry, healthcare organizations are producing data at a tremendous rate that presents many advantages and challenges at the same time. In this review, we discuss about the basics of big data including its management, analysis and future prospects especially in healthcare. A biological system, such as a human cell, exhibits molecular and physical events of complex interplay. In order to understand interdependencies of various components and events of such a complex system, a biomedical or biological experiment usually gathers data on a smaller and/or simpler component. Consequently, it requires multiple simplified experiments to generate a wide map of a given biological phenomenon of interest. This indicates that more the data we have, the better we understand the biological processes. With this idea, modern techniques have evolved at a great pace. (Kaushik, 2019)

Recent publication highlighted the applicability of datasets online and online search engines in understanding disease trends. A large and growing body of “big data” was generated by internet search engines, such as Google for a time period of 2008-2014 by a state-wise distribution. (Young, 2019) Because people often search for information about public health and medical issues, researchers may be able to use search engine data to monitor and predict public health problems, such as HIV. (Figure 1)

Authors sought to assess the feasibility of using Google search data to analyze and predict new HIV diagnoses cases in the United States. They have explained certain limitations to their data. However, their findings and model show remarkable predictive statistics. The authors have discussed the implications of integrating visualization maps and tools based on these models into public health and HIV monitoring and surveillance. Their results indicated that Google Trends was a feasible tool to predict new cases of HIV at the state level.

Another interesting publication combining the data about HIV/AIDS, tuberculosis and silicosis to understand their correlation with use of big data. The author proposed that the big data framework had the potential of addressing the needs of predictive epidemiology which was important in forecasting and disease control in the mining industry. (Jonkya, 2014)

There has been considerable research done by employing tools of data science to improve city health. There are several publications providing very insightful information regarding the use of big data and data science to improve the governing of cities and making better decisions.

Nuaimi et. al. has discussed in detail the use of big data can be instrumental in efficient resource utilization, better quality of life and higher level of transparency and openness. With most cities known to be high population centers and resources being either scarce or expensive, it can be valuable to make a conscious effort to have better and controlled dispensation of these resources. Improved allocation of resources, reduced wastage, better services and efficient models for living and work, the city residents can experience a better quality of life. (Nuami, 2015) This in turn, increases the number of people living in the city and increases taxpaying workforce and consumers for local businesses. The release of public information by the government also increases the level of transparency and use of data efficiently.

Pineo et, al. has used the term ‘urban health indicators’ (UHIs) in their publication to provide 10 key principles to guide the development of the health care indices. Per authors, UHIs refer to ‘summary measures about the physical urban environment’s contribution to human health and wellbeing’. The principles laid out are clear conceptual framework, global and local outlook, evidence-based work, focus on avoiding inequalities, alignment with existing data/indicator systems, peer-reviewed work, informed opinions by users, promote a systematic approach, compatible with spatial awareness and focused on built environment. They advised on several categories for healthy cities index such as air quality, food access, green infrastructure, housing and buildings, leisure and recreation, noise pollution, safety and security, transport and utilities and services. They provided a causal framework for a relationship between urban environment exposure, behavioral outcomes and health outcomes depending on evidence-based from the data. (Pineo, 2018)

Gourevitch et. al. tried to develop a Web-based application and utility comprising of 5 separate domains and 37 parameters: social and economic factors, physical environment, health behaviors, health outcomes, and clinical care. The authors created a dashboard for the largest 500 US cities using the metrics calculated to the city level and, where possible, subcity level from multiple data sources, including national health surveys, vital statistics, federal administrative data, and state education data sets. Continuous data input from city partners helped create and maintain the Dashboard, ensuring that measures can be compared across user-selected cities and linked to evidence-based policies to spur action. (Gourevitch, 2019)

Dr. Lumpkin has discussed about the kind of culture which needs to be developed in order to find innovative solutions for health problems. It would be difficult for cities unless they work collaboratively with other sectors of government, the health care sector, and business. Dr. Lumpkin has emphasized on the following four points: a. development of a shared value of health and social cohesion, b. multisectoral collaboration, c. improved and equitable opportunities for healthy choices and the improved quality, and d. efficiency, and equity of health and health care systems. (Lumpkin, 2015)

Fielding has explained in detail about the gains public health made gains in the last century, making a significant contribution to the expansion of life expectancy in the United States by an eye-popping 30 years using discussion from CDC research and information. The scope of public health would now be evolved to include new threats, especially terrorism and climate change. Understanding different social, physical and economic factors are major determinants to achieve healthier communities. The actual applications of such concepts can be clearly seen in the larger metropolitan areas. New initiatives will be required in order to implement new policies, by reaching out to community leaders, industrial sectors, and government bodies. (Fielding, 2015)

There is tremendous amount of data made available freely by the government at data.gov as well as the source of data for our publication at the bigcitieshealth.org. The Big cities Health data sets contains indicators such Environment, HIV/AIDS, Infectious disease, Injury/Violence, Social and economic factors, Food Safety, Cancer, Life Expectancy and Death Rate (Overall), Chronic disease, Maternal and child health, Sexually Transmitted Infections and Demographics. There have been some data visualizations posted on the website https://www.bigcitieshealth.org/. These illustrations prove that this data can be explored for many more visualizations and can be used to draw many more interpretations.

The project focused on applying the principles of healthcare data visualization to understand the information presented in these large datasets. These datasets represent the conditions experienced by the patients present in these cities. The project aimed to understand healthcare and public health trends depending on population demographics. The data presented here had the limitations of availability, and there were gaps in data which could not be alleviated. The project was undertaken with the assumption that some information might be missing, as these data were real world data points.

Method

The dataset used was obtained from the https://www.bigcitieshealth.org/ and exported as separate Excel files with different indicators and factors. Factors and indicators such environment, HIV/AIDS, infectious disease, injury/violence, social and economic factors, food safety, cancer, life expectancy and death rate (overall), chronic disease, Maternal and child health, sexually transmitted infections and demographics were evaluated. Using HIV/AIDS as an indicator and importing the data into Power BI resulted in Figure 2 which shows data about HIV/AIDS by year. This visualization can be used to show a decline in new cases. This decline can be attributed due to several factors such as widespread acceptability of patients, development of new therapies and outreach of communities across various social and economic demographics from 2010-2016. Entire datasets with different indicators can be plotted to visualize significant trends and associations for different major cities and their common health issues.

Such illustrations can be presented as a comprehensive review of this dataset. However, it was cumbersome to perform several dataset additions using Power BI. Upon review, I explored the software R to create these visualizations, and examples are found in Figures 3A - F. These illustrations show the various formats of presentations to make the data more intuitive and understandable. The majority of visualizations created have the year (time factor) plotted on the x-axis to understand the trend and maintain consistency. Data is stratified by race, marked by different colors and shapes in Figures 3A–F for two separate cities – Boston, MA and Las Vegas, NV – to look at all-cause mortality rate. If one looks at the data visualizations in separate windows, Figure 3A has different races portrayed as different shapes and colors, and 3B has separate colors for races and increasing sized dots for years from 2010 – 2015. Both figures look tangled and do not delineate separate features well. Figure 3C employs different sized circles as indicators for race and a spectrum of blue colors for year (x-axis). Unfortunately, It is difficult for readers to quickly discern separate races with circle sizes. Figure 3E uses increasing size of circles as year (x-axis) and race as different colors, which is aesthetically unappealing. Figure 3F contains data from Boston, Las Vegas and the U.S. total, but it looks very hectic with too much information crammed in very little amount of space. Moderation of data was key to understand all aspects of the information presented.

Presentation of the data and choice of tools is an equally important parameter for visualization. Similar efforts were put in to portray life expectancy data in Figure 4A – 4F. These figures depict life expectancy at birth (in years) for three separate cities - Figures 4A-B are for San Diego County, CA; Figures 4C-D are for Portland Oregon and 4E-F are for Seattle, WA. Comparing Figure 4A (with data divided into panels by race) and 4B (data combined in a single panel), it can easily be seen that there was a distinct trend of all races. In general, Asians had the highest life expectancy and Blacks continued to have lowest life expectancy among the races. But visually all data points are clear in 4A and somehow more confused in 4B. It was easier to separate out this data in 4A. This observation was confirmed with data for Portland, OR in 4C and 4D. Individually paneled appearance in 4C clearly showed separation and 4D showed a mixing of points, which can confuse the reader. From 4C, it was very clear the overall life expectancy rates were highest among Asians / Pacific Islanders, and lowest among Blacks, dipped by a few years in 2013 for American Indians/Alaskan Natives and Hispanics. Significantly, the same information was difficult to deduce from Figure 4D. The data for Seattle, WA was displayed in 4E (bar graphs) and 4F (panels separated by race). Even though bar graphs generally show data well, in this case, it was obvious that splitting the data in panels was very helpful to observe trends. Hence, most explorations of this data set focused on cities were divided by race, with years on the x-axis for consistency.

The dataset contained information for most U.S. cities for a variety of parameters considered below.

Results and Discussion

Demographics

All the cities as well as the U.S. Total were stratified by race. The total population of cities shown in Figures 5A–5I capture a snapshot of the entire dataset, instead of each city. Most cities showed a clear trend of increase in population, except for Cleveland, OH (Figure 5D) and Detroit, MI (Figure 5G). These trends can be used at the federal level to allocate city resources. At the city level, an increasing population challenges city administrators in areas such as food supply, water supply, housing, schooling, community parks, roads and maintenance of public transport.

An additional parameter in the visualized datasets was the racial make-up of cities. Figures 6A – 6M display the racial diversity of the population of various cities. Cities such as Boston, MA contains a diverse racial profile, while cities such Houston, Los Angeles, and Miami are heavily biased by a large Hispanic population. Cities such as Detroit, Cleveland, Baltimore, and Chicago were seen to have a majority Black population, whereas cities such as Kansas City, MO, Fort Worth, TX, and Denver were predominantly White.

Ease of transportation was evaluated using transit score (Figure 7A), walkability (Figure 7B) and bike score (Figure 7C) for the year 2018. As expected, major metro areas such New York City, San Francisco, Boston dominated both the transit score and walkability owing to their high population density, dense public transportation network and abundance of retail shopping outlets in close proximity. However, Minneapolis, MN, Denver, Co and Chicago, IL, emerged with a better bike score which is not intuitive due to severe nature of winters in these cities. This data showed us that it is premature to make assumptions of the accessibility of a city.

Food Safety

Food safety data was provided by two separate indicators. Figure 8 showed the percent of children (tested) under age 6 with elevated blood lead levels for Boston (8A) and Cleveland (8B). Boston showed a decreasing trend from 2011 to 2015 in both males and females, with data ranging from 2 - 4%. Limited data was available for Cleveland and it showed much higher percent of children tested with elevated lead levels with results ranging from 0–15%.

Figure 9 showed the rate of laboratory confirmed infections caused by Shiga toxin-producing E-coli for Cleveland (9A), Dallas (9B), Denver (9C), Fort Worth, TX (9D), San Jose, CA (9E) and Phoenix, AZ (9F). Figure 9B clearly shows 5 -10 % of E coli infections were in Hispanic and Asian / PI population over the years 2012 – 2016 in Dallas. There also was a general upward trend seen in Denver in all racial populations, but especially Black, White and Hispanic. There was an increasing infection trend observed for the Black population in San Jose per 9E, and an otherwise average infection rate of 3-6 %. Data from Phoenix (9F) showed low infection rates at maximum rate of 6%, and generally less than 2% during 2012 – 2014.

Smokers

The datasets were divided into two separate categories of percent of adults who currently smoke (Figure 10A – 10H) and percent of high school student who currently smoke (Figure 11A- 11G). For most cities, the percent of adults who smoke was observed to be between 15-25%, while significant higher numbers with racial backgrounds were seen at Columbus, OH (Black and White), Detroit, MI (Black), Las Vegas (Black), Philadelphia (Black and Hispanic), and Phoenix (American Indian). Percent of high school students who smoke were found to be generally in the 4 -10% range for the period of data collection. It should be noted that this data was limited and cannot be used overall to determine a trend; however, the data can be used as a snapshot of the conditions at the time. Keeping that in mind, it was observed that Charlotte, NC (Black and White), Philadelphia (White), San Francisco (White) and Seattle, WA (American Indian and Hispanic) showed higher percentages.

Obesity

Obesity is known to be one of the leading causes of various negative health conditions such as cardiovascular conditions, hypertension, diabetes, stroke, among others. Figures 12A-12J were created with data with separate panels for racial backgrounds as percent of adults who are obese. Significant readings with greater than 25% populations were found in Boston (Black and Hispanic), Charlotte (Black), Columbus, OH (Black and White), Denver (Black and Hispanic), Detroit (All), Las Vegas (Black, Hispanic, and White), New York City (Black, Hispanic, Other), Philadelphia (All), San Antonio (Hispanic), Seattle (American Indian, Black, Hispanic) and U. S. Total (All, American Indian, Black, Hispanic and White). Populations with Asian / PI racial background showed the least obesity, in the overall data, generally close to 10 %. Similar to the adult population, obesity data was captured for high school students as a percent (Figures 13A-13J). The general trend over the years have been close to 10% overall. Some cities such as Boston (Hispanic), Charlotte (Black and Hispanic), Denver (Other), Detroit (Black and Hispanic), Las Vegas (Black and Hispanic), Los Angeles (Hispanic and Overall), New York City (Black and Hispanic), Philadelphia (Black, Hispanic and White), Seattle (Asian/PI, Hispanic), U. S. Total (American Indian, Black, and Hispanic) had higher data points. There was limited data available in this dataset; however, detailed information about the obesity prevalence in adults and high school students could be used as crucial results for understanding the overall public health.

Life Expectancy at Birth

There was a complete dataset on the life expectancy, which was divided by racial makeup of the cities. Figures 14A-14J highlight the diversity in the life expectancy for these cities. Overall data suggested that the average for most cities was between 74 and 80 years. Notable from these data were higher rates for Hispanic and Asian populations in Boston, Las Vegas, Indianapolis, New York City, Oakland, Portland, OR, San Diego County, CA and Seattle. Conversely, lower than overall values were seen in the Black demographic in Boston, Indianapolis, Las Vegas, New York City, Oakland, Portland, OR, San Diego County, CA. and Seattle.

All-Cause Mortality

All-cause mortality rate data the provided for overall (age-adjusted per 100,000 people) population and various demographics depending on sex, and race (Figures 15-15L). Higher mortality rates were observed in Boston (Black and White), Chicago (Black), Columbus (White and Asian), Denver (Black and Hispanic), Indianapolis (Black and White), Kansas City, MO (Black), Las Vegas (White), Long Beach, CA (American Indian), Minneapolis (American Indian), and New York City (Black and White). These data help illuminate overall policy structure when coupled with geospatial data of the populations. Combinations of data sources help in directing resources such as community centers, nursing centers, outreach efforts, among others.

Heart Disease

Heart Disease has been one of most significant chronic conditions affecting the children and adults alike. The dataset provided an age-adjusted breakdown of cities and can be seen in Figure 16A-16L. The general trend showed an increase in Portland, Las Vegas, Minneapolis and Kansas City, MO. The individual panels displayed increased levels over various races. Conversely, some of the cities showed stable heart disease related mortality rates such as in Long Beach, New York City, Oakland, CA, and San Diego.

All Types Cancer

Cancer mortality rates provided in the dataset was divided by cities shown in 17A-17Q, age-adjusted per 100,000 people. The general trend over the years for all the cities showed a decreasing trend. Mortality values generally vary from 100 – 200 per 100,000 people. Overall, the population from non-white racial backgrounds (Back and Hispanic) showed higher rates of cancer mortality. Notably, American Indian demographic in Minneapolis and Denver, White demographic in Las Vegas, and Columbus, OH, Black demographic in Oakland, New York City, Kansas City, MO, Chicago, and Boston showed significantly higher data.

Conclusion

The Big Cities dataset was downloaded as Microsoft Excel files and R Studio software was used to create visualizations. Different kinds of graph types were explored to simplify and standardize presentation of data over the period 2010 to 2018. Though the dataset provided a large number of indicators, for the scope of this project, there were still limitations. Since most data was available by racial background, multiple paneled appearance was chosen to separate out the data and obtain maximum resolution of data. Multiple city data were employed to visualize the total population, racial distribution, life expectancy, percent adults who smoke, percent high school students who smoke, percent of adults who are obese, percent of high school students, food safety measures, all-cause mortality rates, chronic disease – heart disease, and all-cause cancer mortality. Individual indicators were visualized, and factors were discussed with observed trends. Multiple data points put together could be used by public health officials, to inform efforts to develop effective tools to improve public health.

The R coding used in this study is available from the author on request.

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Figure Footnotes

Figure 1. Average percentage of difference in search terms by all 50 states.

Figure 2. HIV related mortality rates visualized in Power BI as a comparison.

Figure 3. Different methods to find the best appearance and presentation of data by using All-Cause Mortality Rates.

Figure 4. Different methods to find the best appearance and presentation of data by using Life Expectancy Rates.

Figure 5. Demographics – Total Population for different cities.

Figure 6. Demographics – Race / Ethnicity (Percent).

Figure 7. Social Factors for various cities for 2018 – (A) Transit Score (B) Walkability (C) Bike Score.

Figure 8. Percent of Children (Tested) Under Age 6 with Elevated Blood Lead Levels over the years.

Figure 9. Rate of Infections Caused by Shiga Toxin-Producing E-Coli over the years.

Figure 10. Percentage of Adults who Smoke.

Figure 11. Percentage of High School students who Smoke.

Figure 12. Percentage of Adults who are Obese.

Figure 13. Percentage of High School students who Smoke.

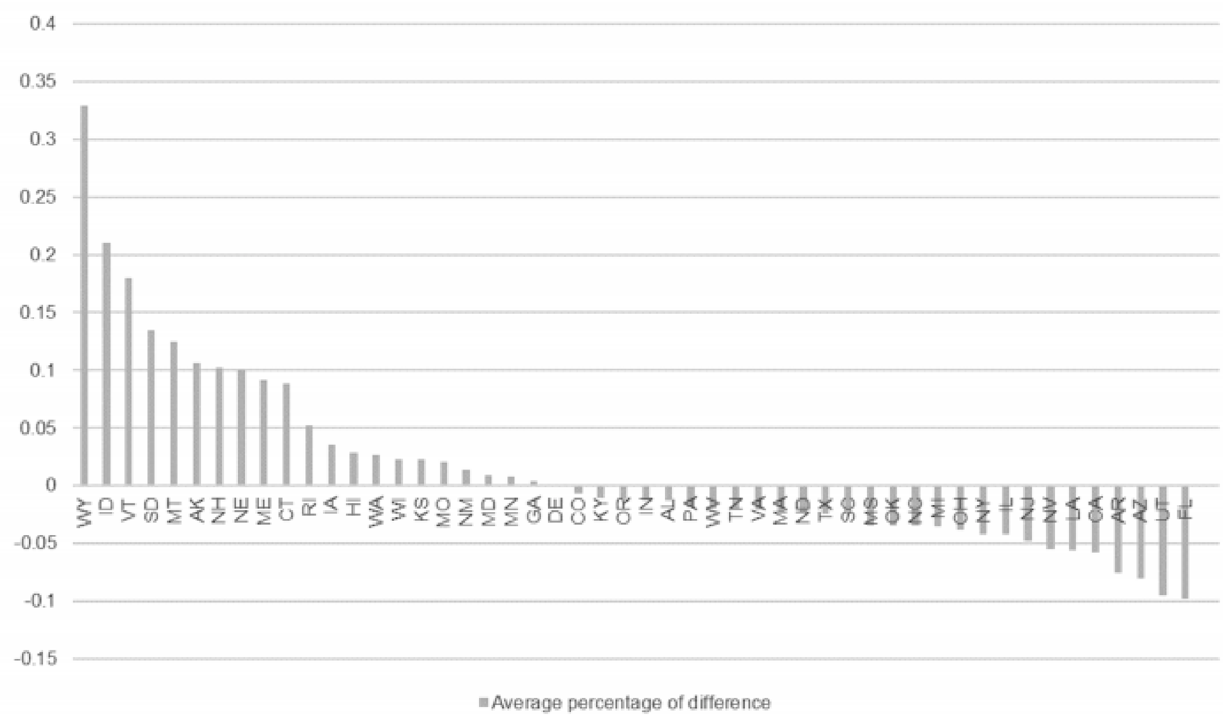
Figure 14. Life Expectancy at Birth (Years).

Figure 15. All-Cause Mortality Rates

Figure 16. Chronic Disease - Heart Disease

Figure 17. All-Types Cancer Mortality Rates

Figure 1



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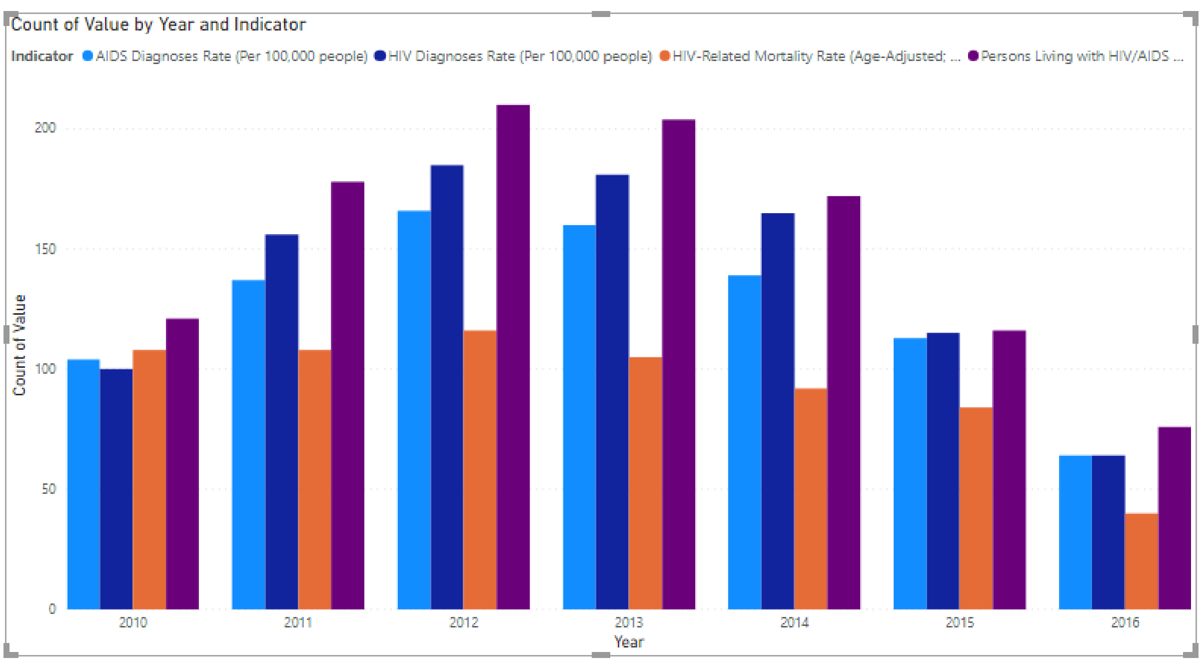
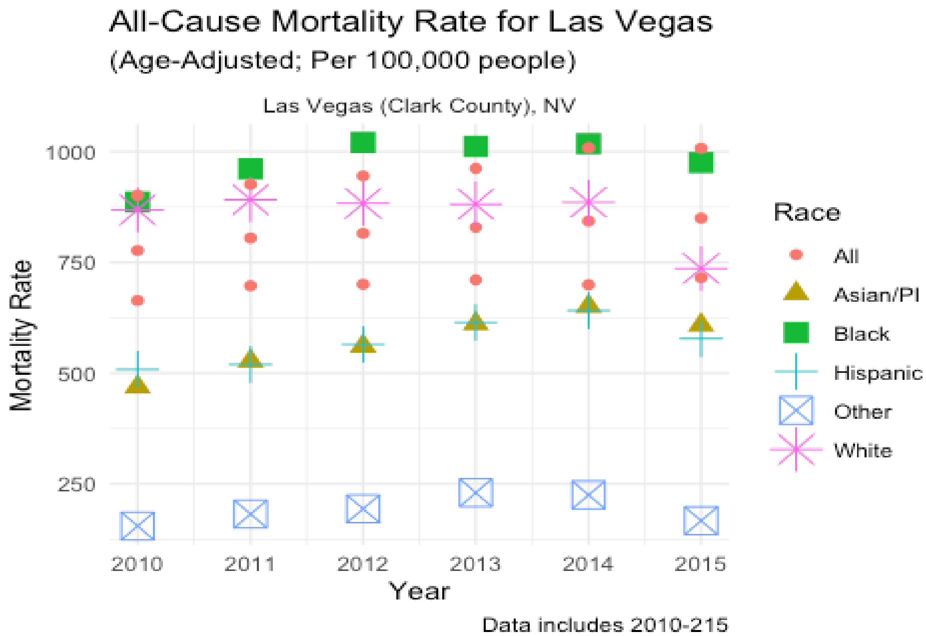


Figure 3A



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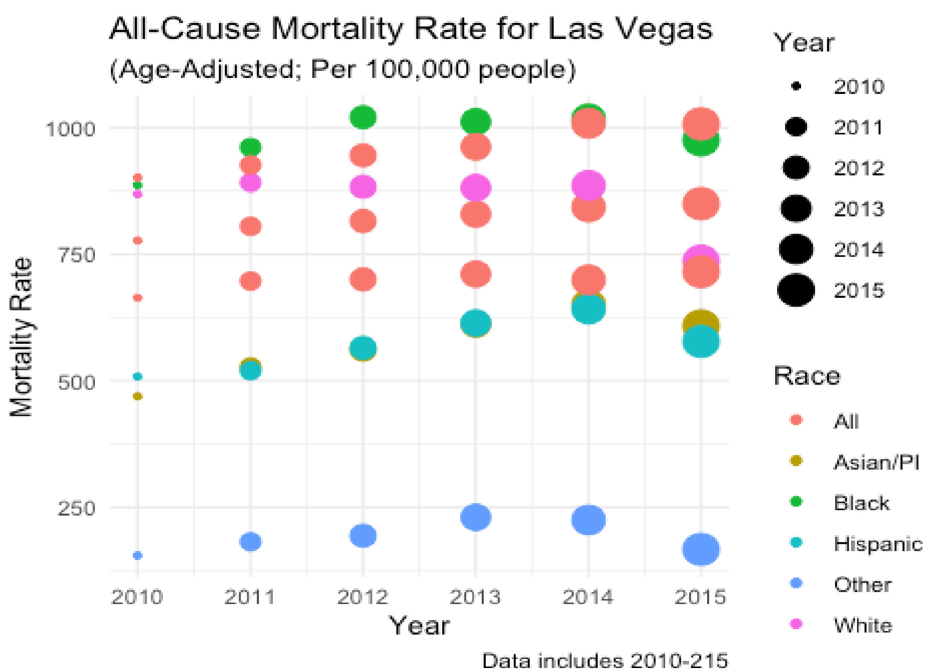

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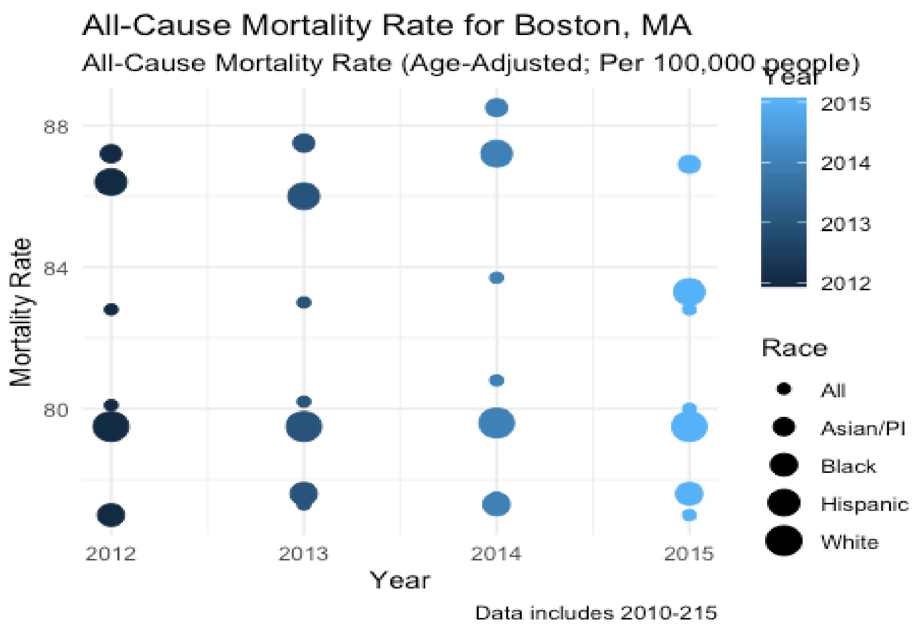

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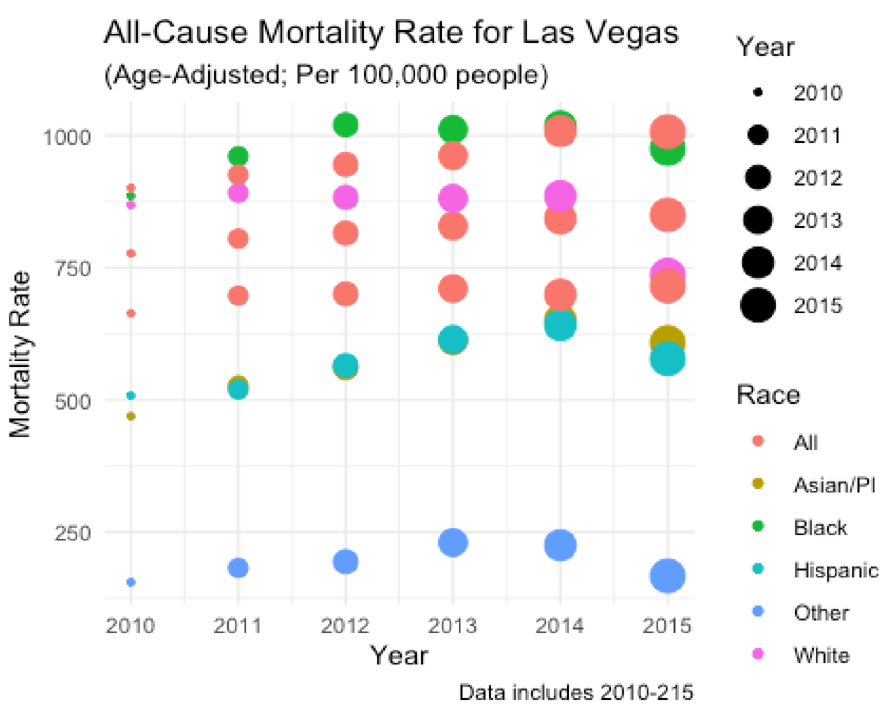

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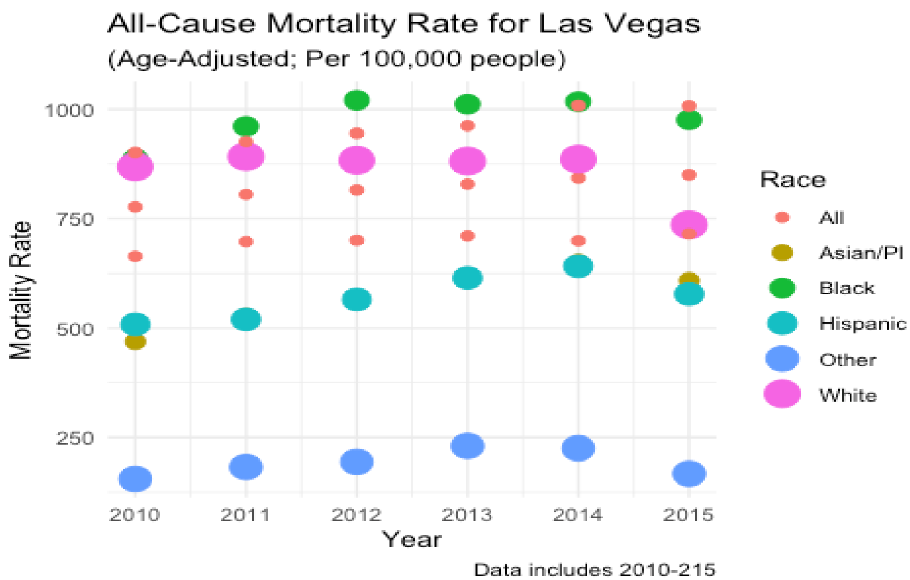

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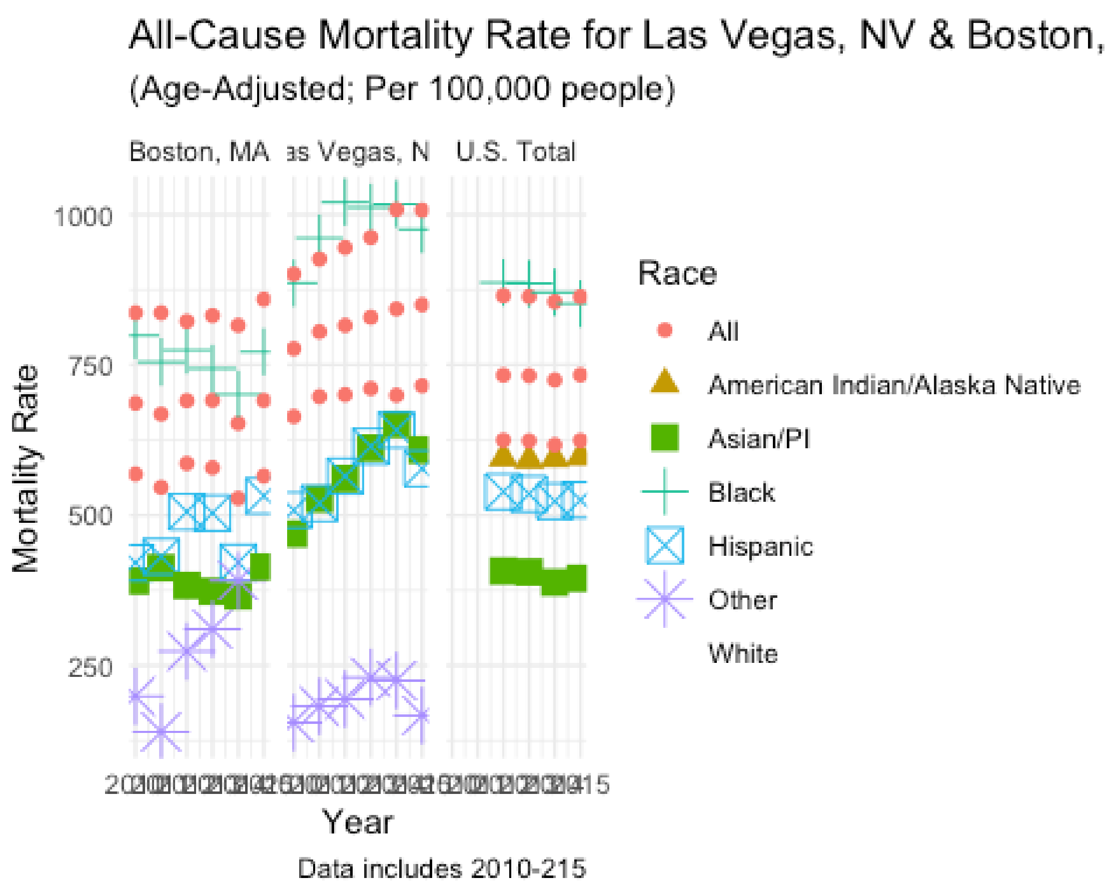

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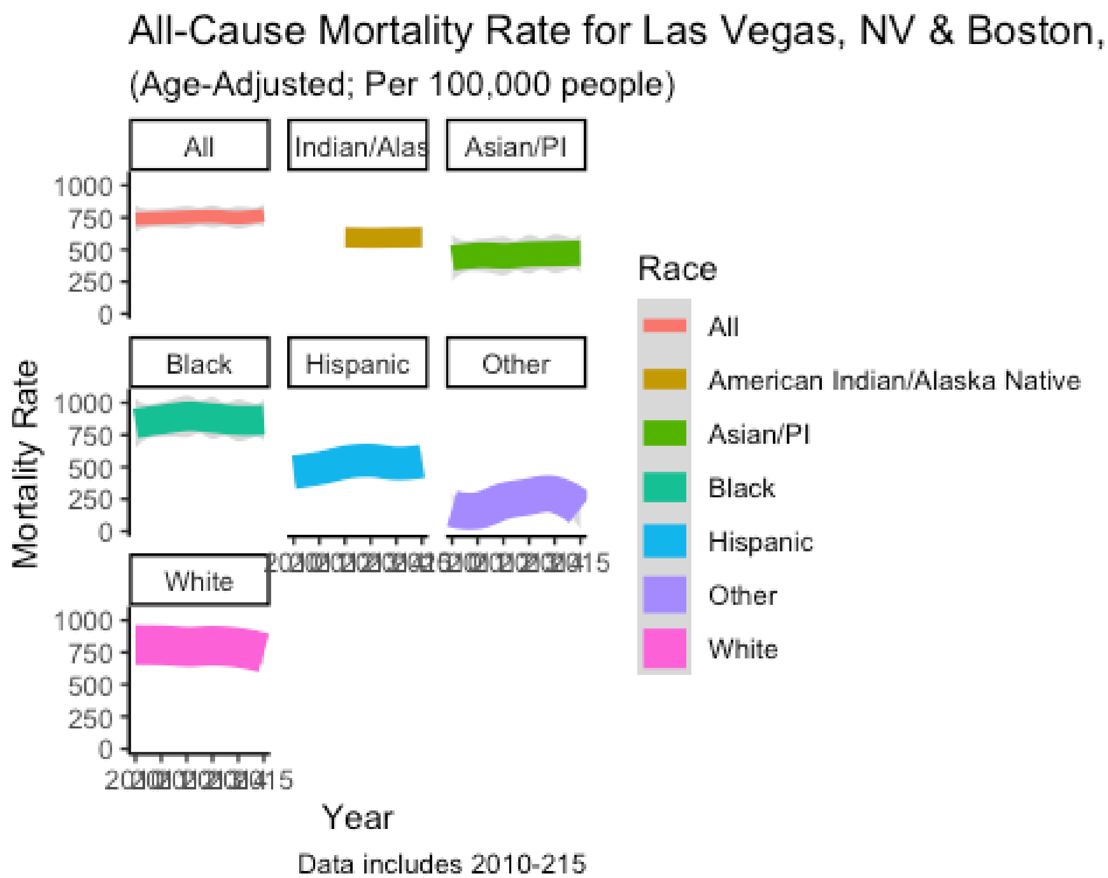
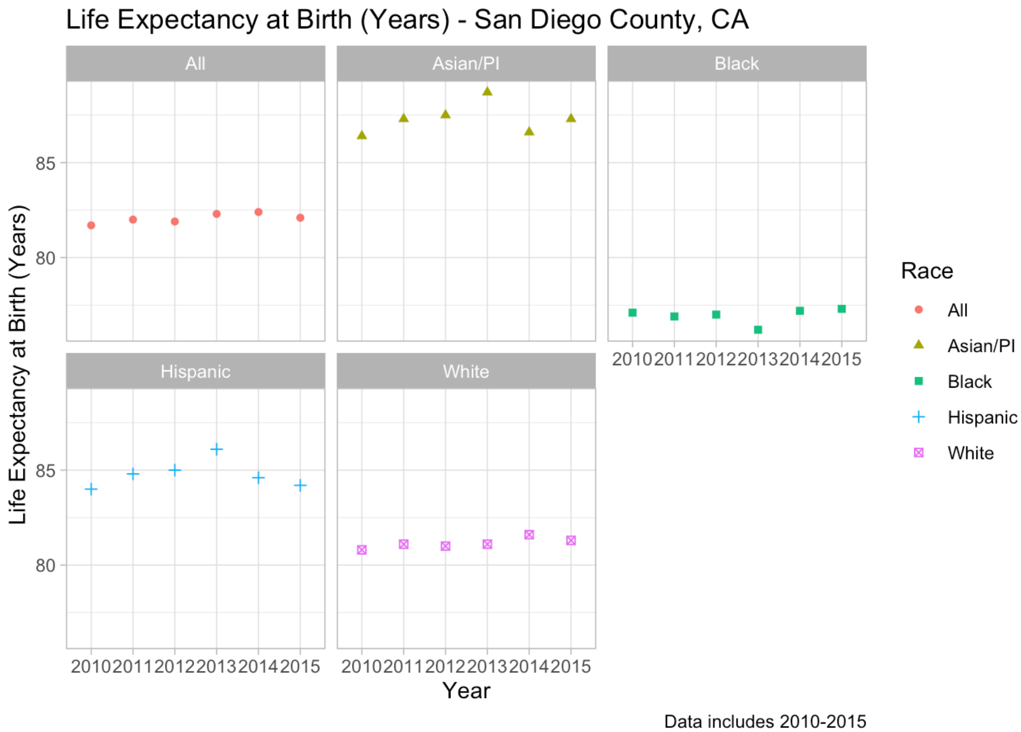

All-Cause Mortality Rate for Las Vegas, NV & Boston,
(Age-Adjusted; Per 100,000 people)
All
Indian/Alas
Asian/PI
Black
Hispanic
Other
White
Mortality Rate
1000
750
500
250
0
Year
Data includes 2010-215
Race
All
American Indian/Alaska Native
Asian/PI
Black
Hispanic
Other
White

Figure 4A



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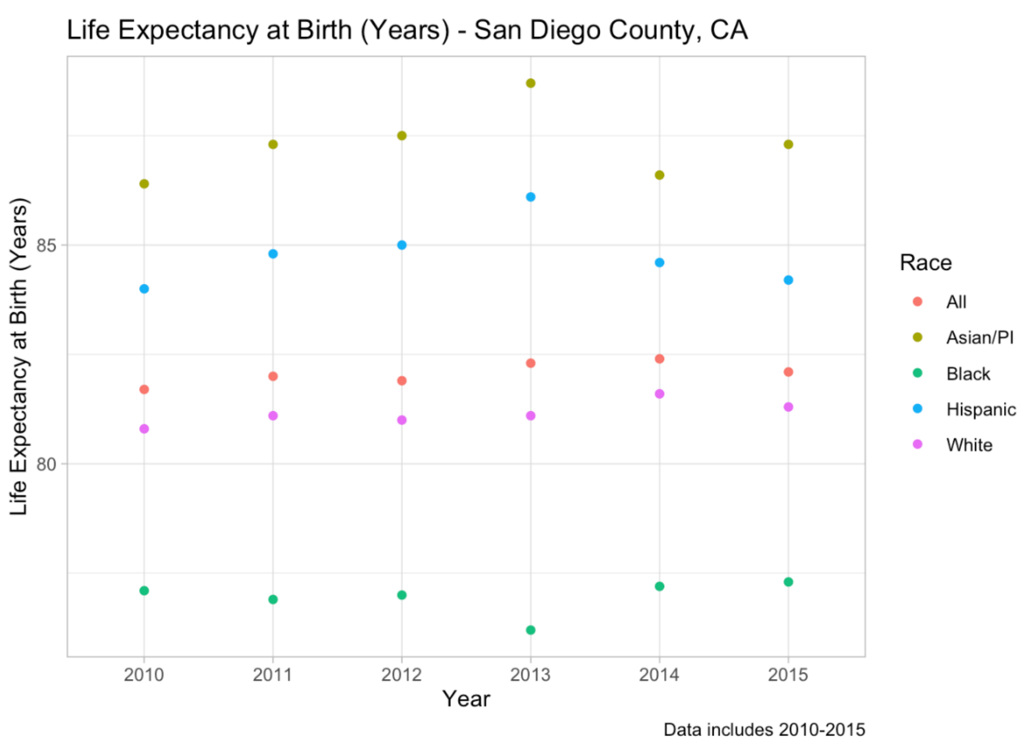

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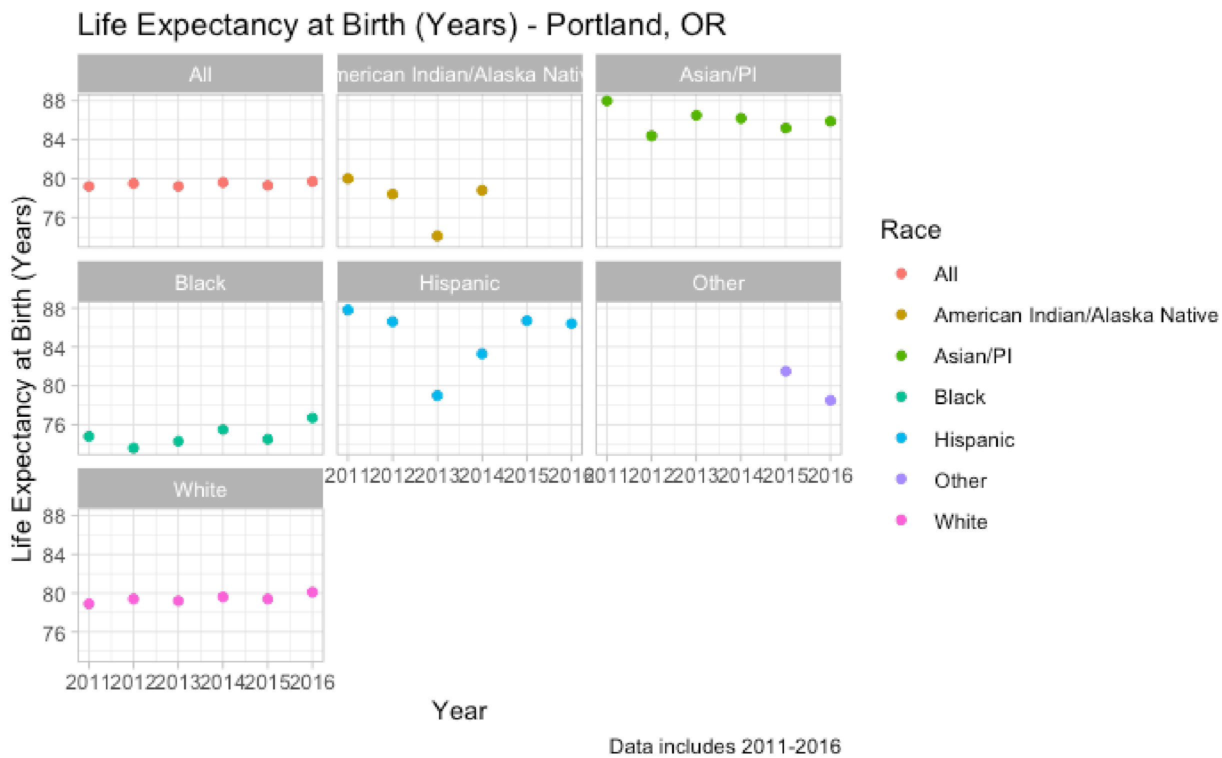

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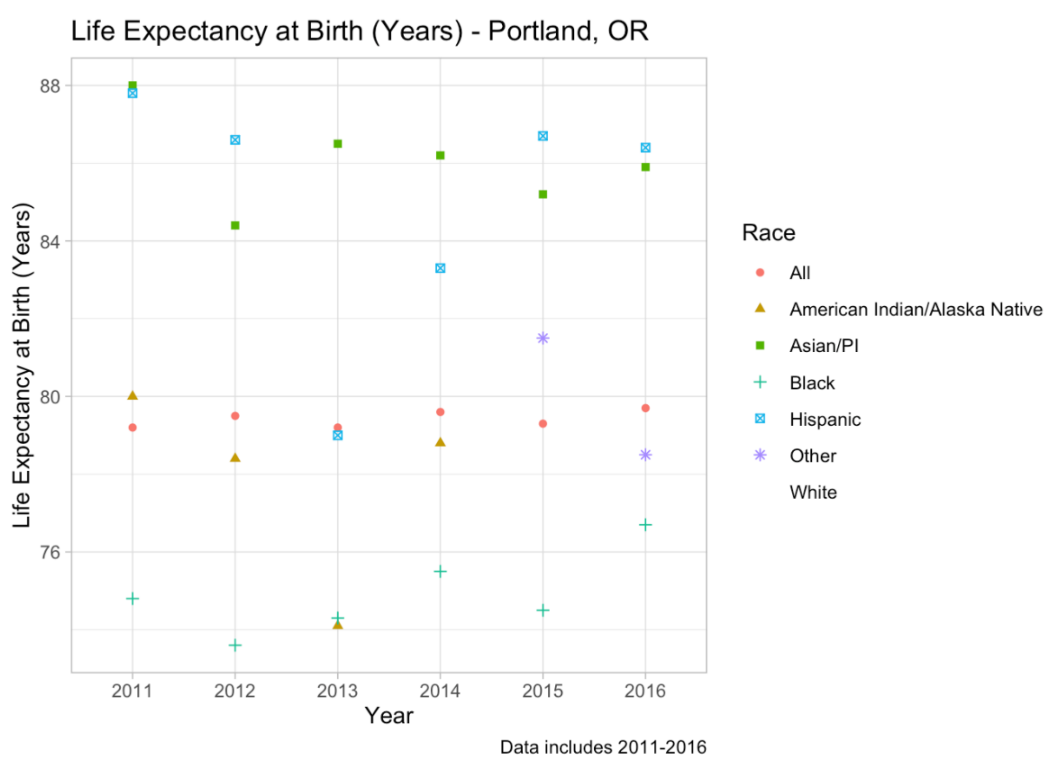

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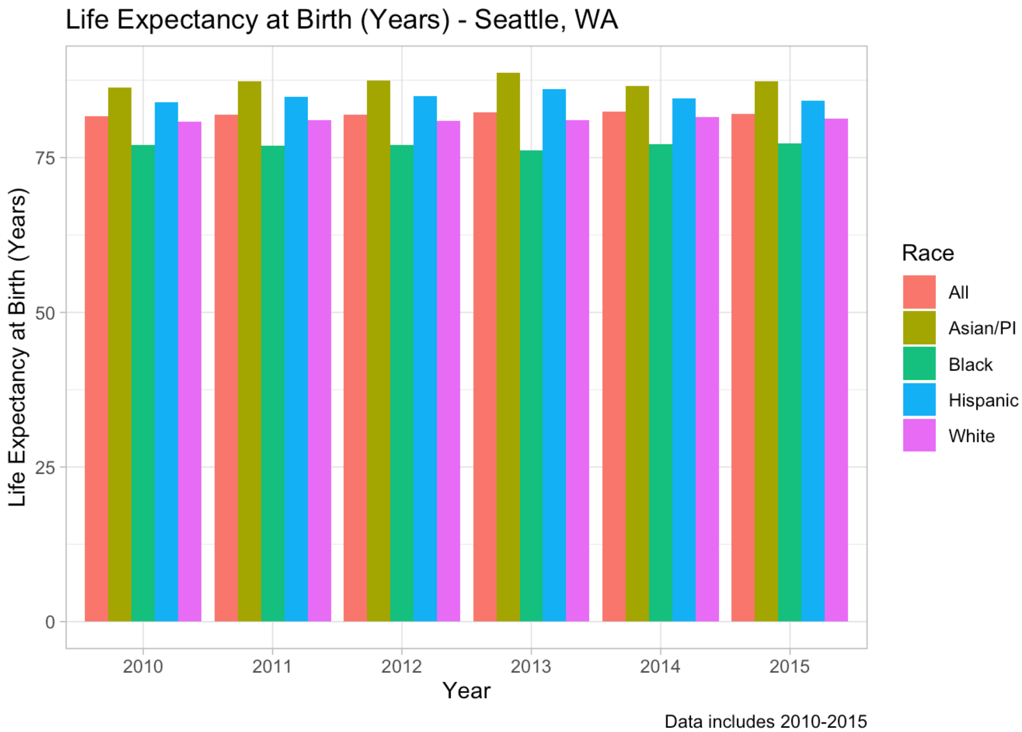

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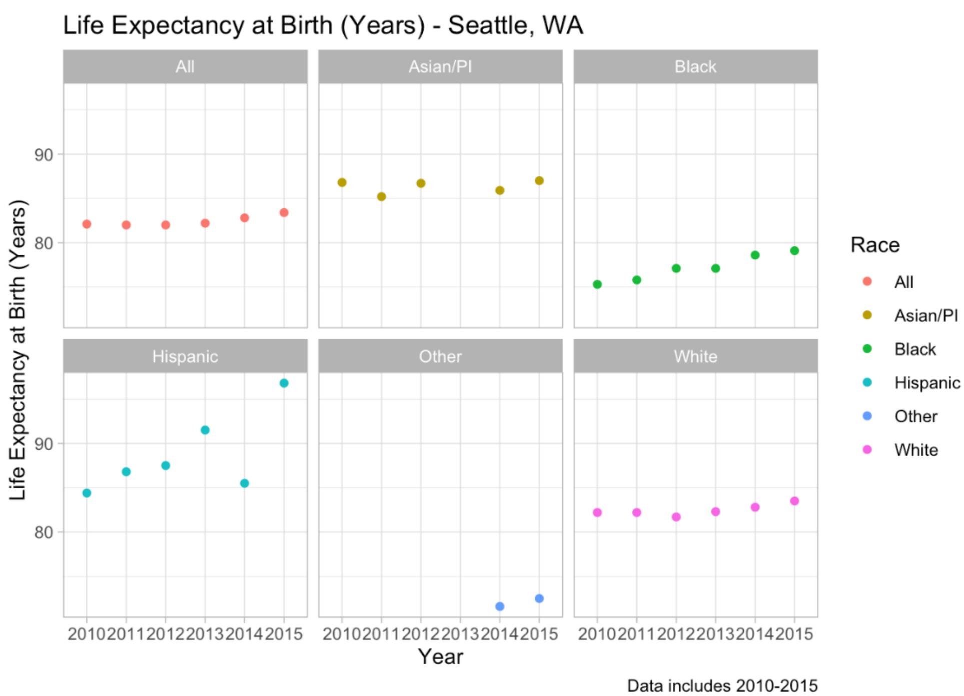


Figure 5A

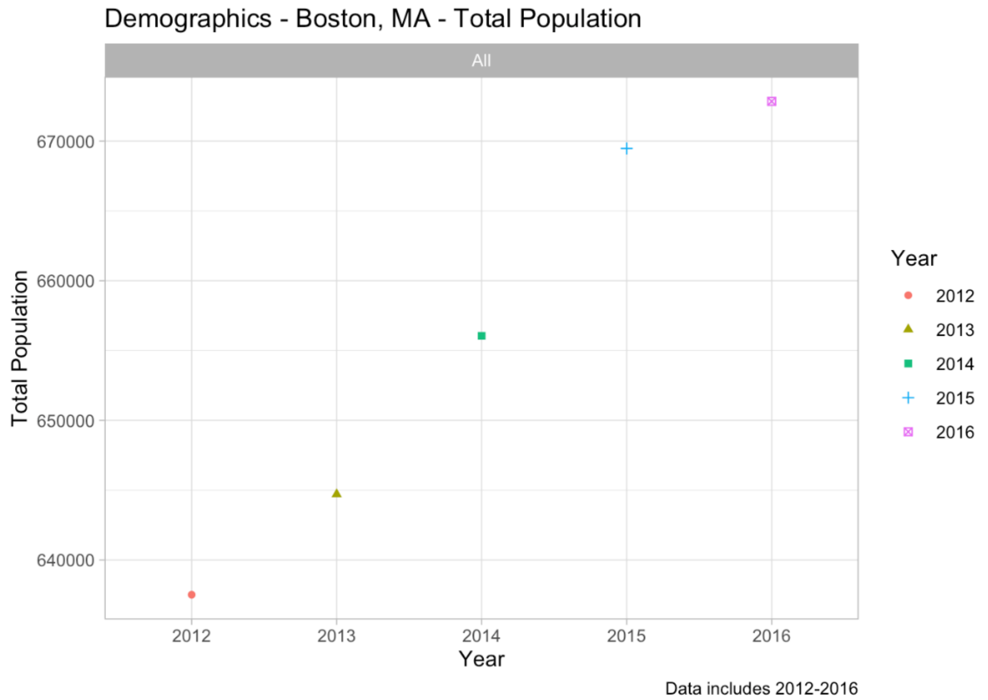
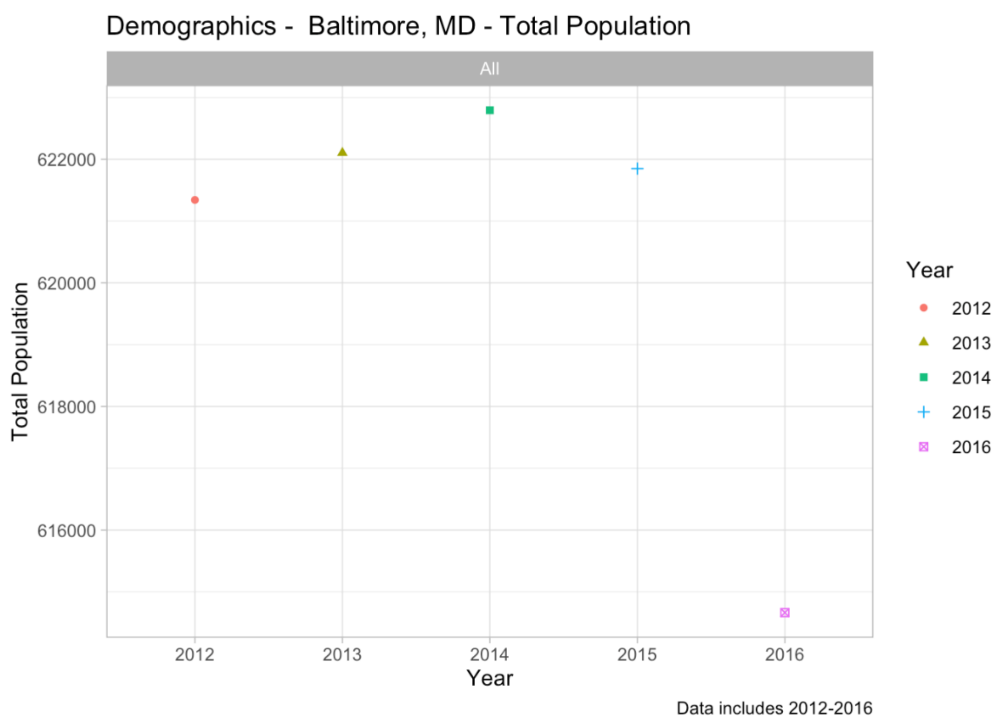


Figure 5B



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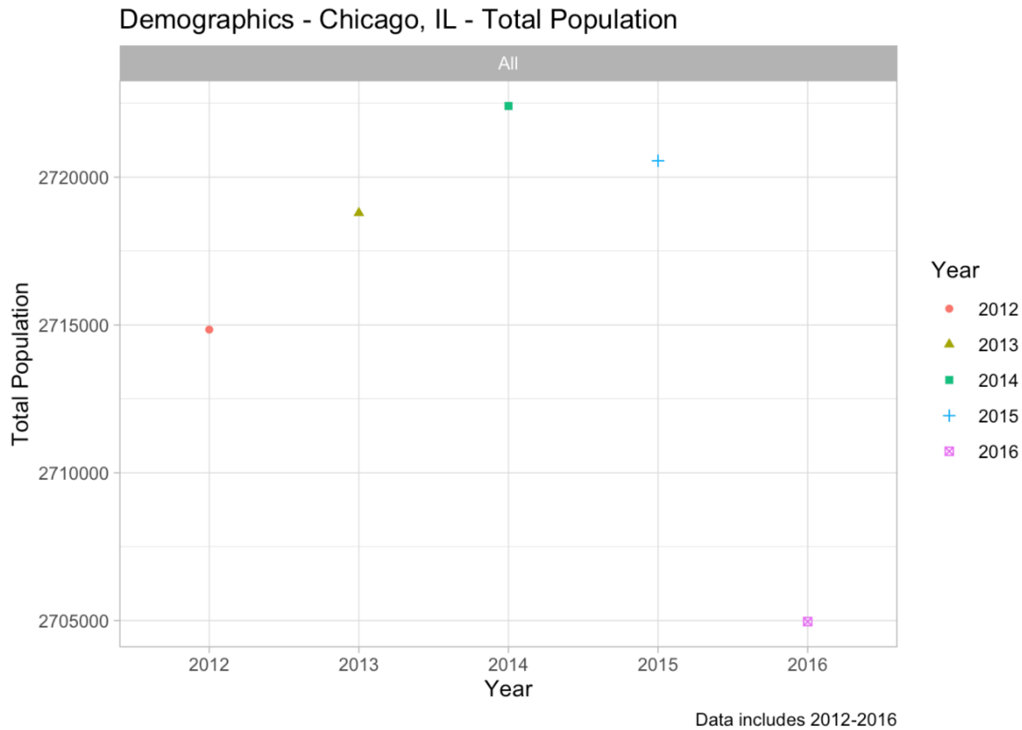

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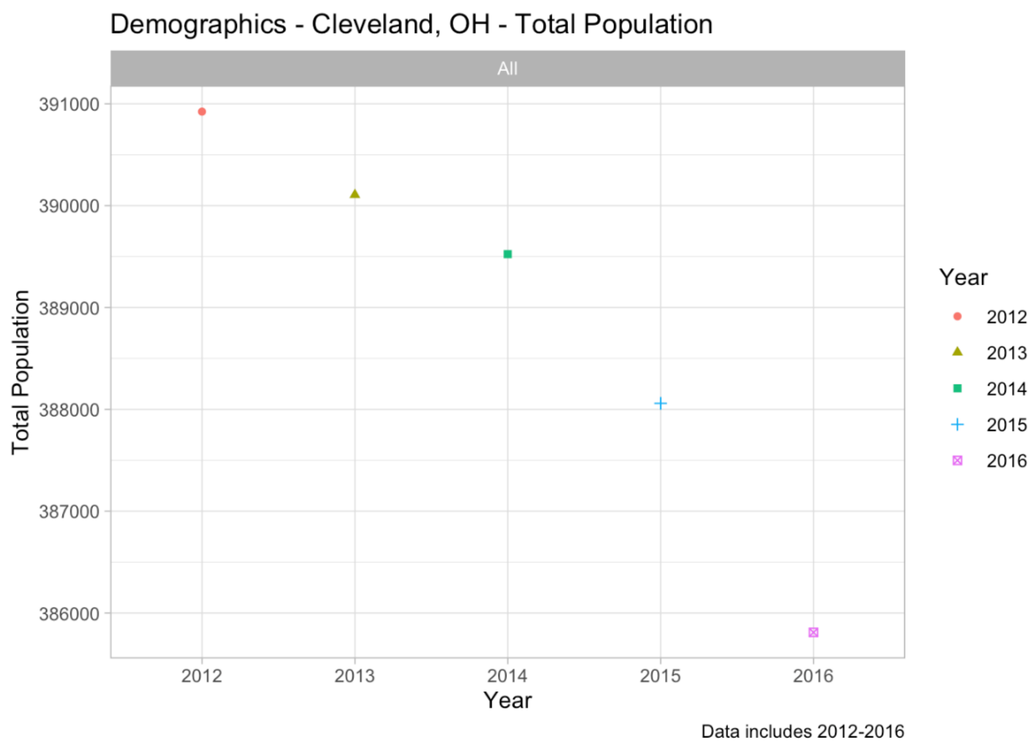

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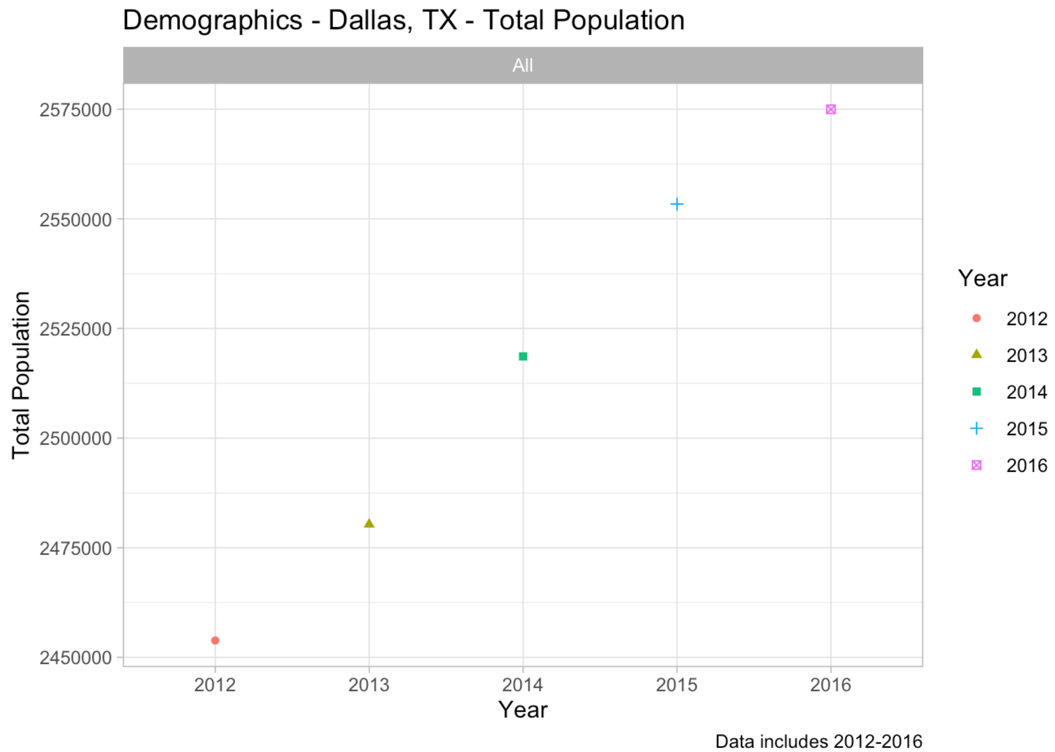

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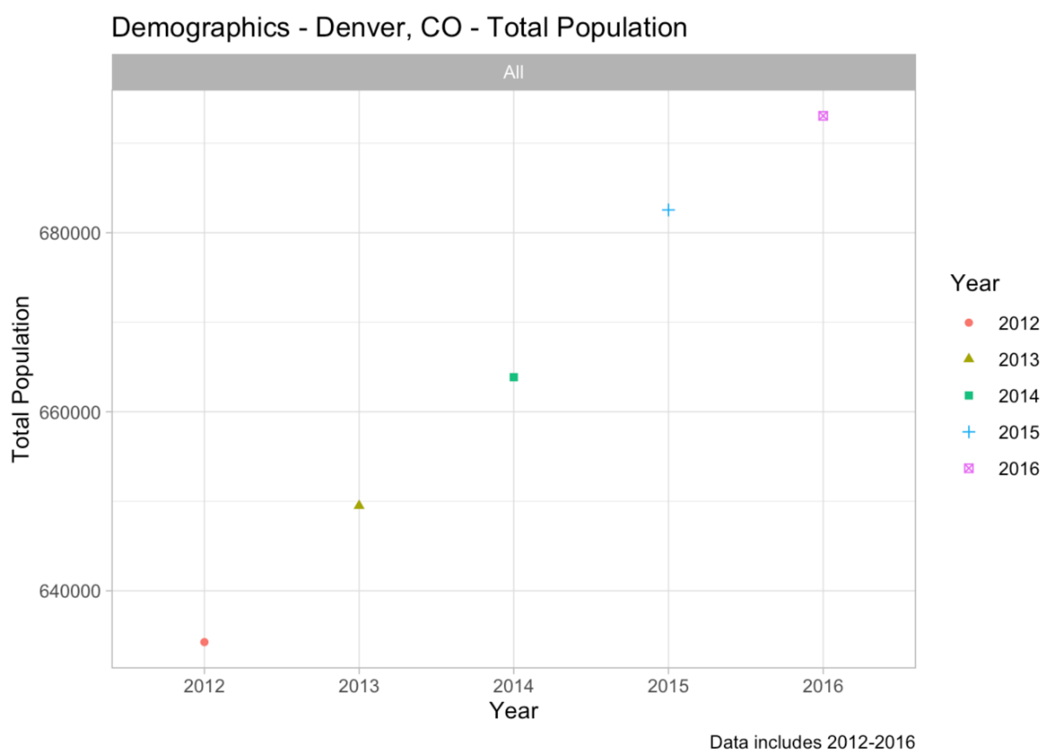


Figure 5G

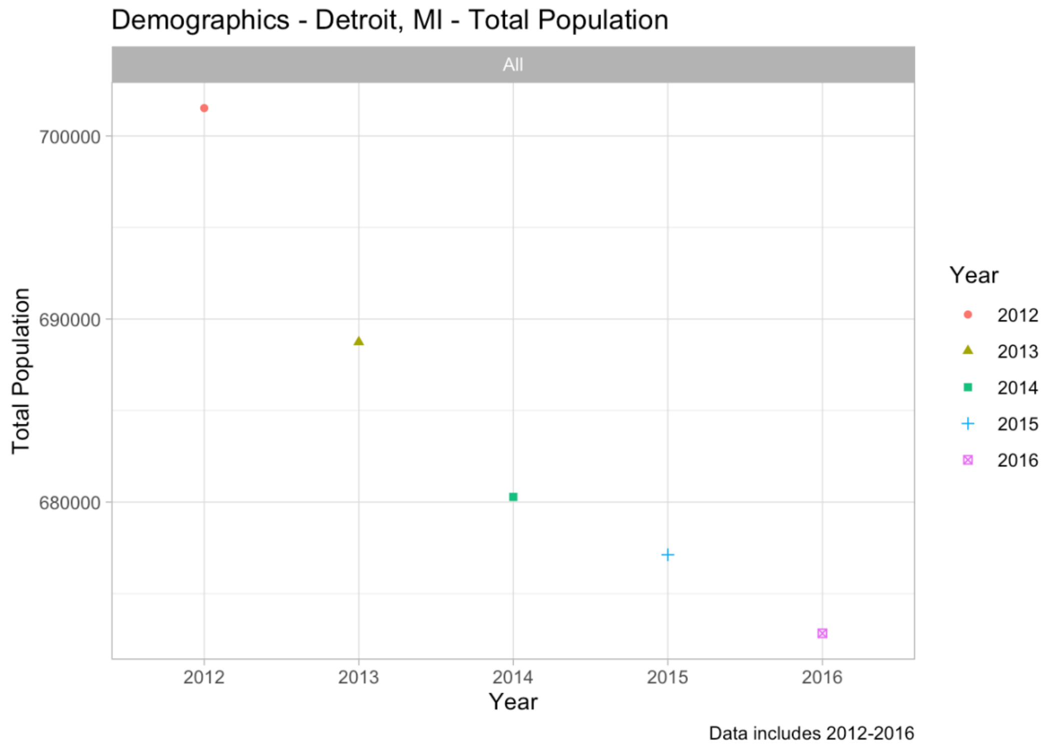


Figure 5F

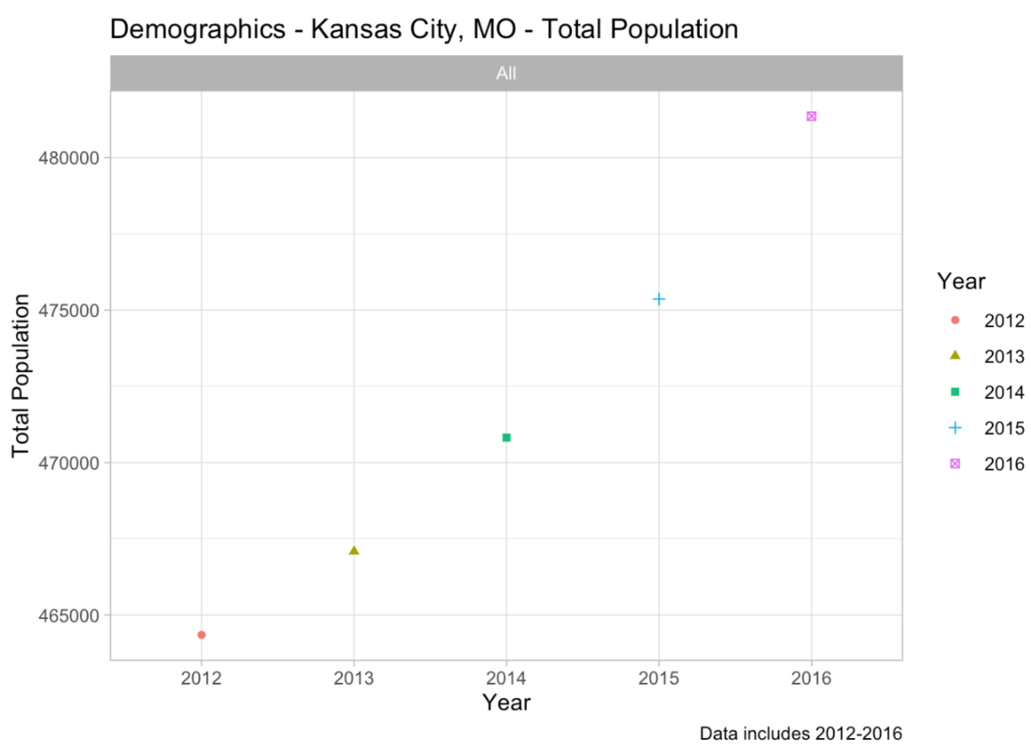


Figure 5H

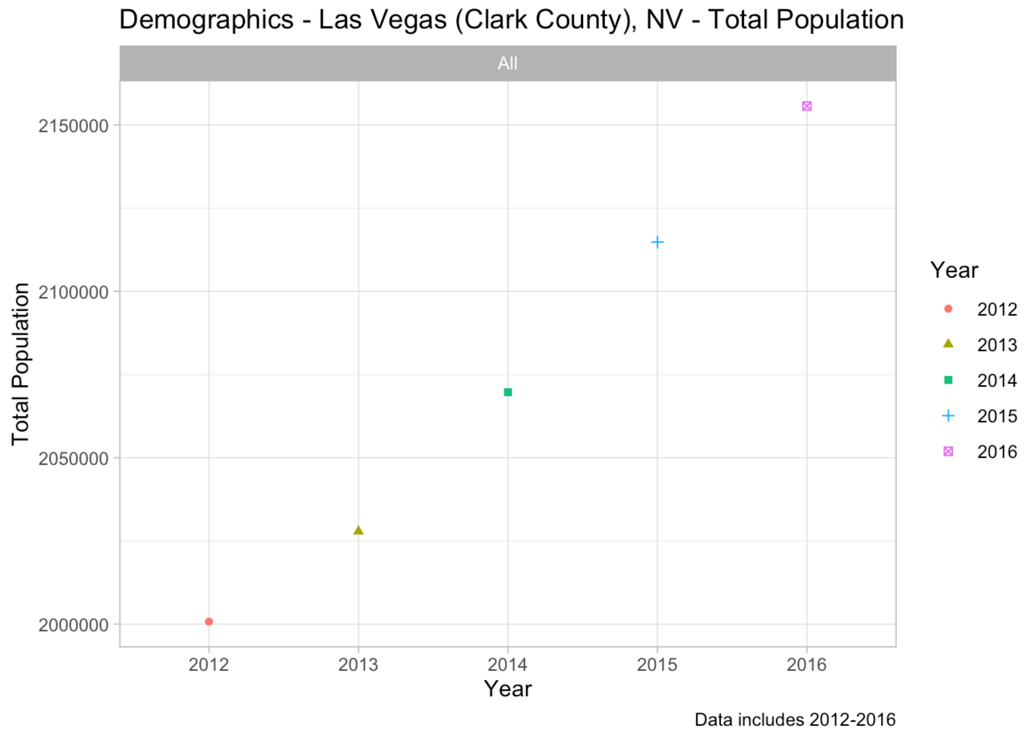


Figure 5I

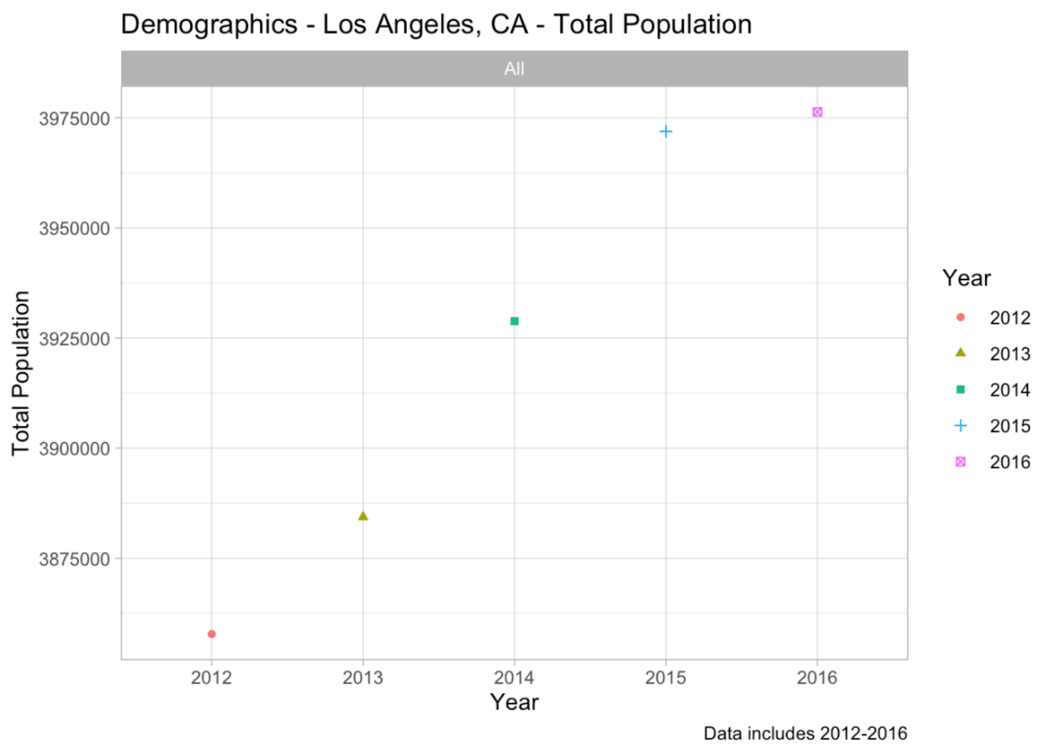


Figure 6A

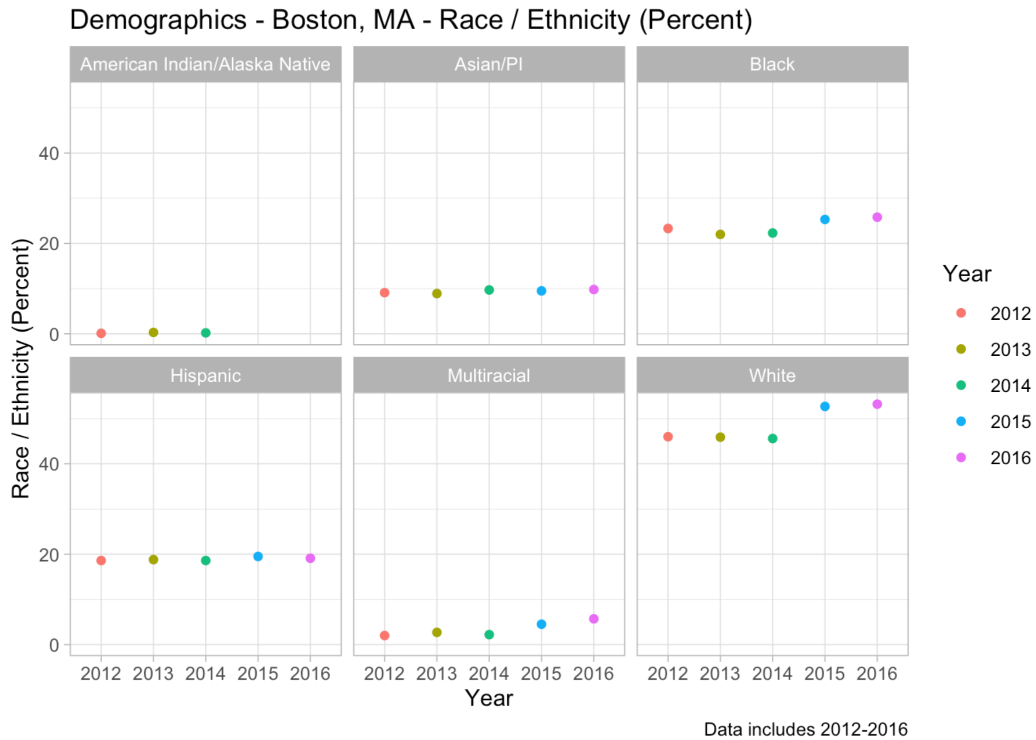
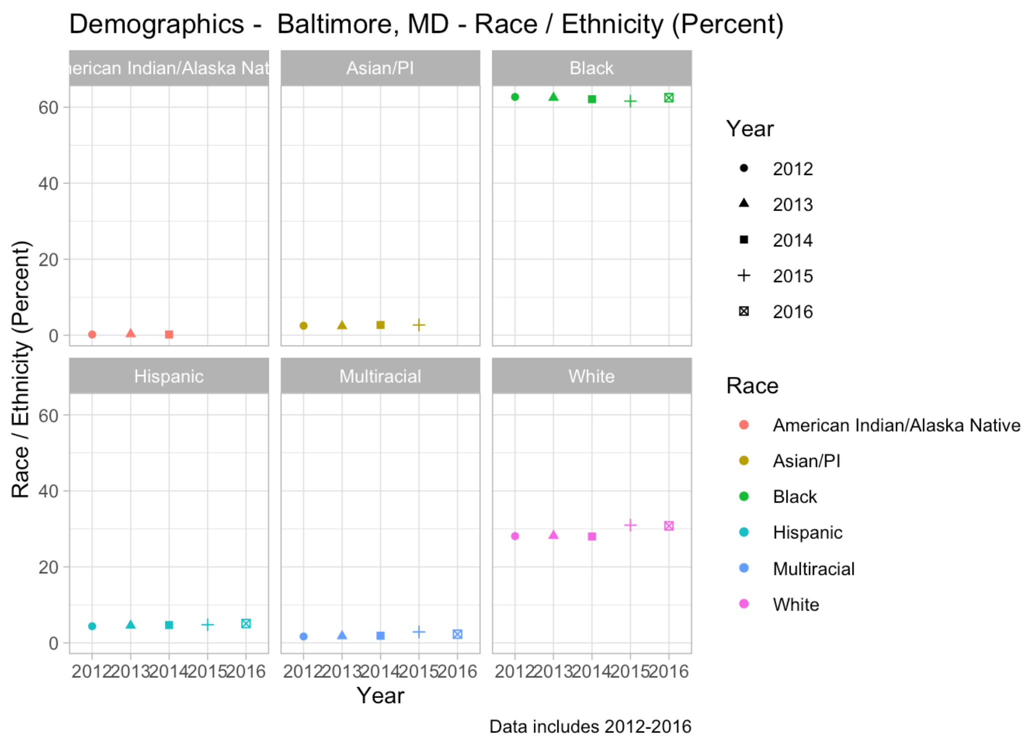


Figure 6B



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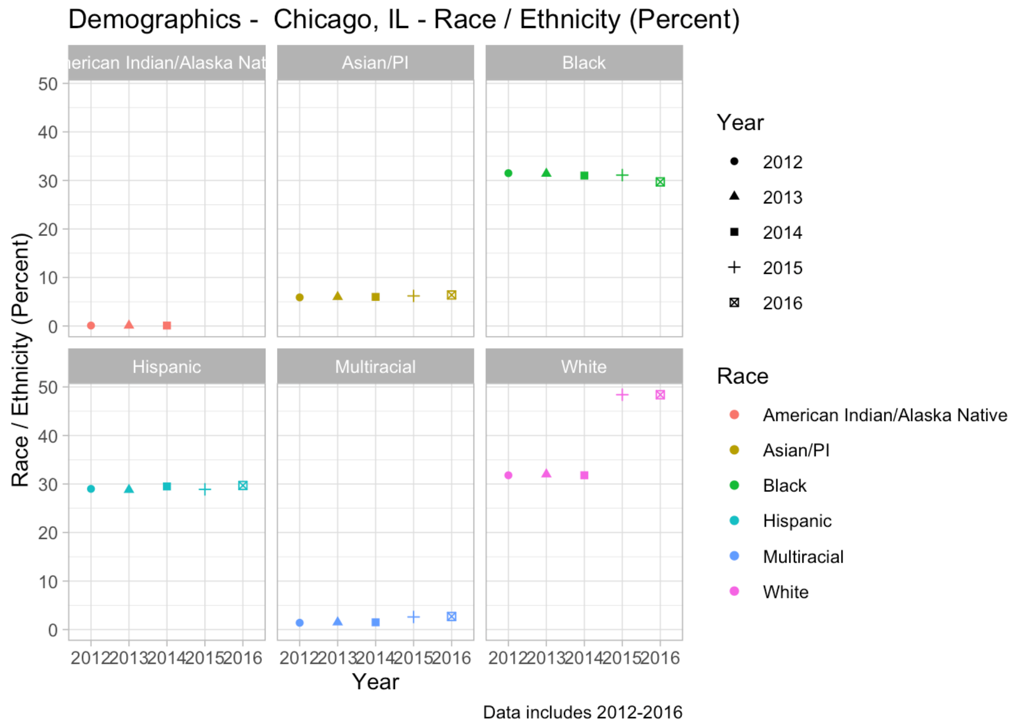

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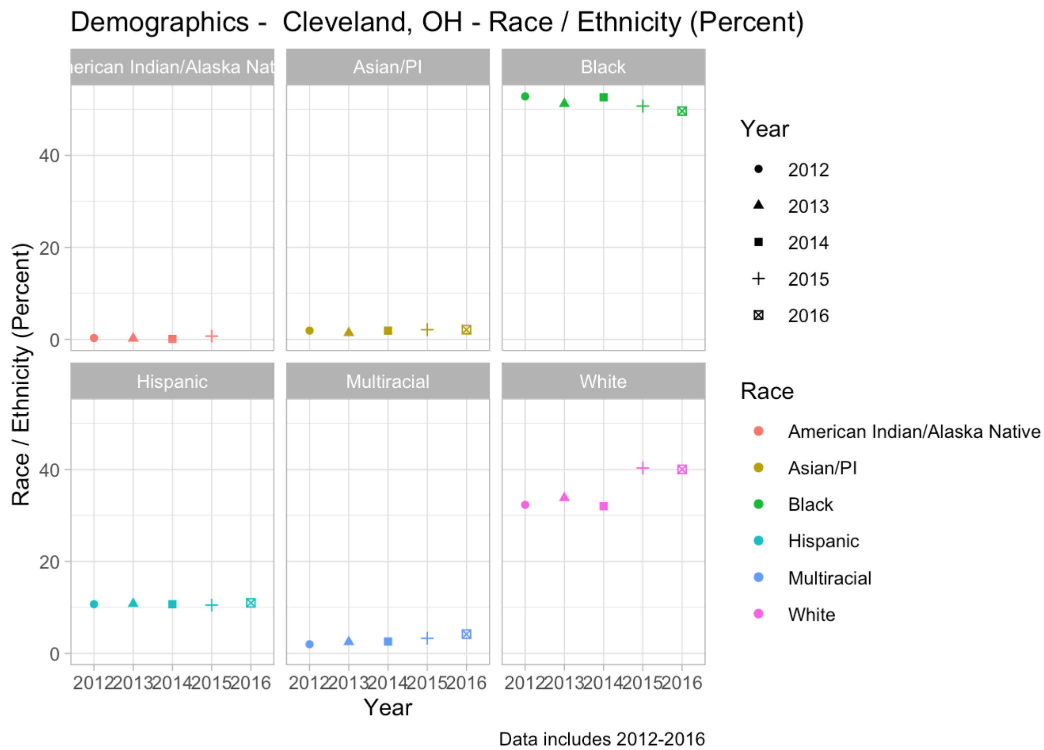

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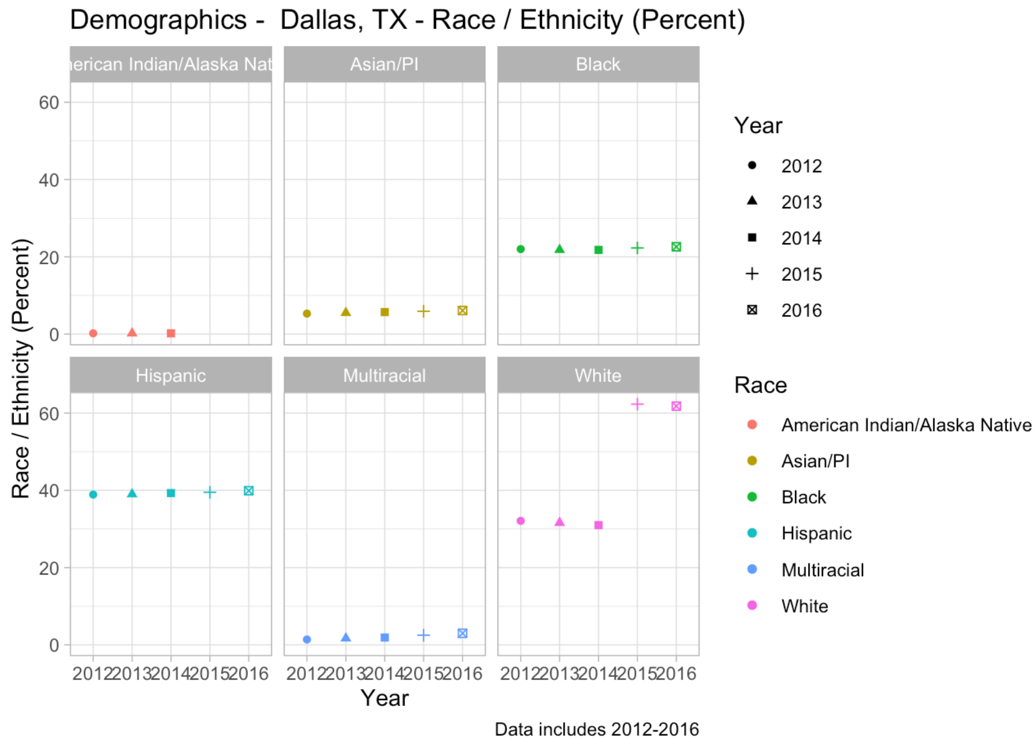

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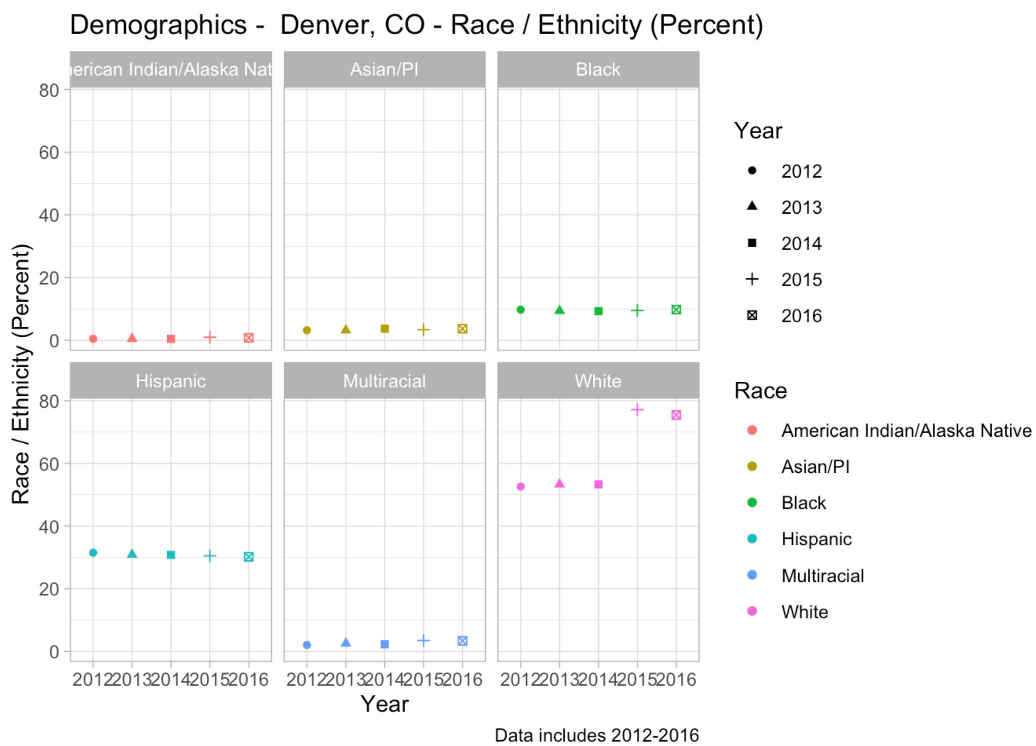
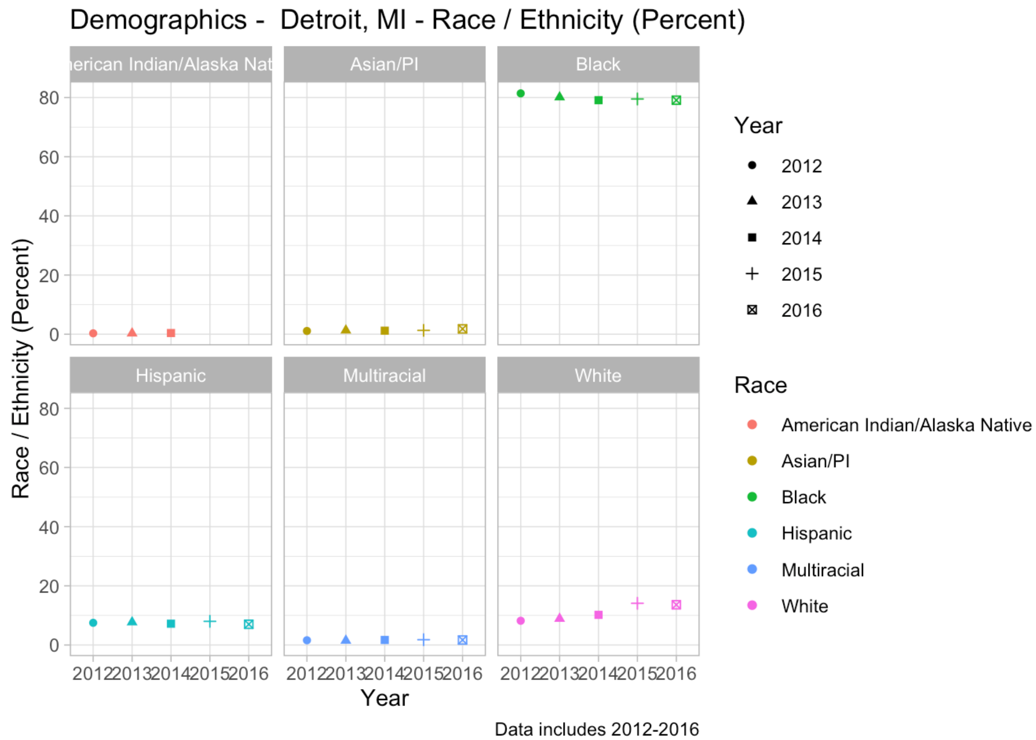


Figure 6G



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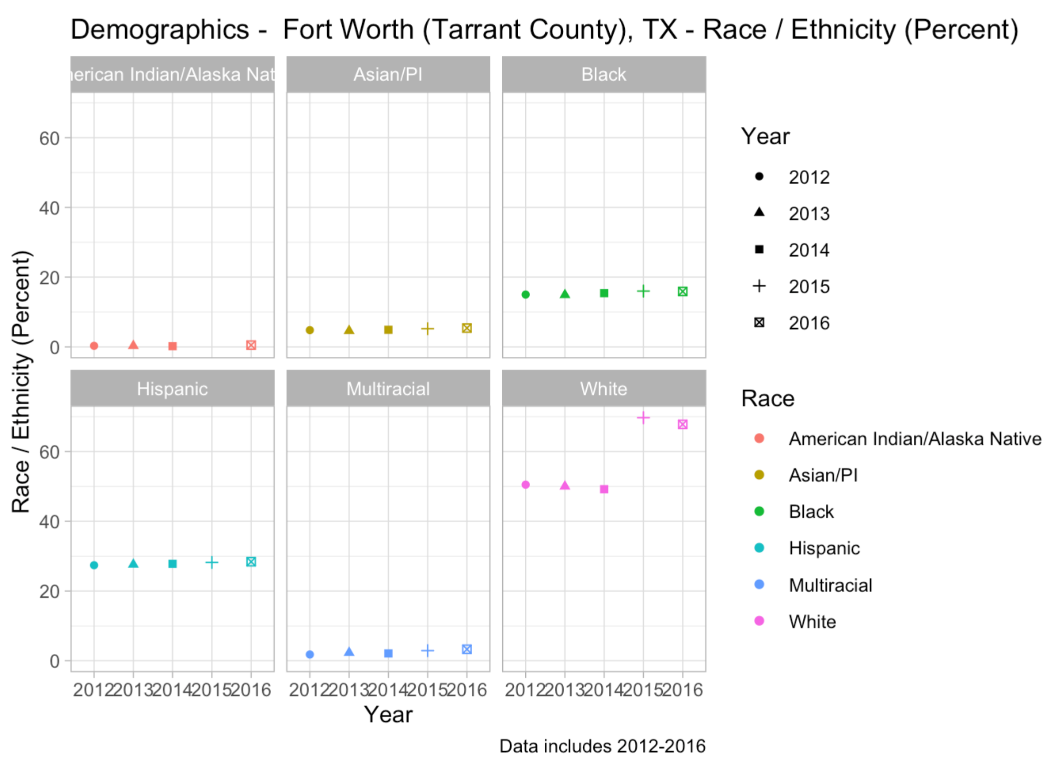


Figure 6I

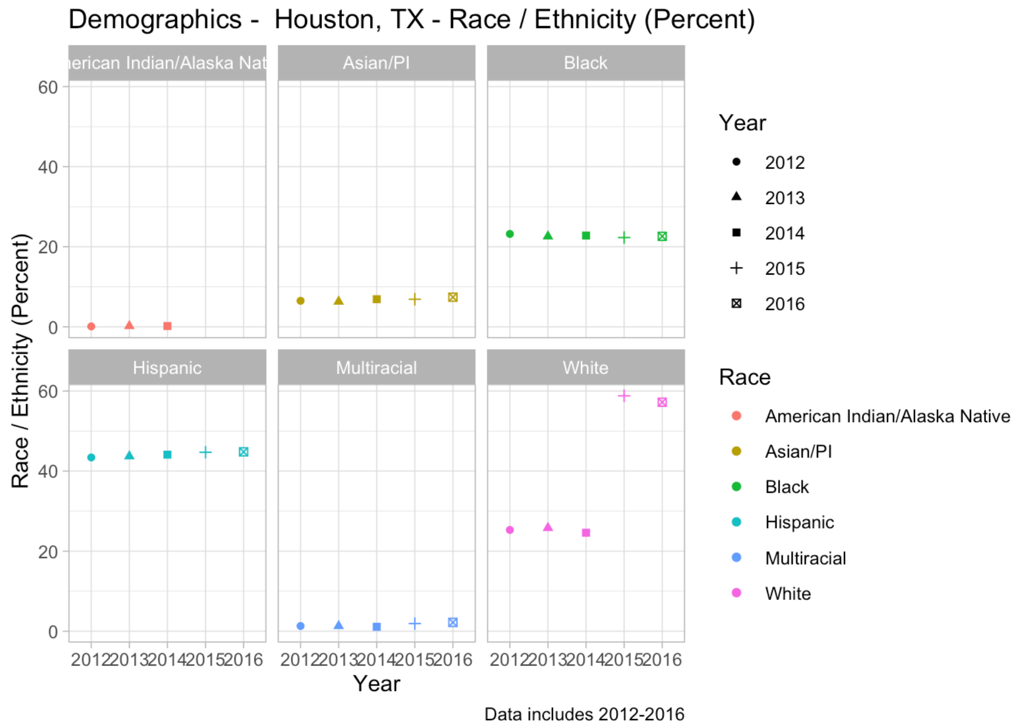
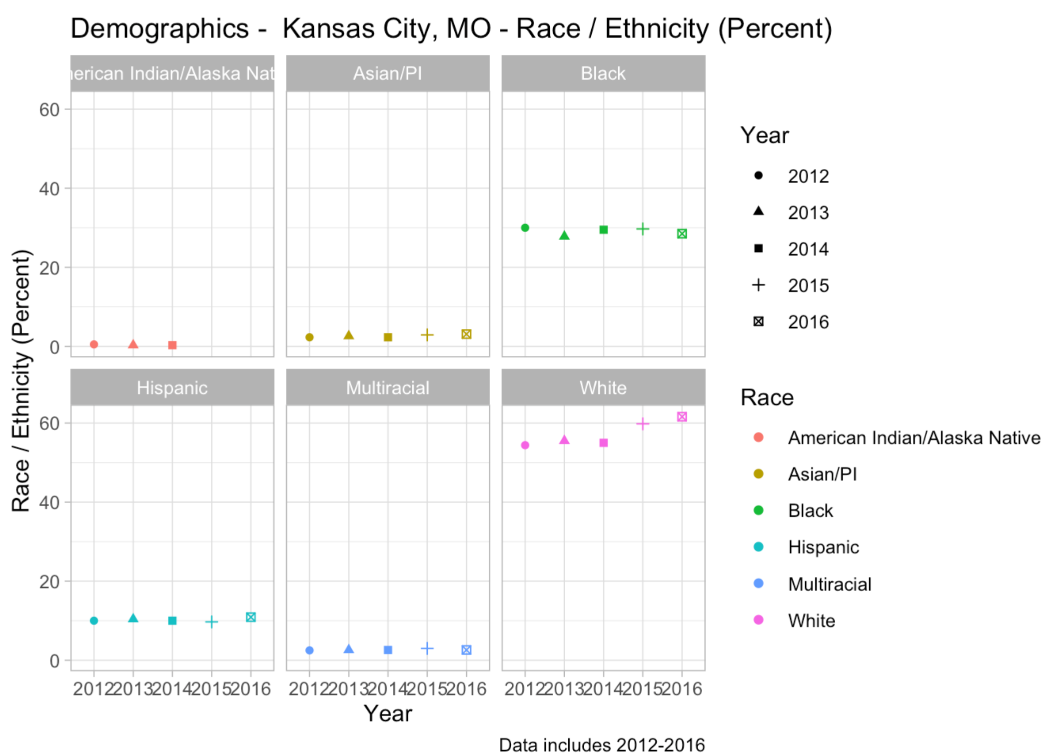


Figure 6J



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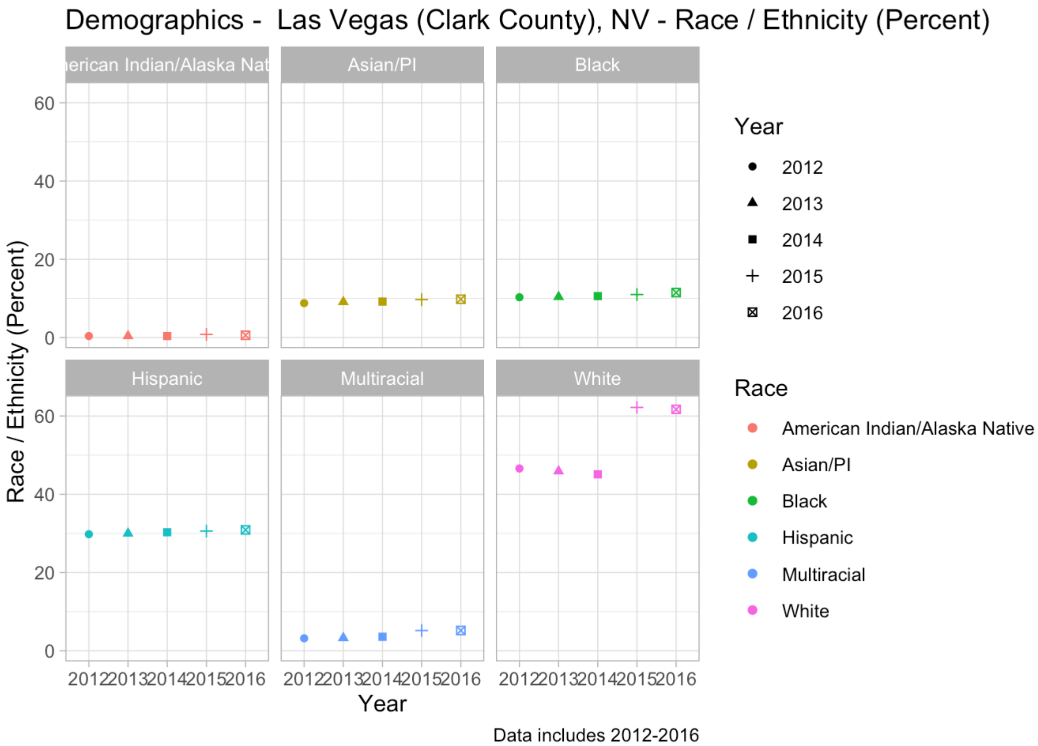


Figure 6L

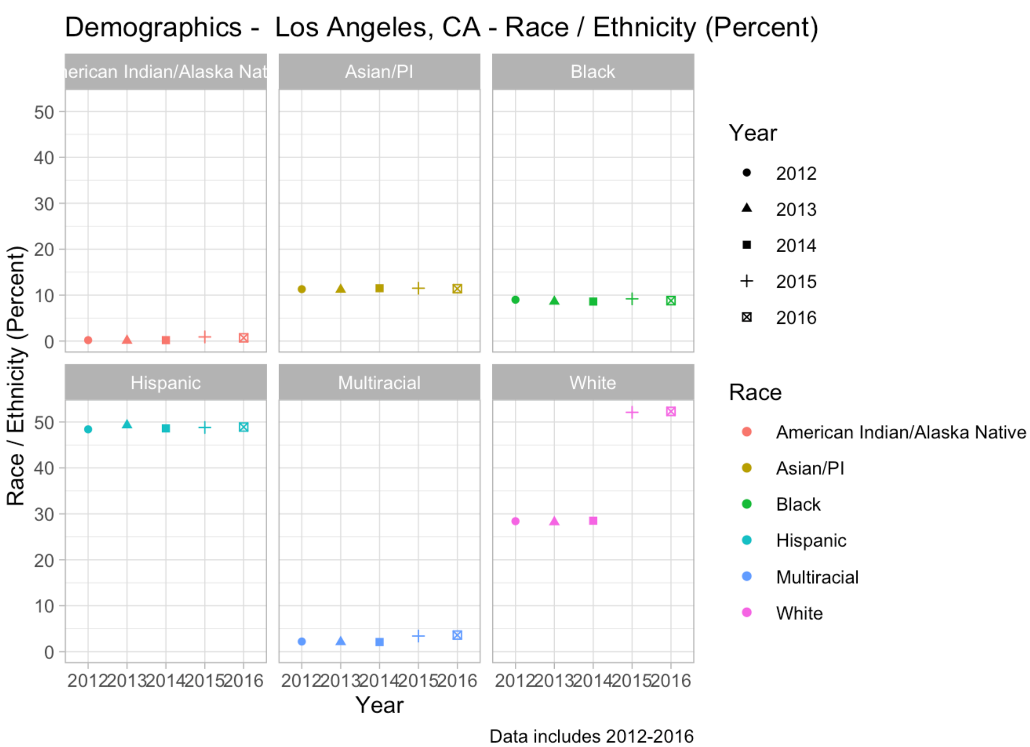


Figure 6M

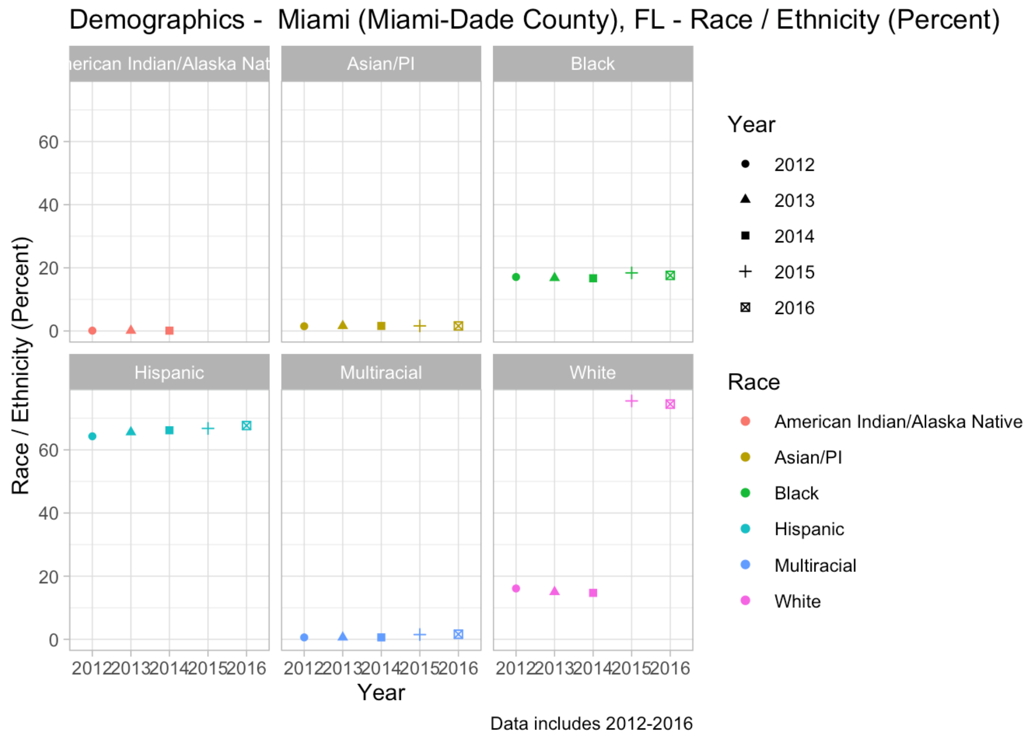


Figure 7A

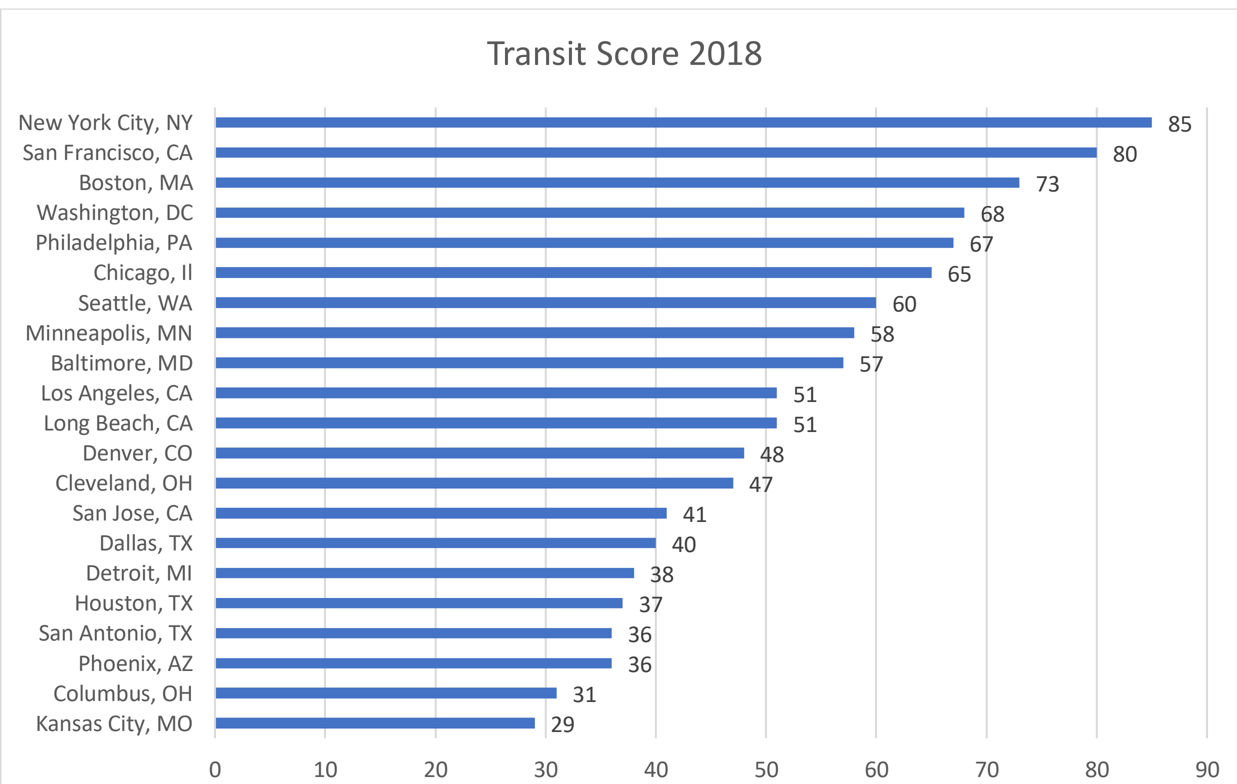


Figure 7B

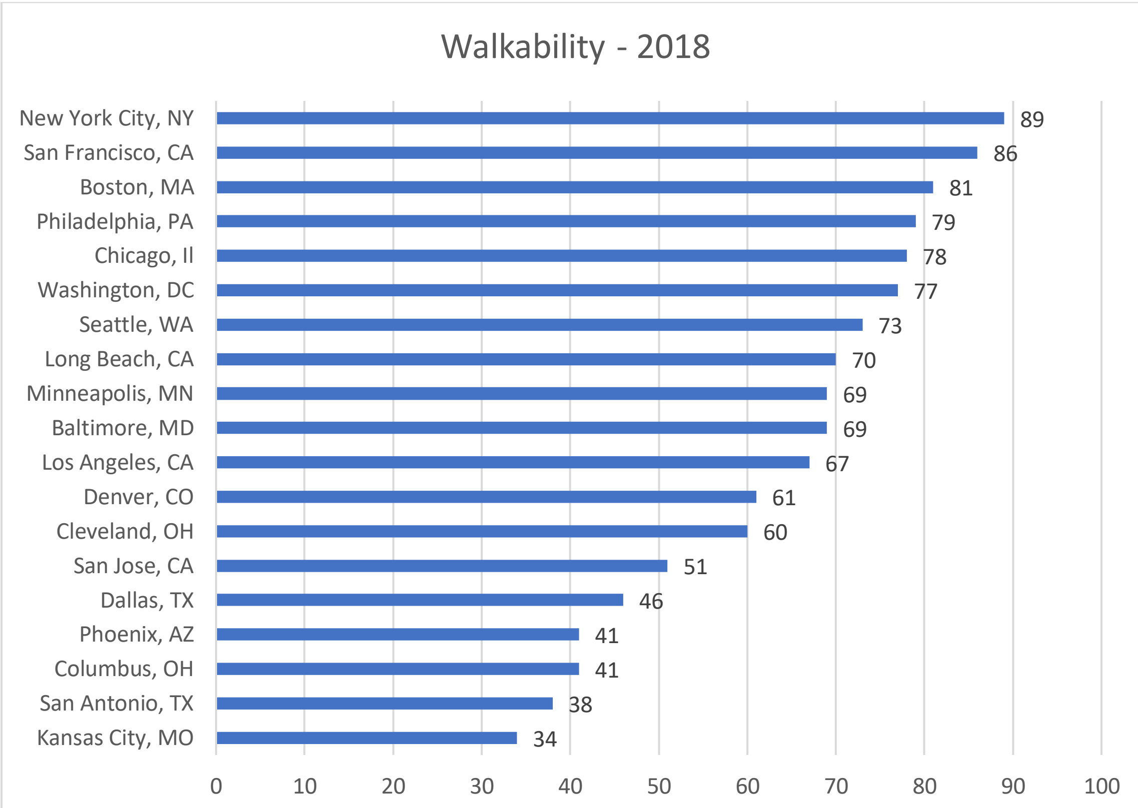


Figure 7C

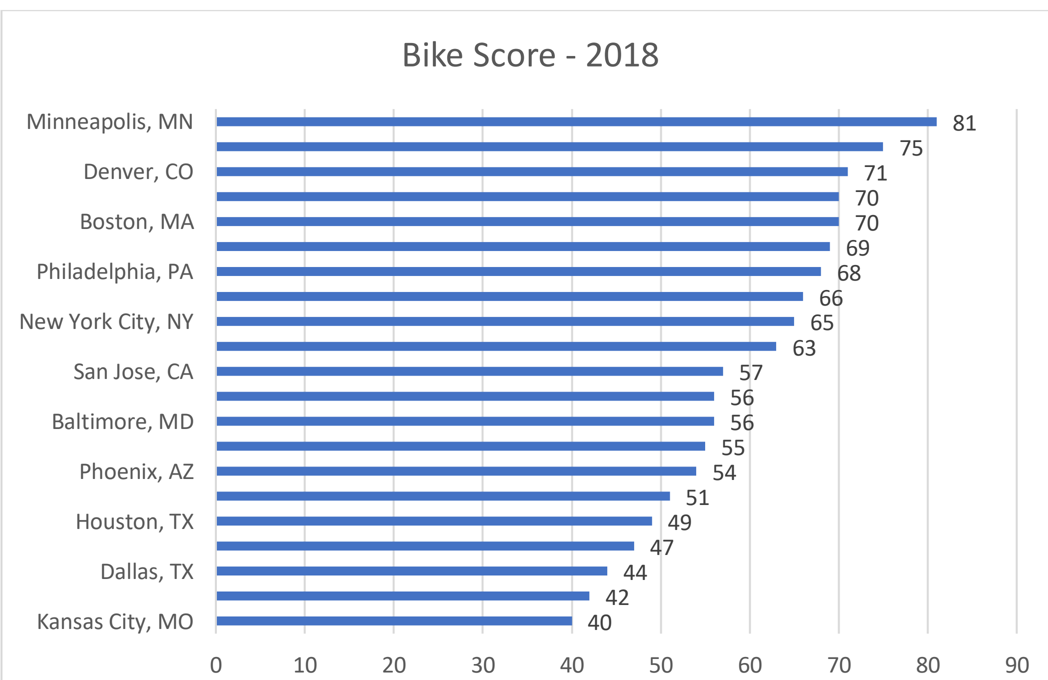


Figure 8A

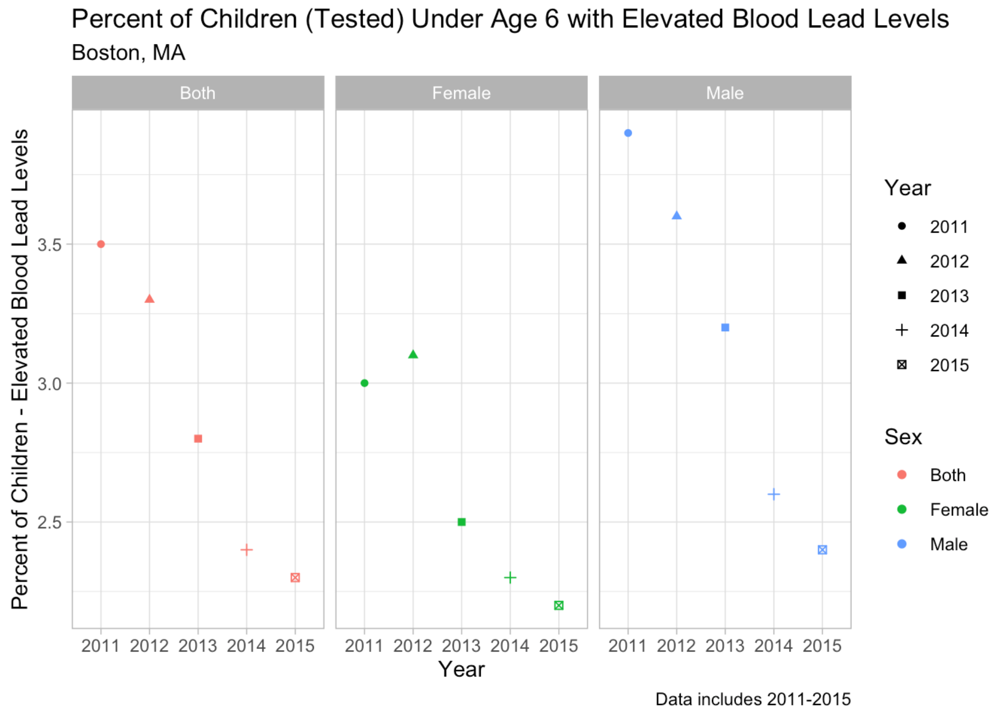


Figure 8B

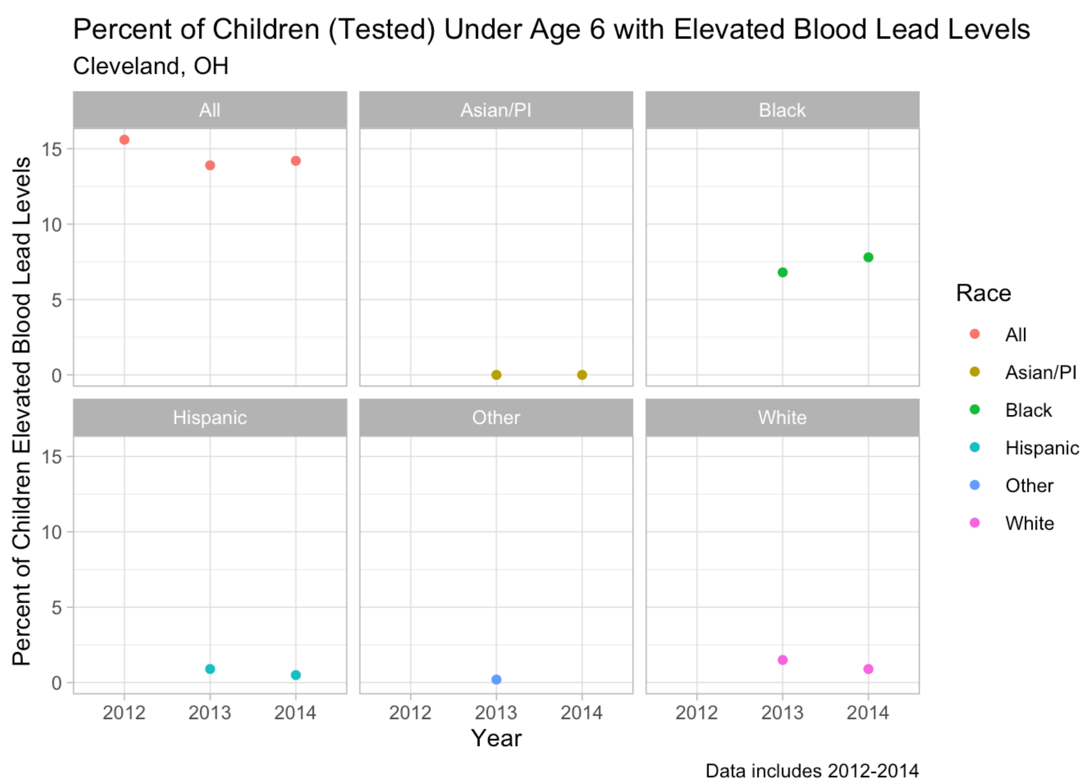
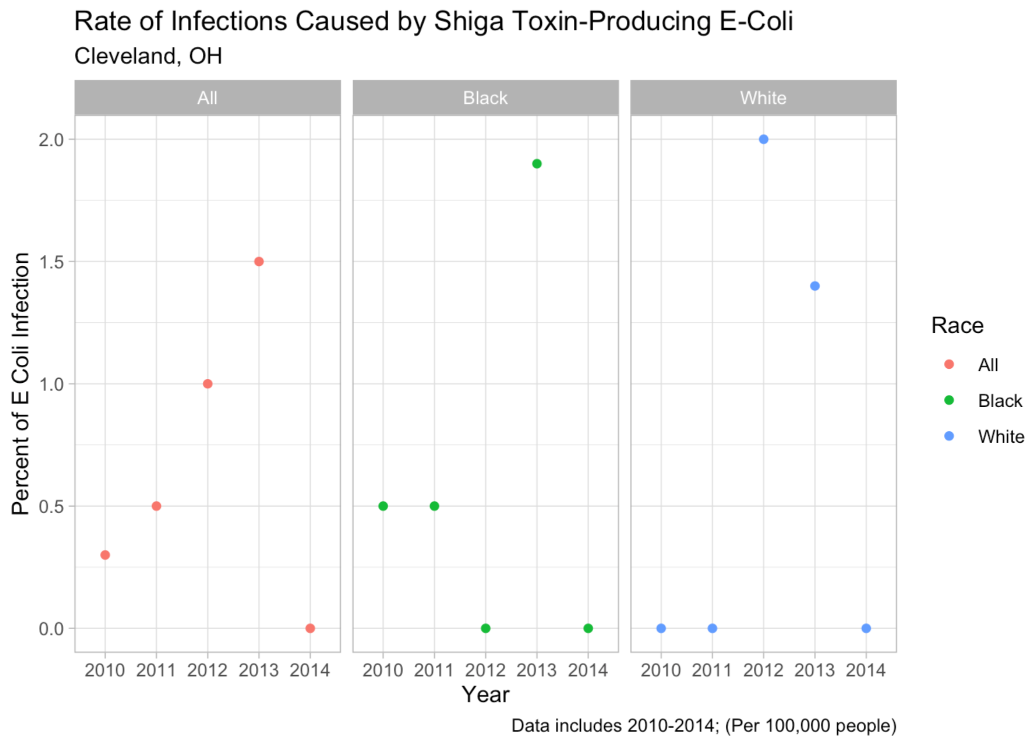


Figure 9A



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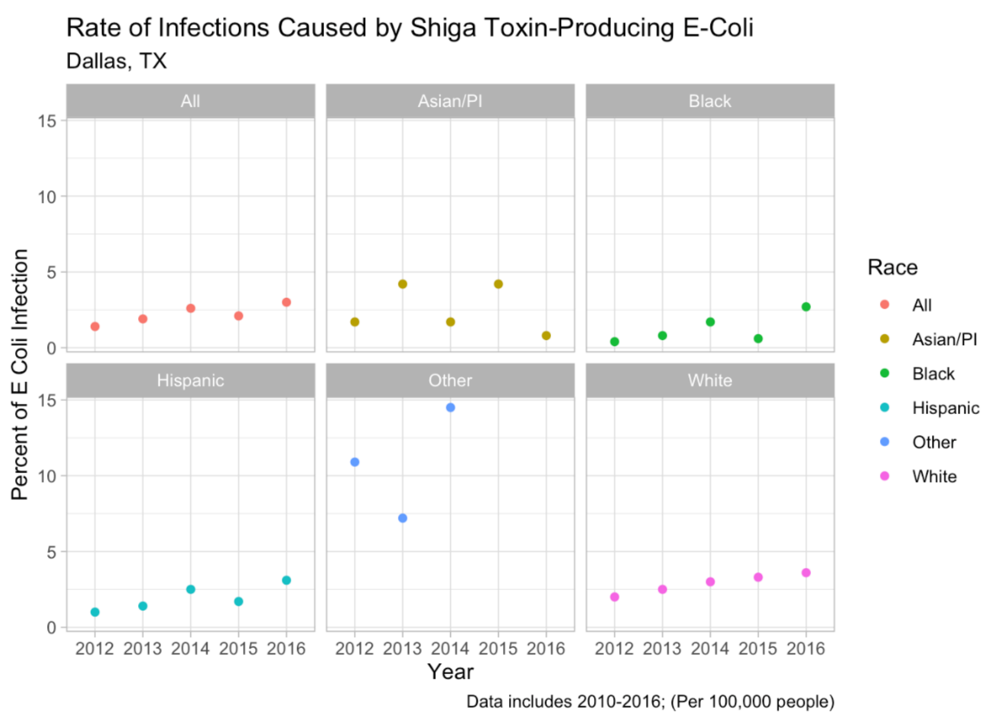


Figure 9C

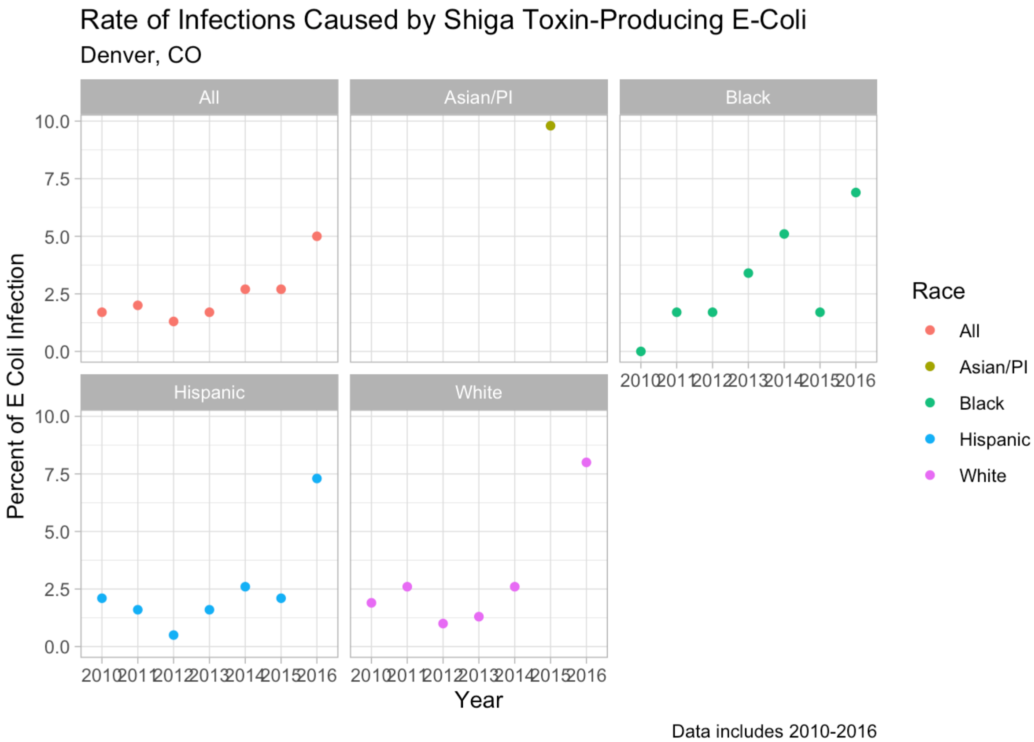
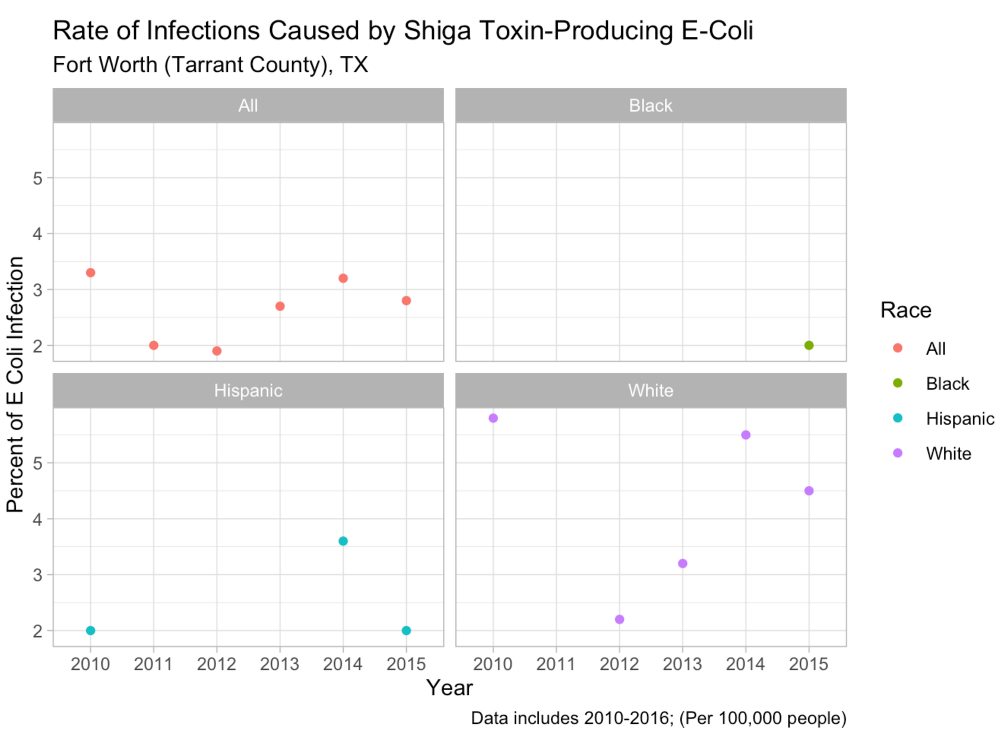


Figure 9D



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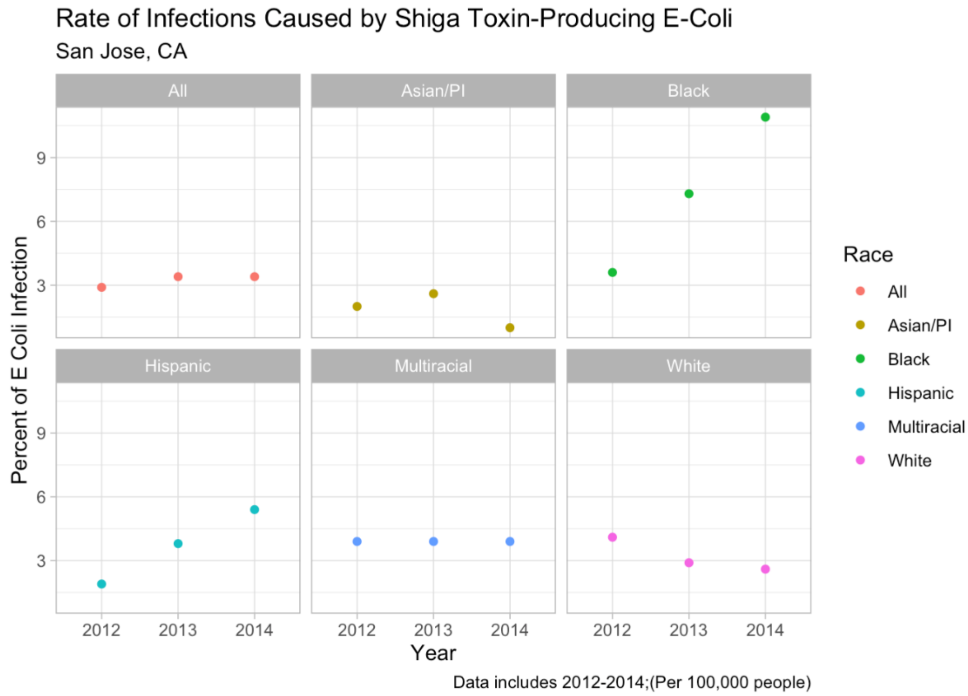

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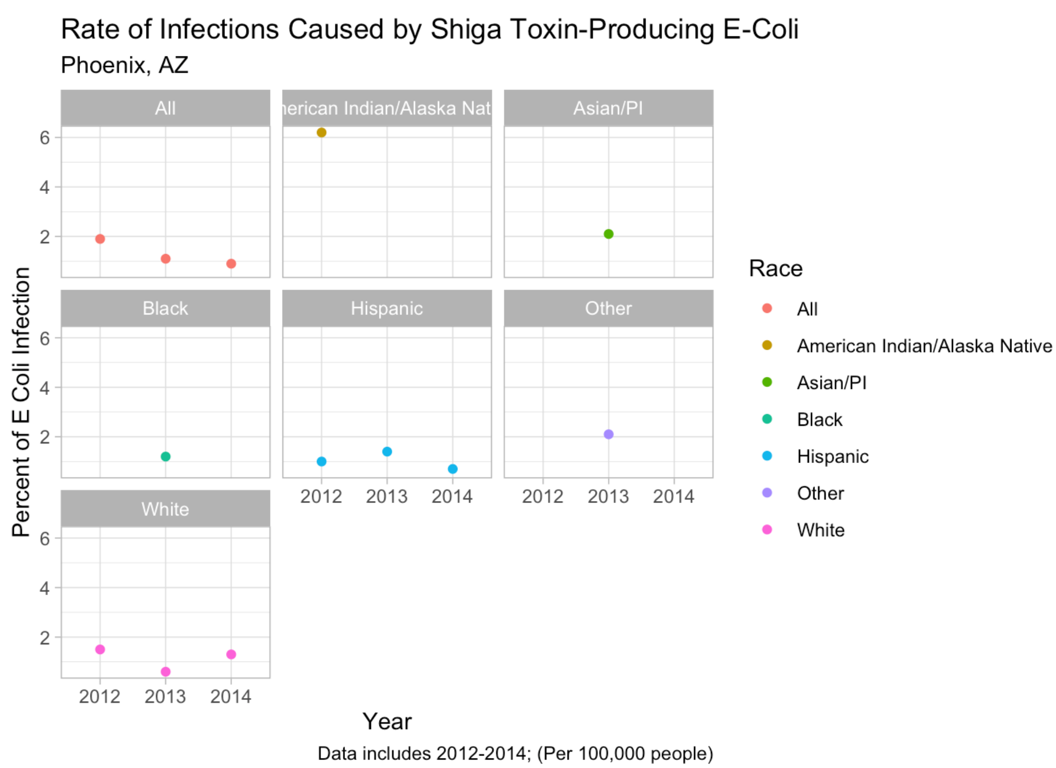


Figure 10A

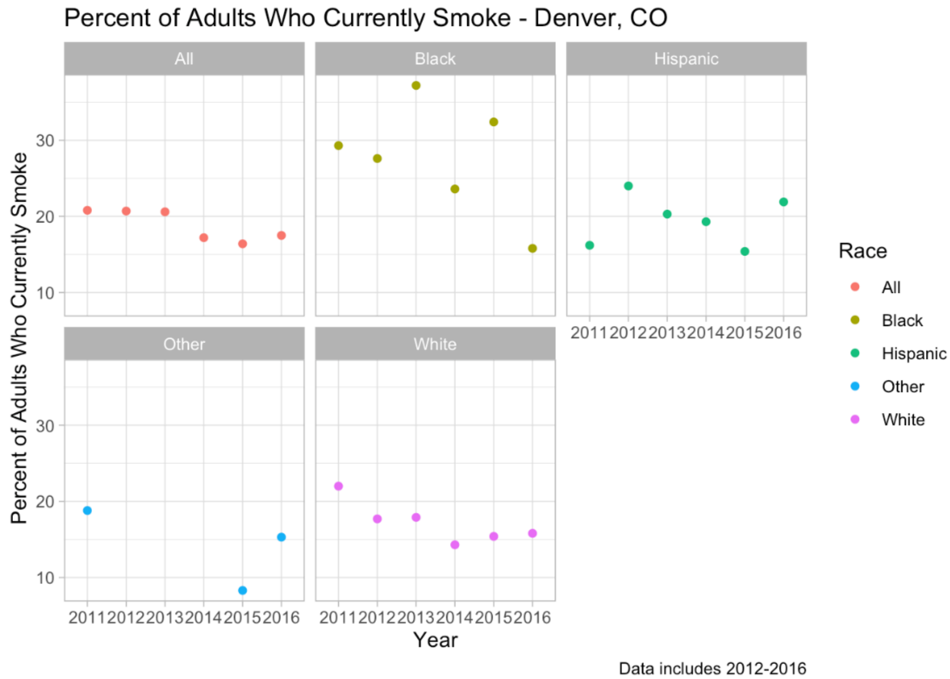
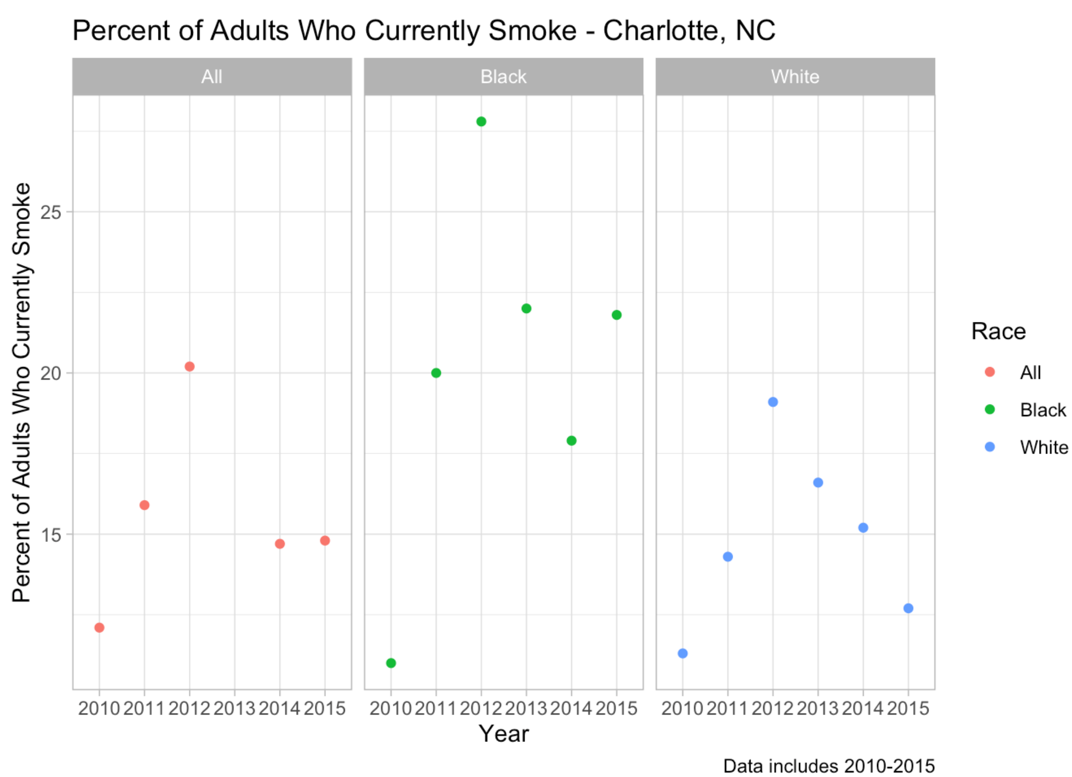


Figure 10B



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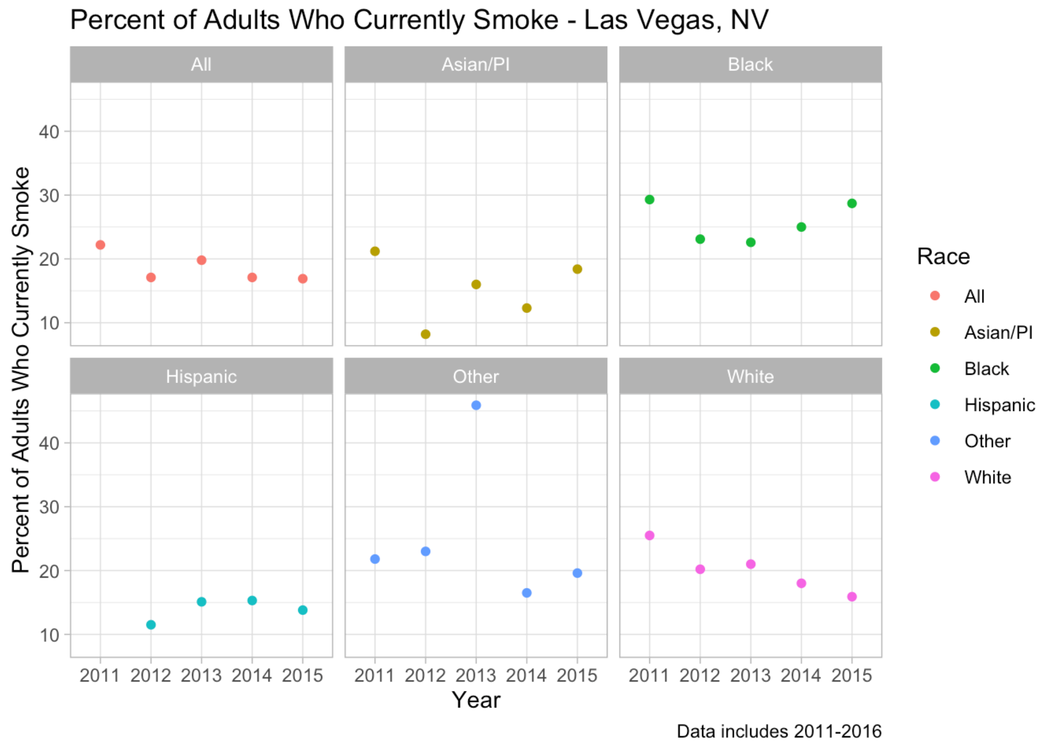

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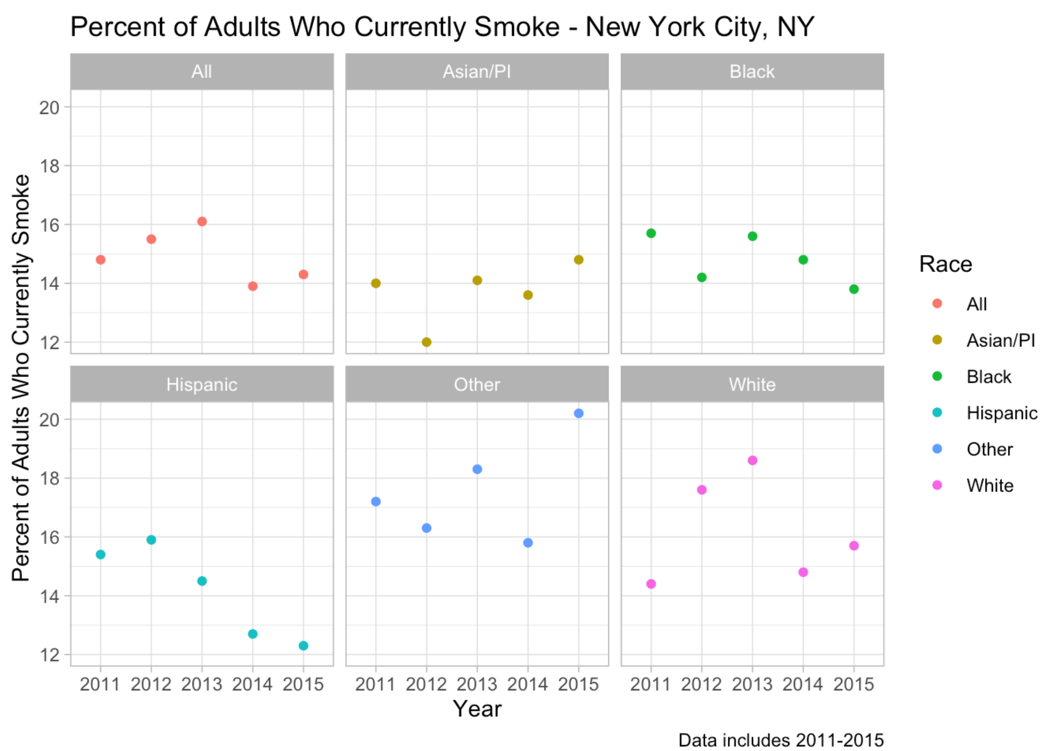

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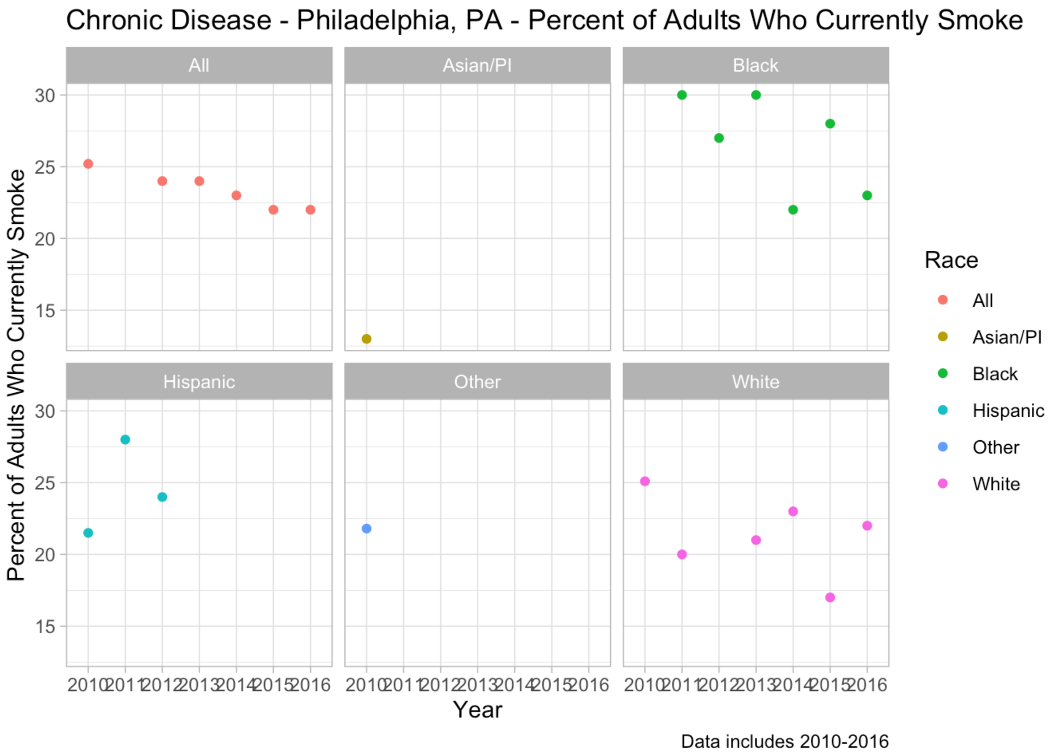

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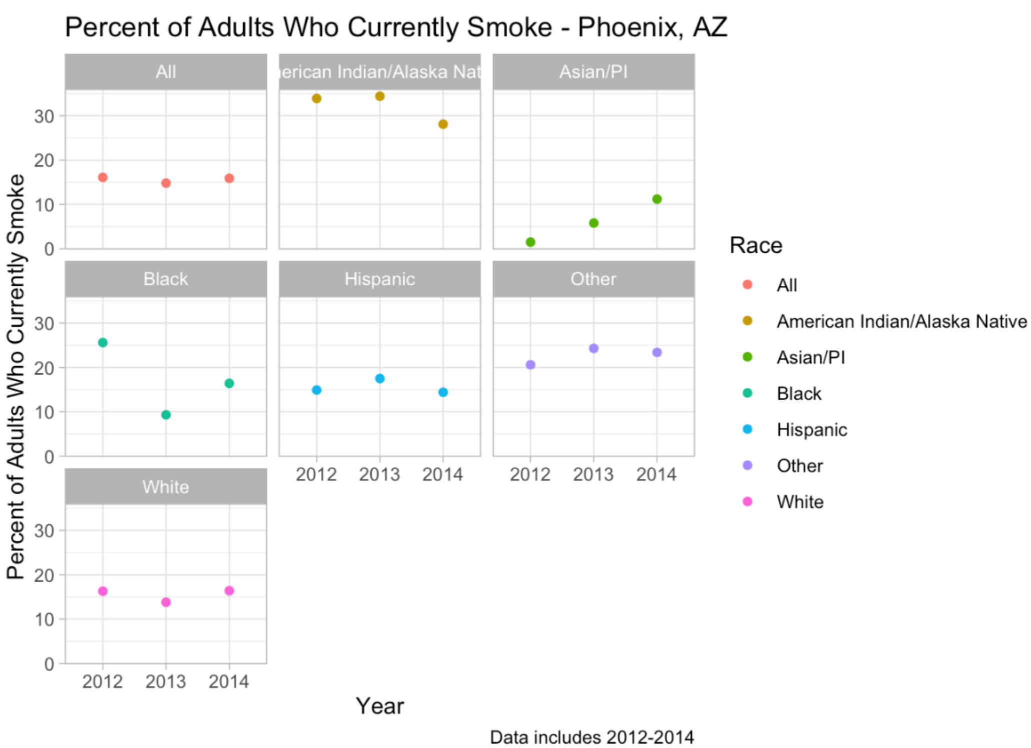


Figure 10G

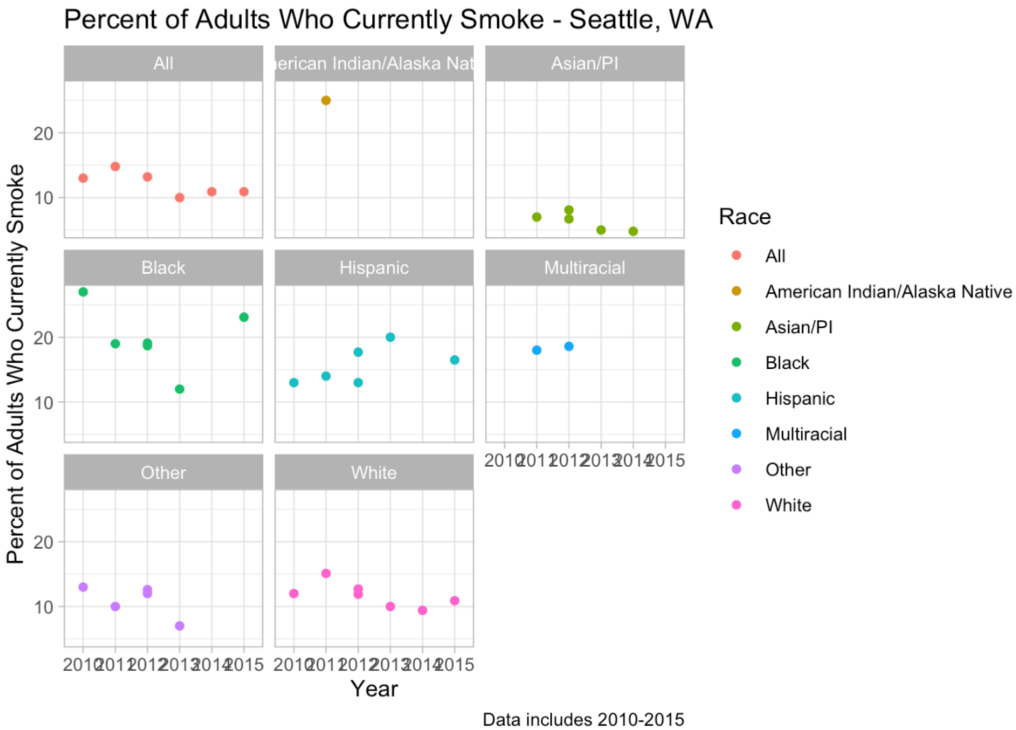


Figure 10H

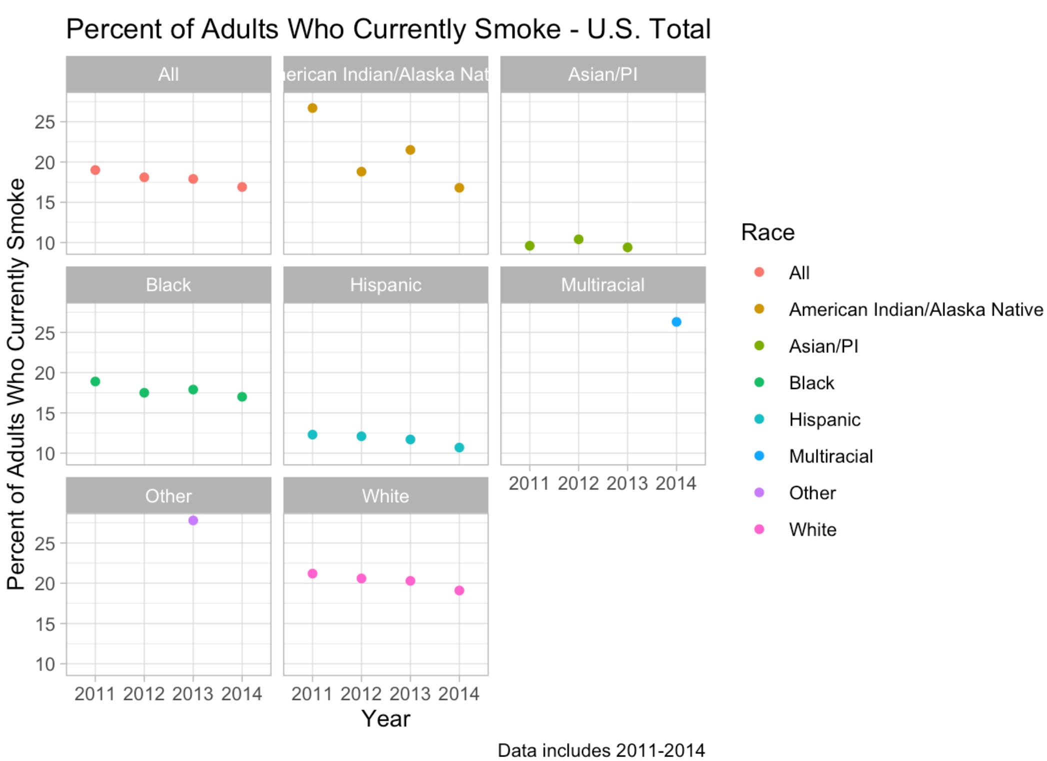
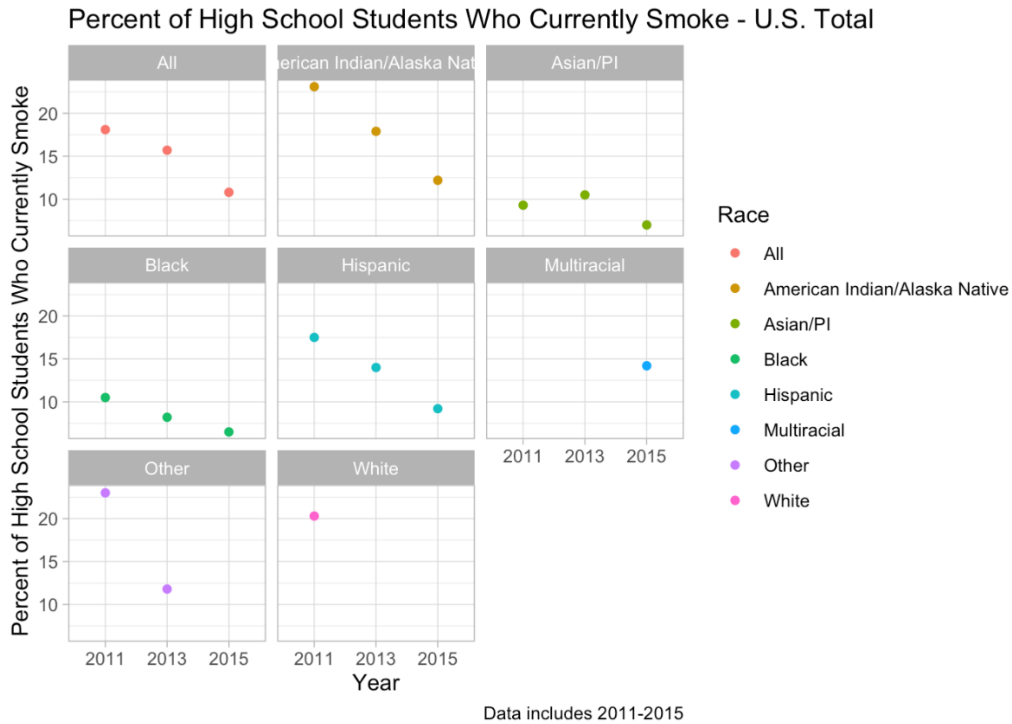


Figure 11A



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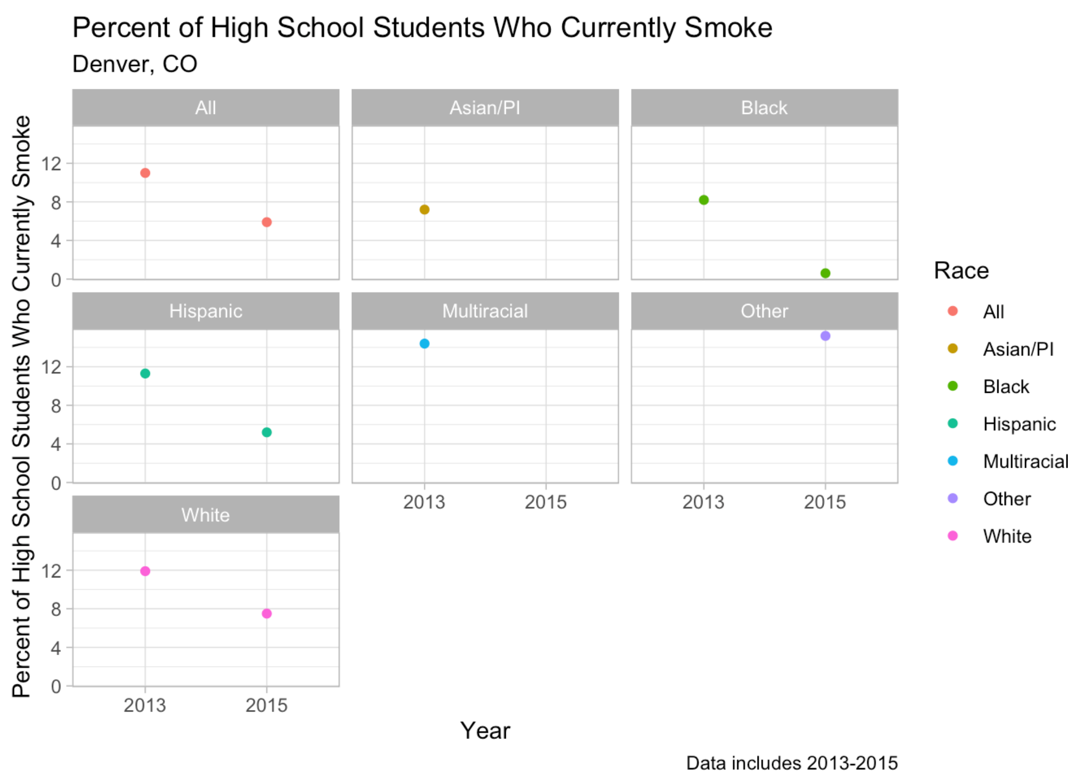

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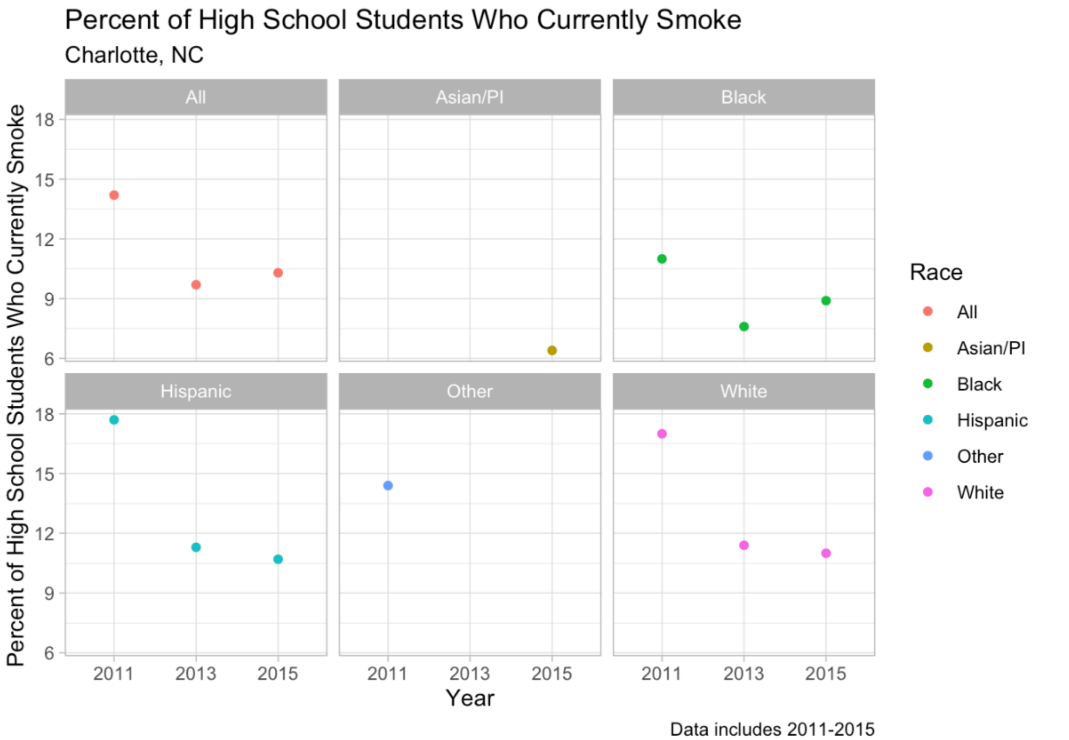

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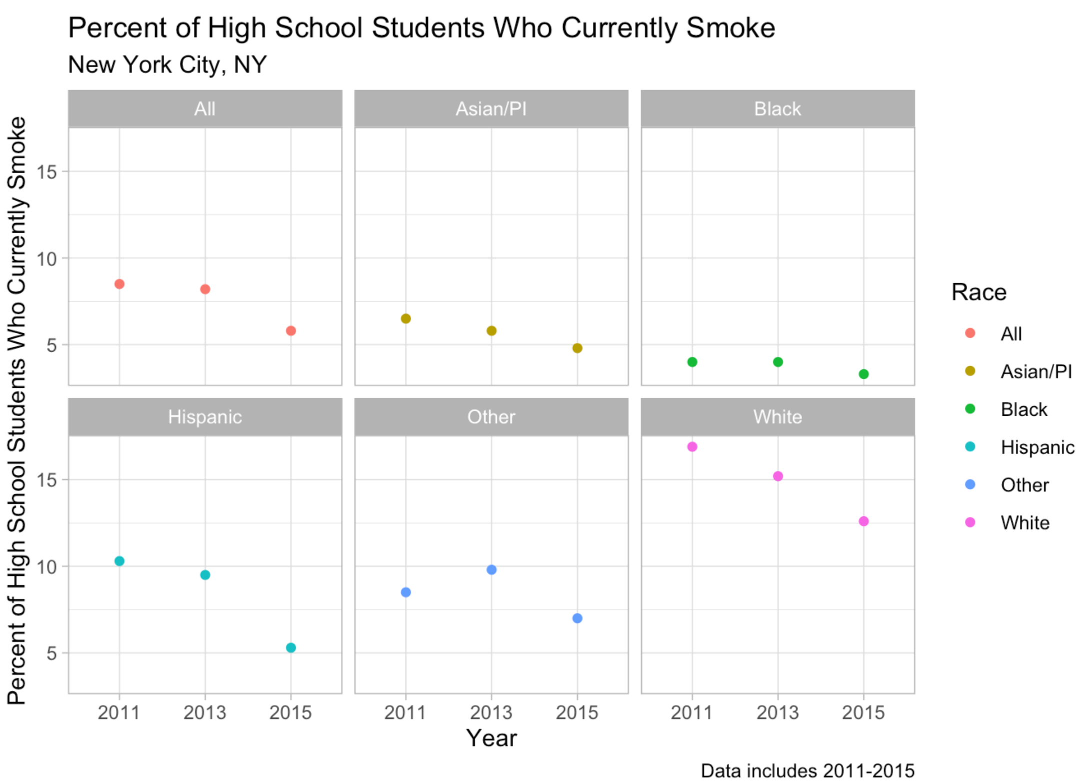

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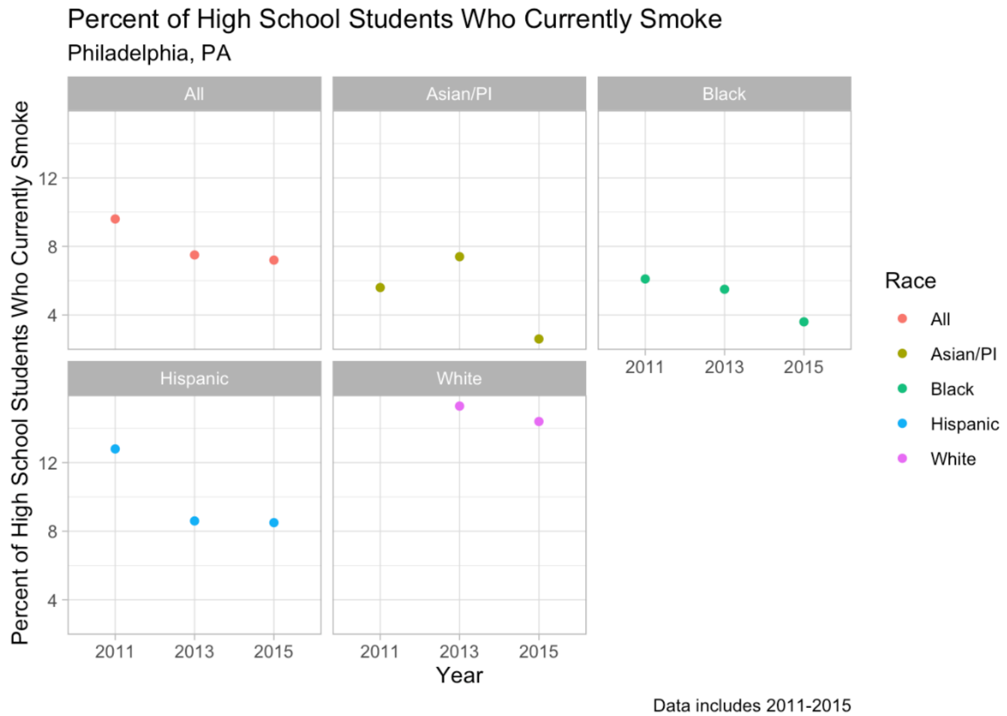

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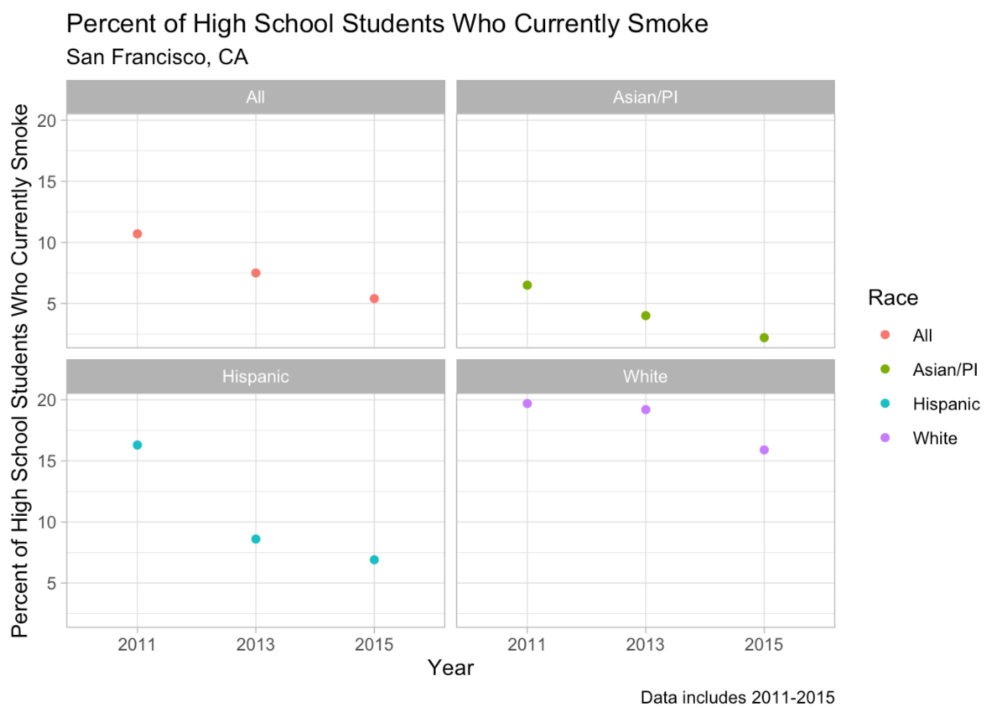

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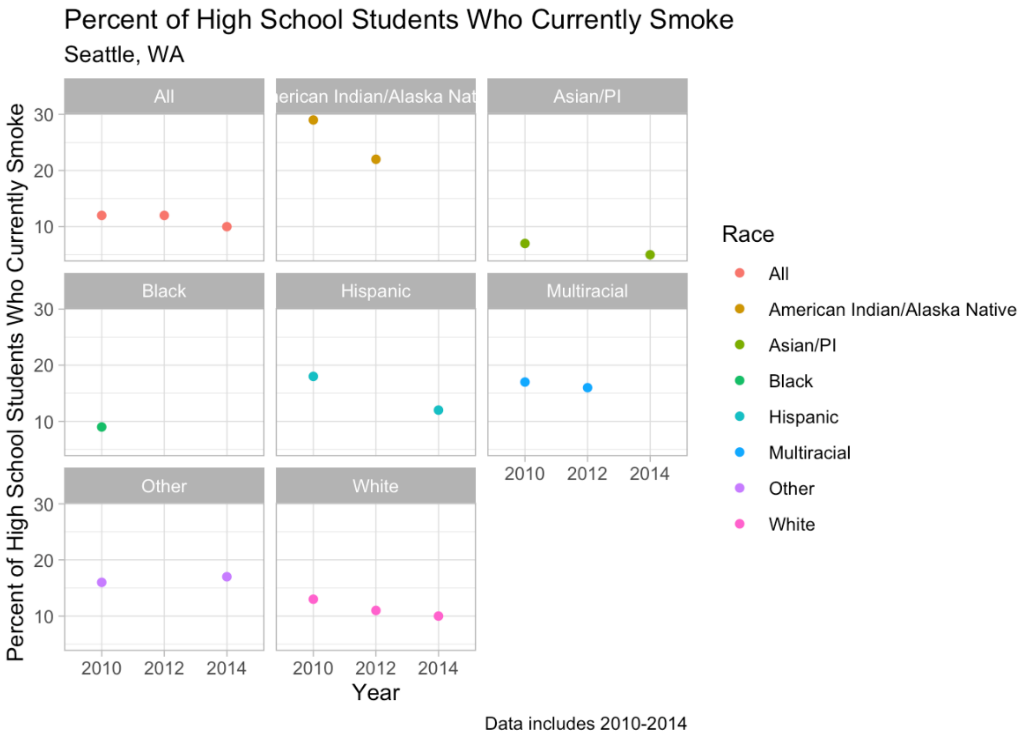
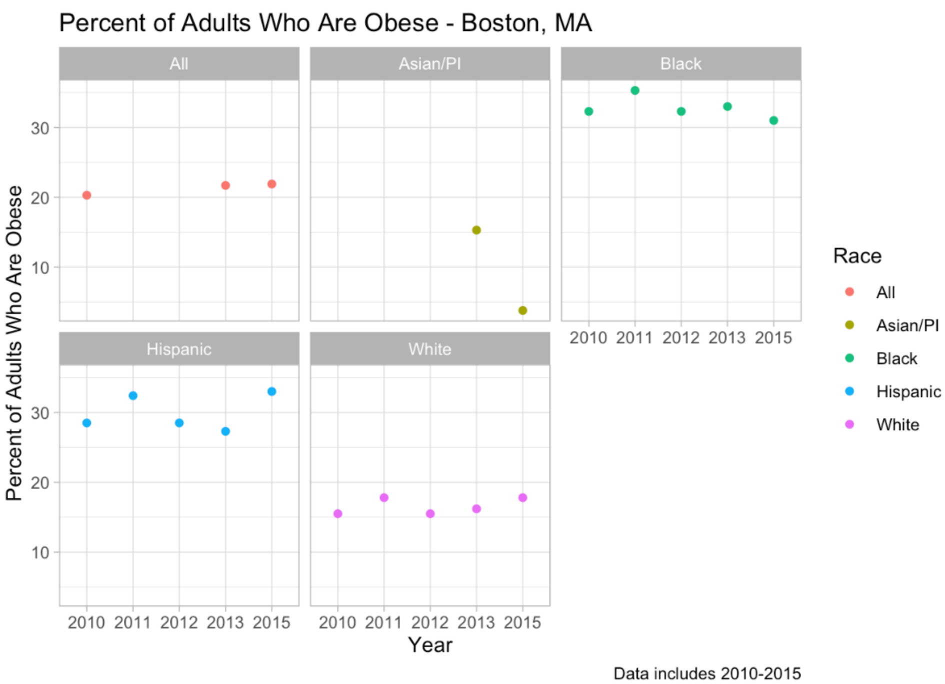


Figure 12A



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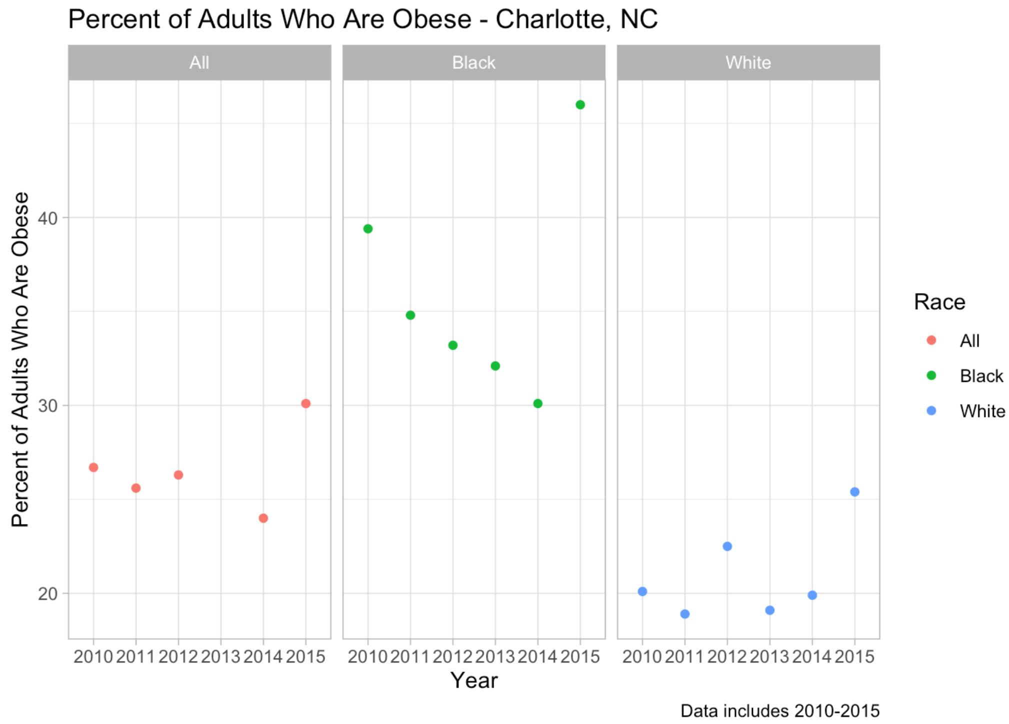
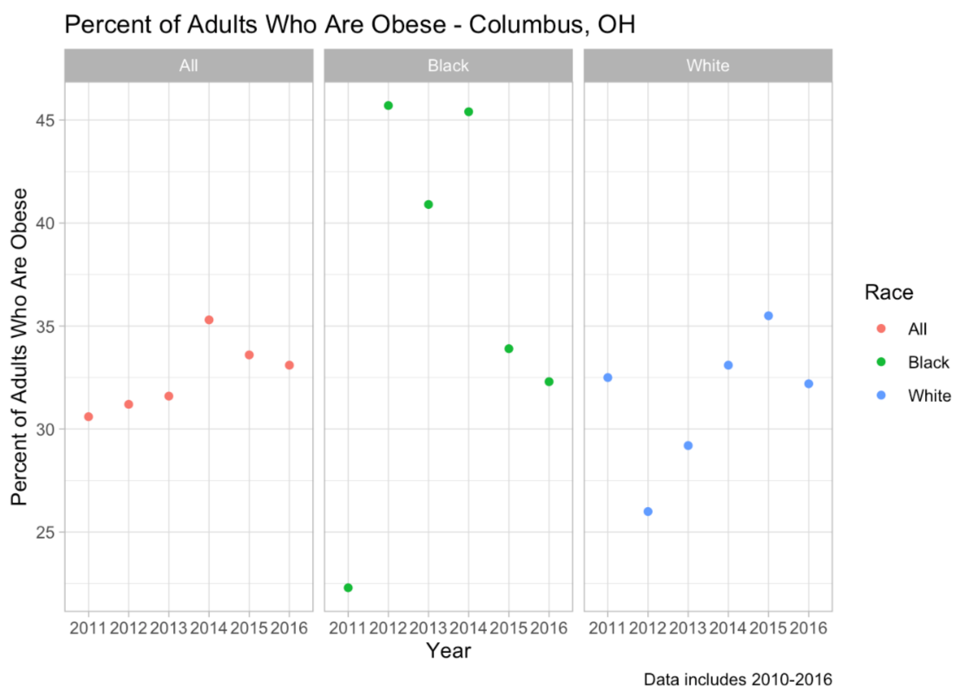


Figure 12C



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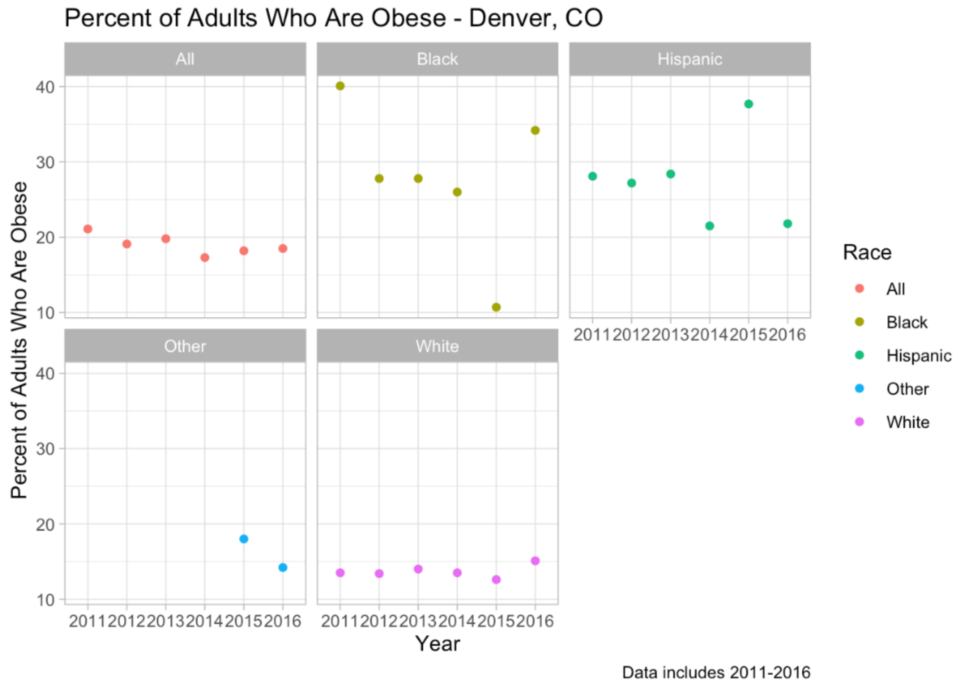

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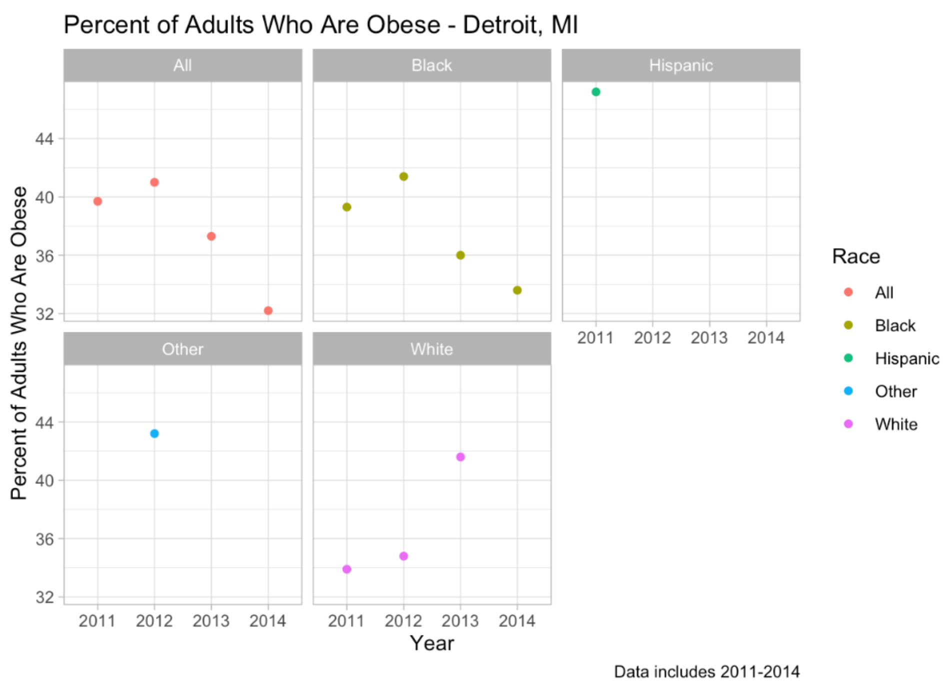

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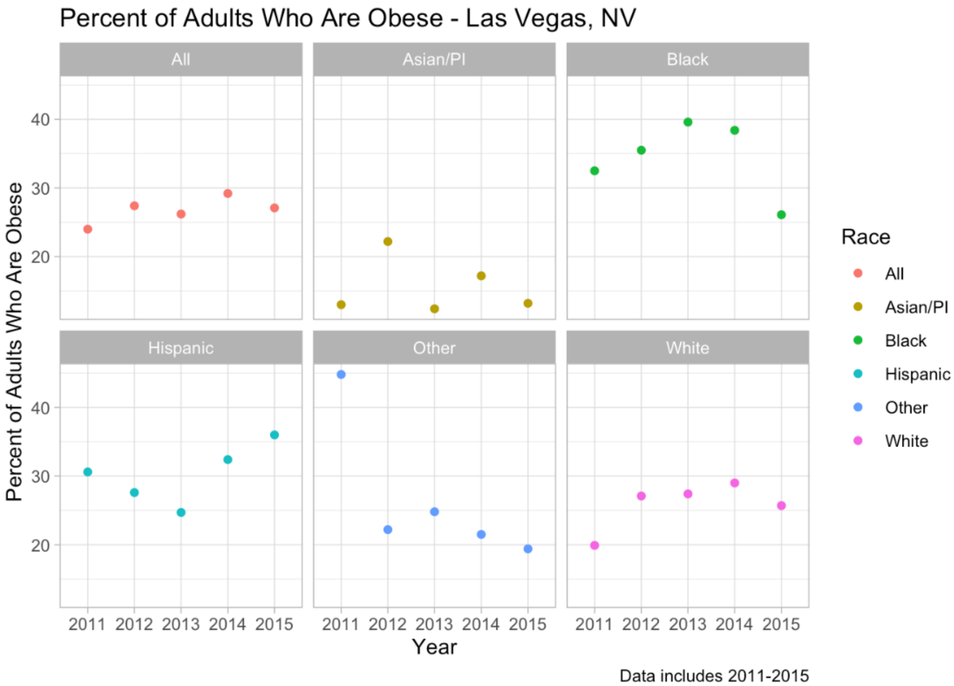

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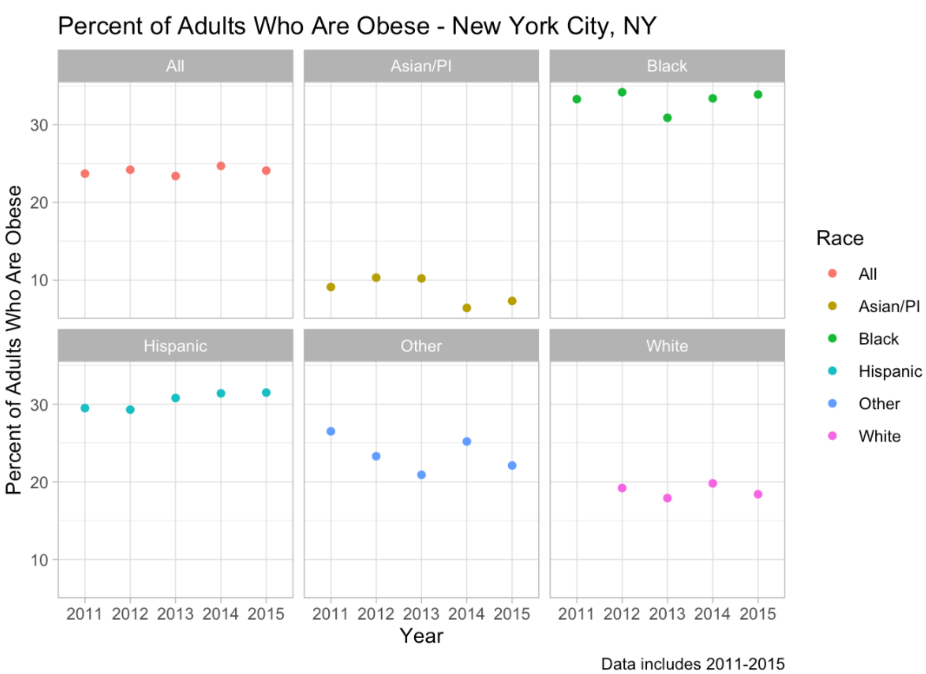


Figure 12H

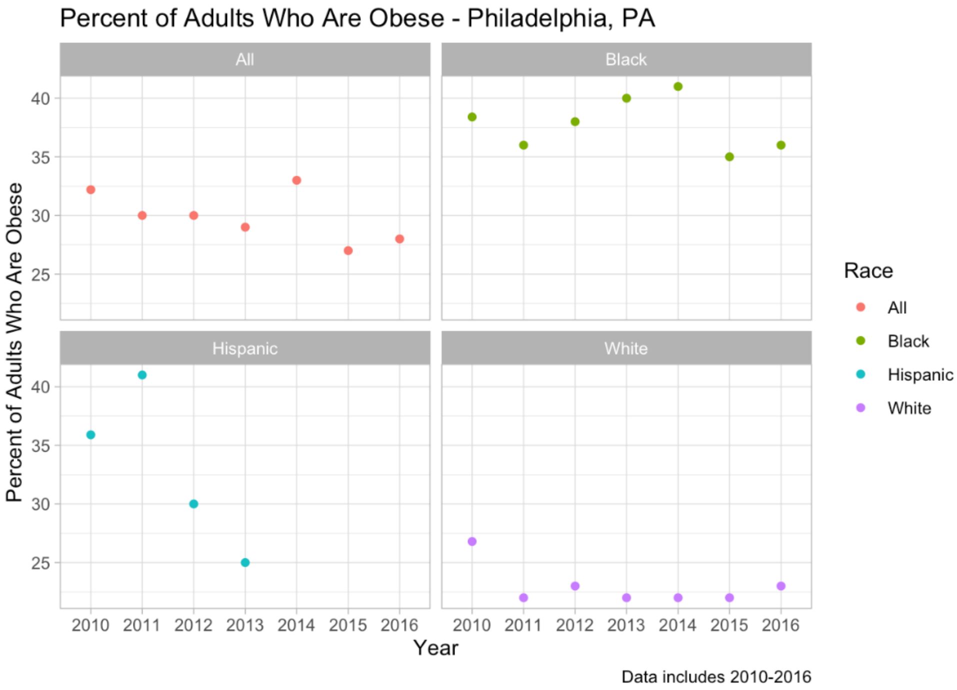


Figure 12I

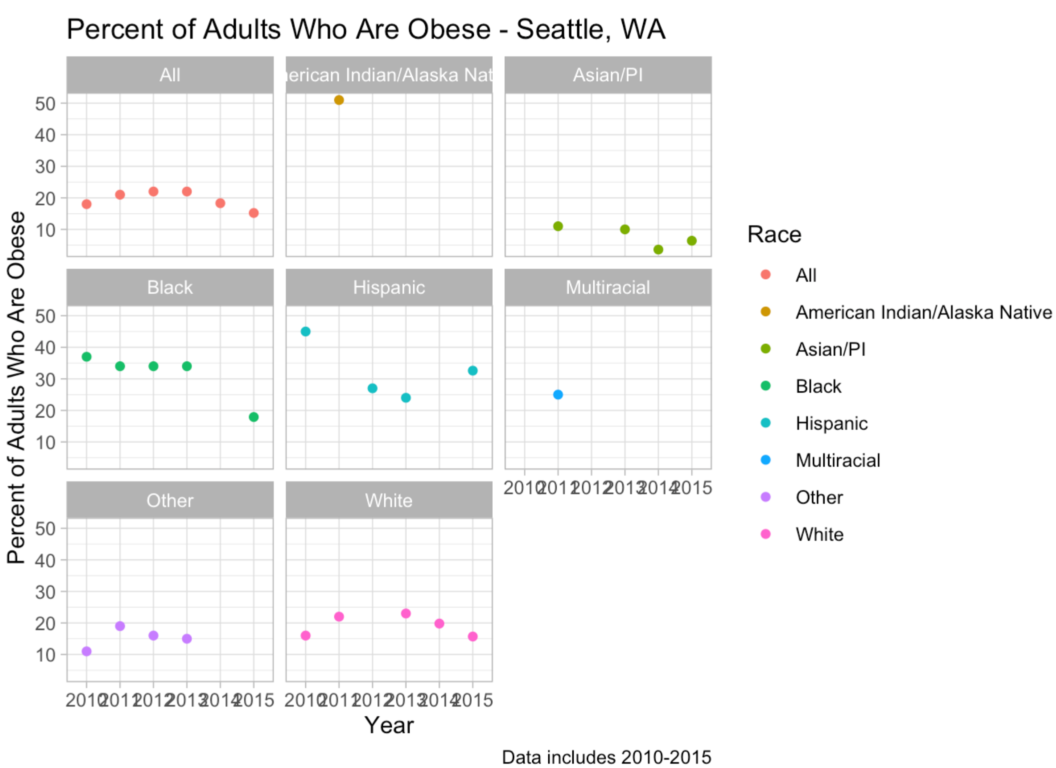


Figure 12J

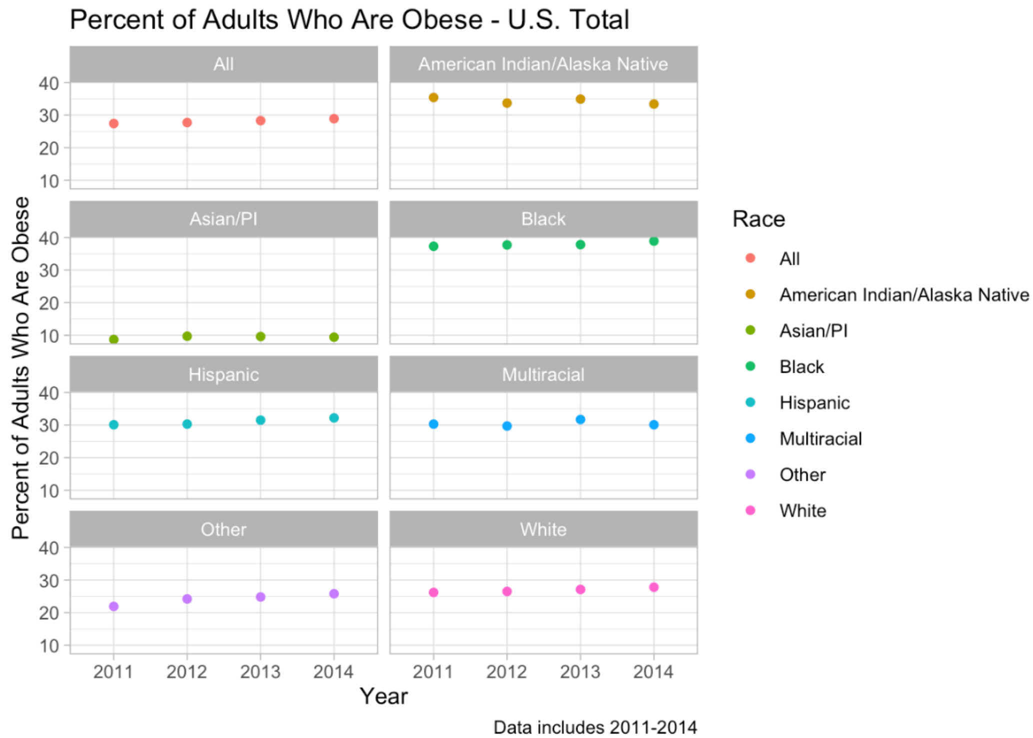


Figure 13A

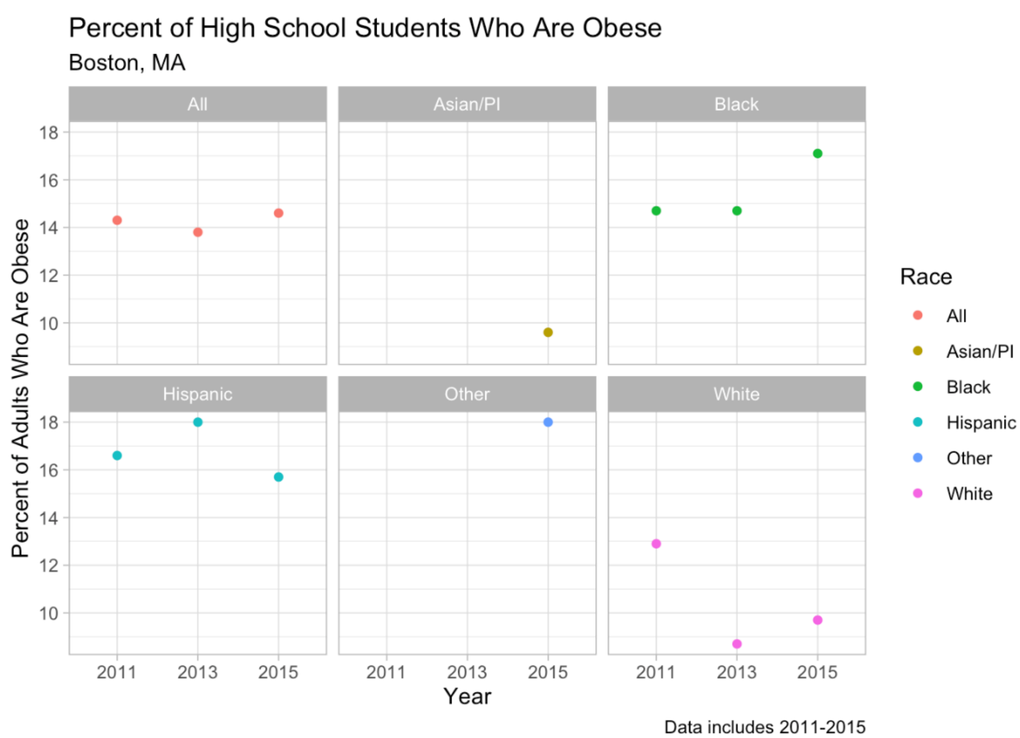


Figure 13B

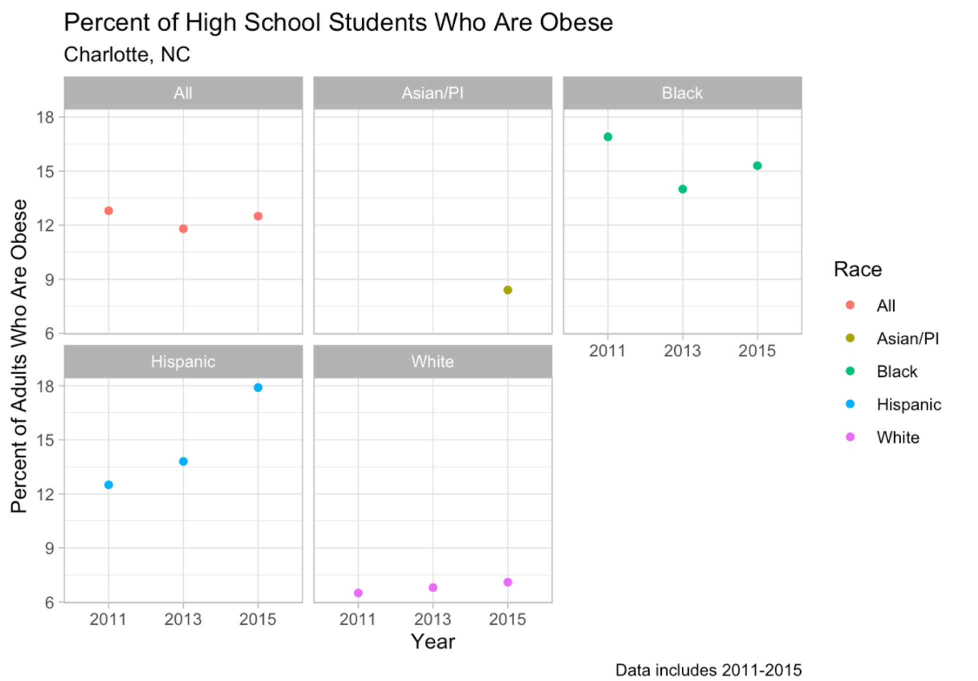
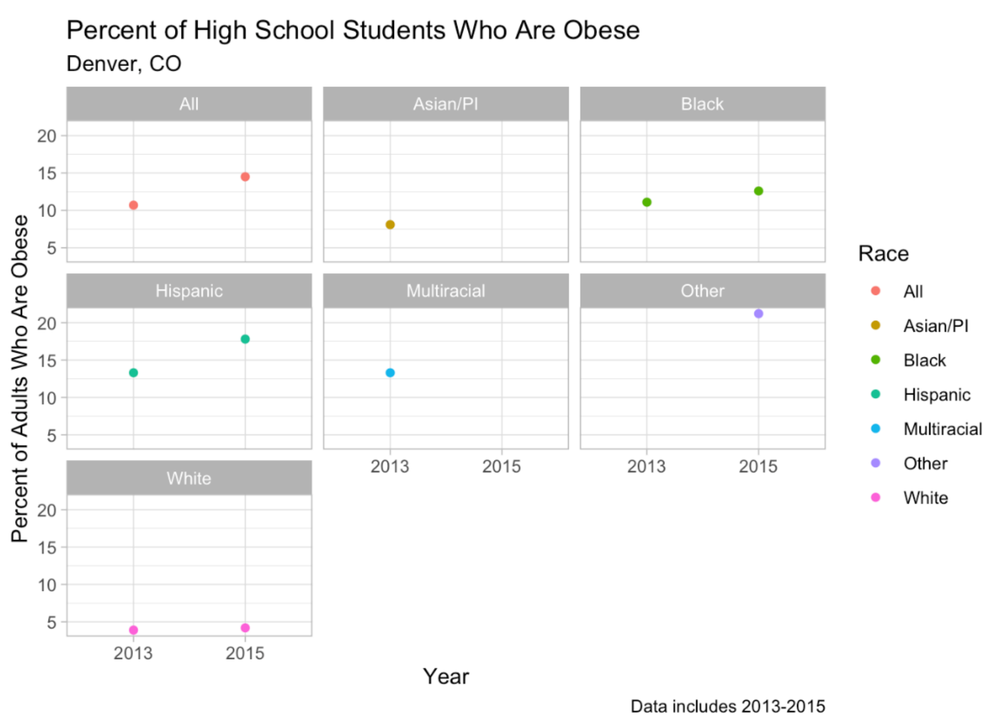


Figure 13C



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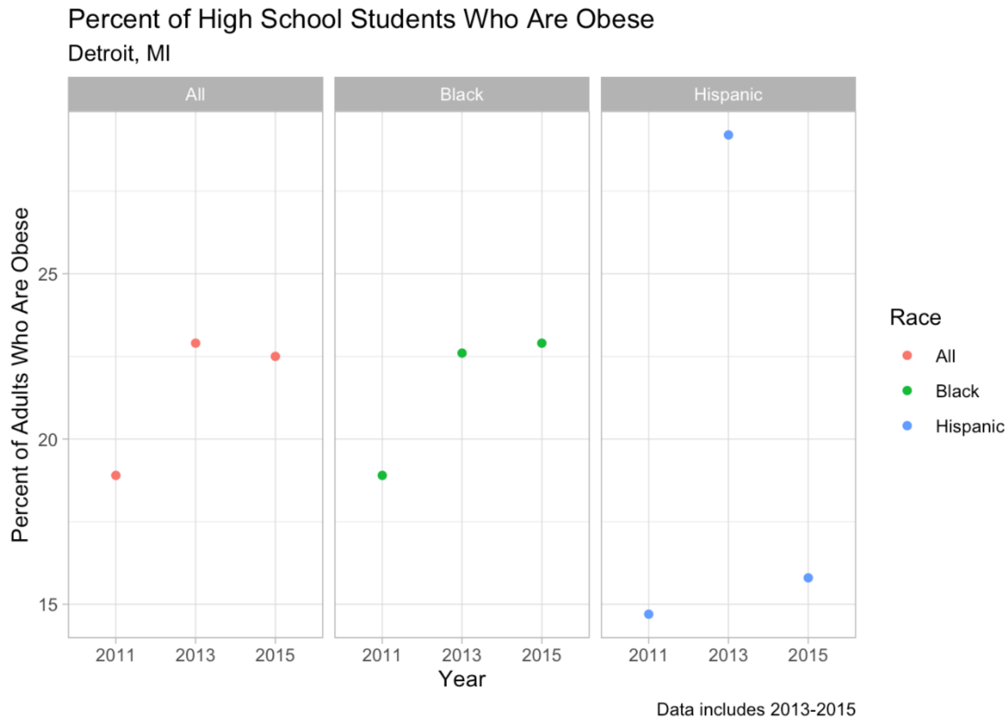

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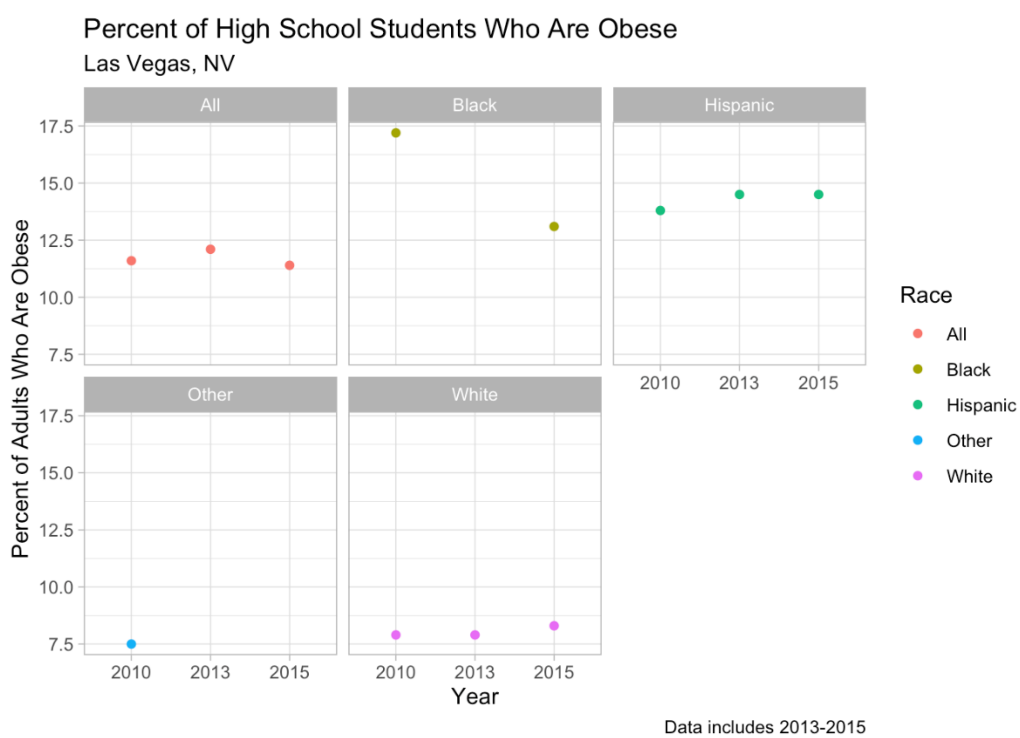

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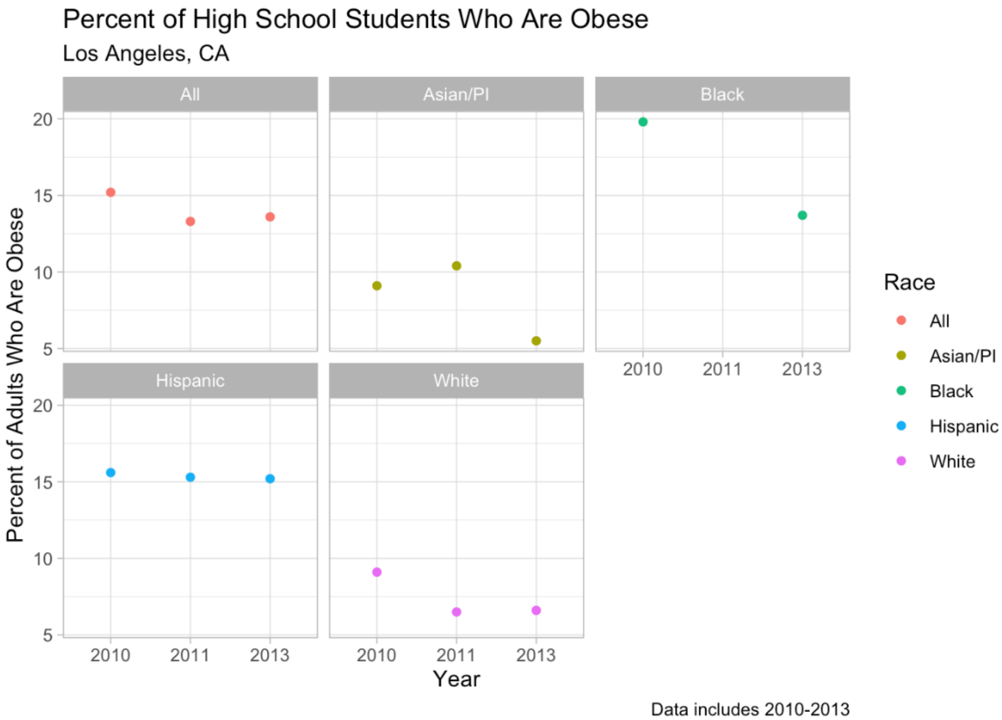

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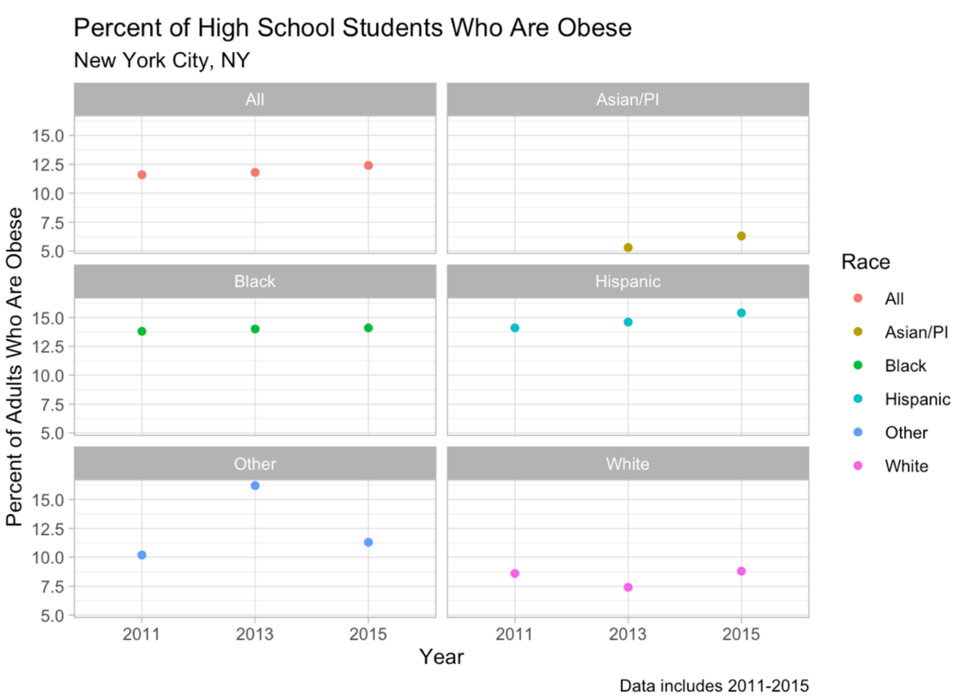


Figure 13H

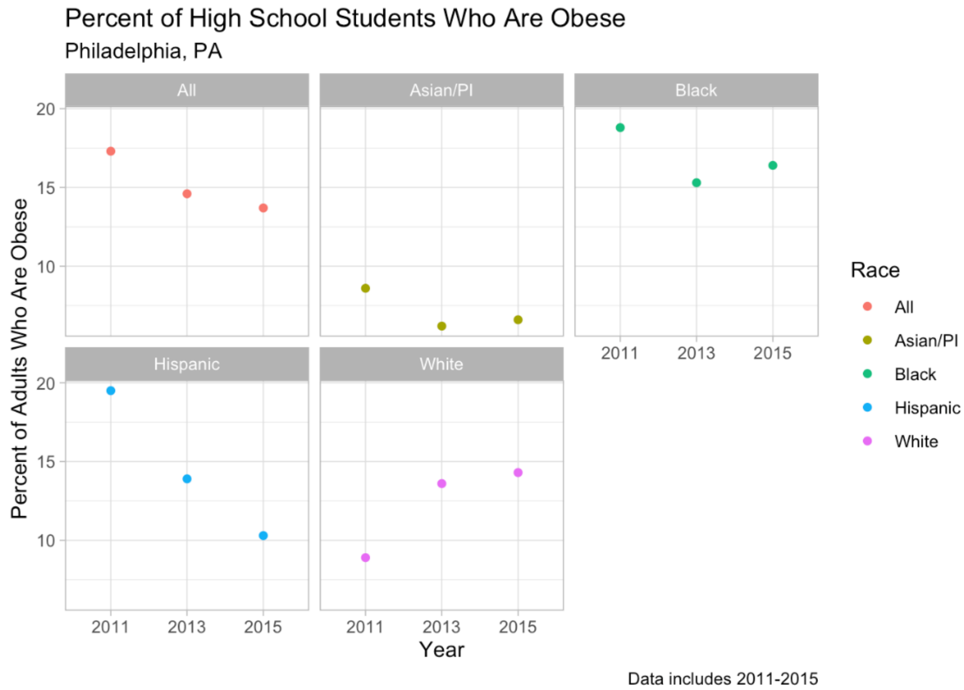


Figure 13I

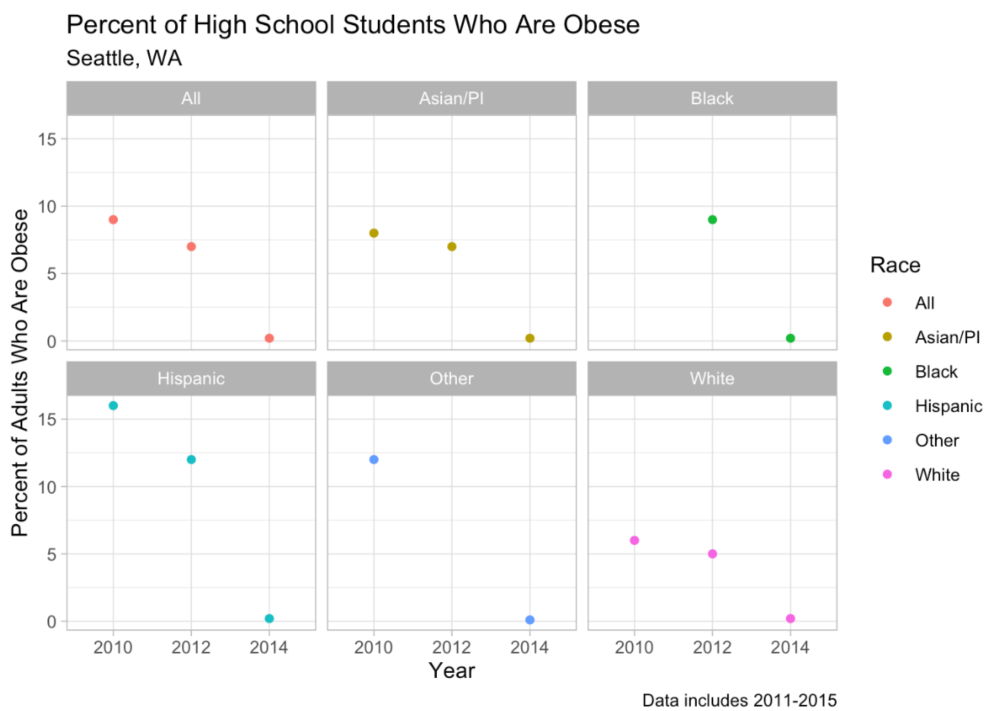


Figure 13J

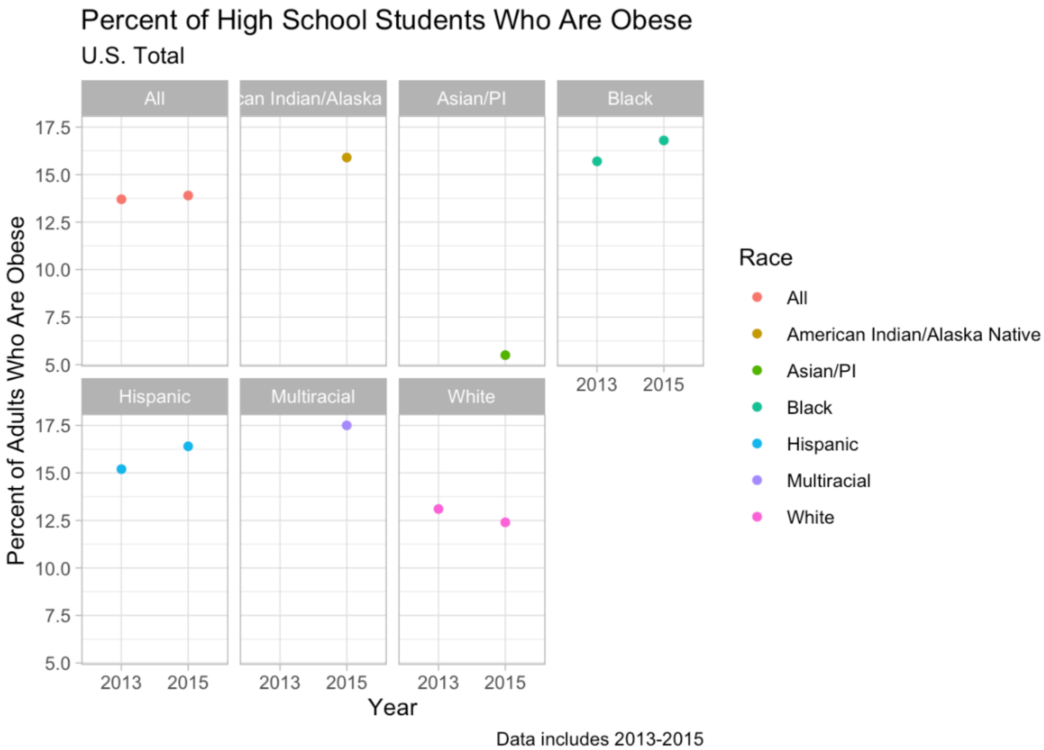


Figure 14A

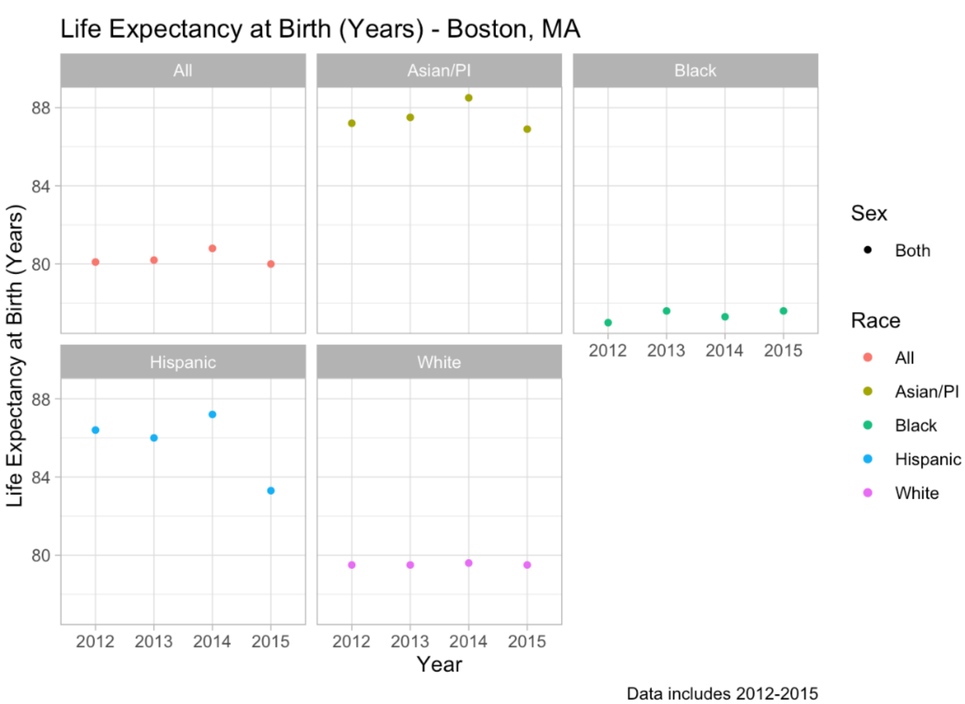


Figure 14B

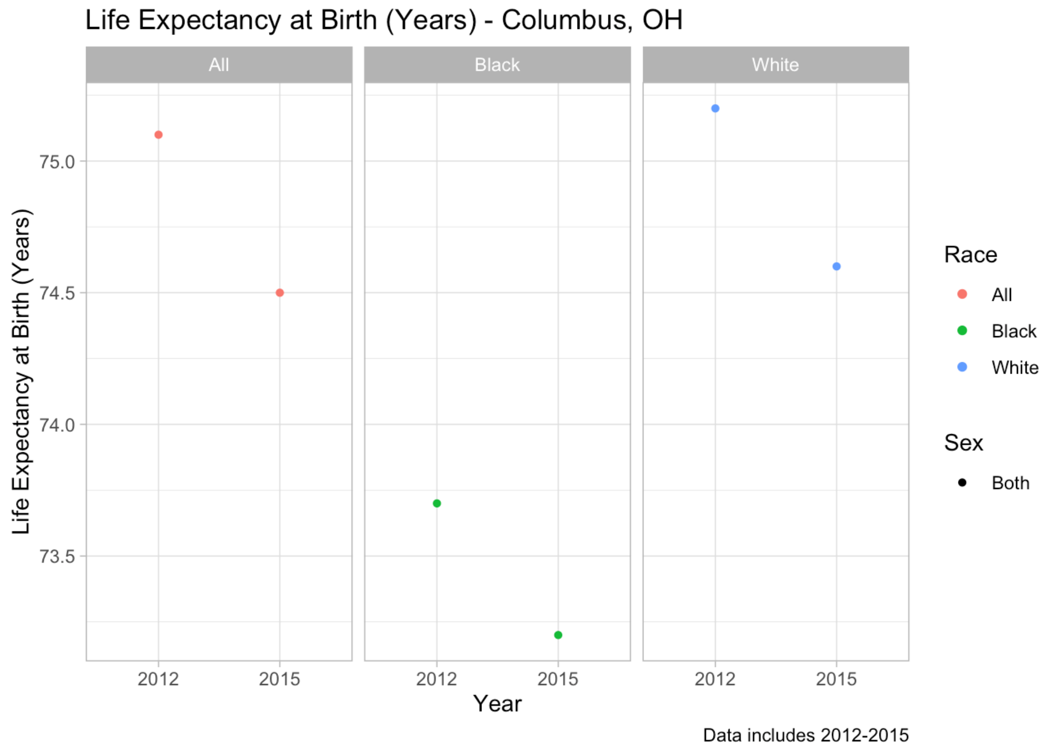
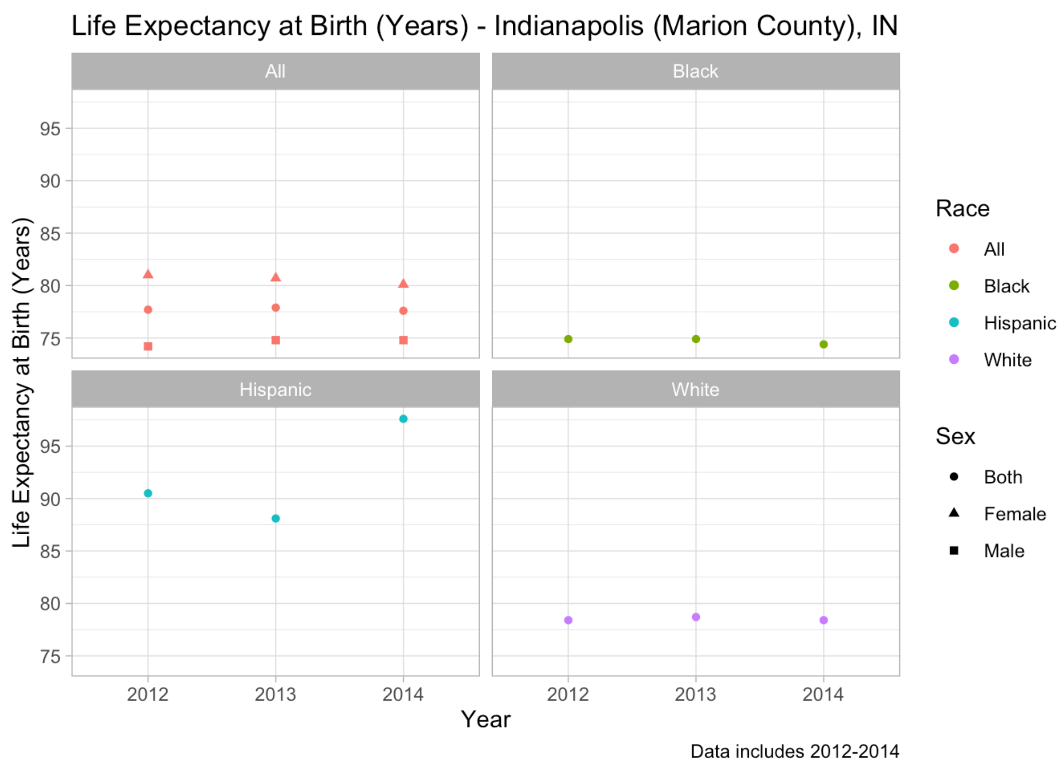


Figure 14C



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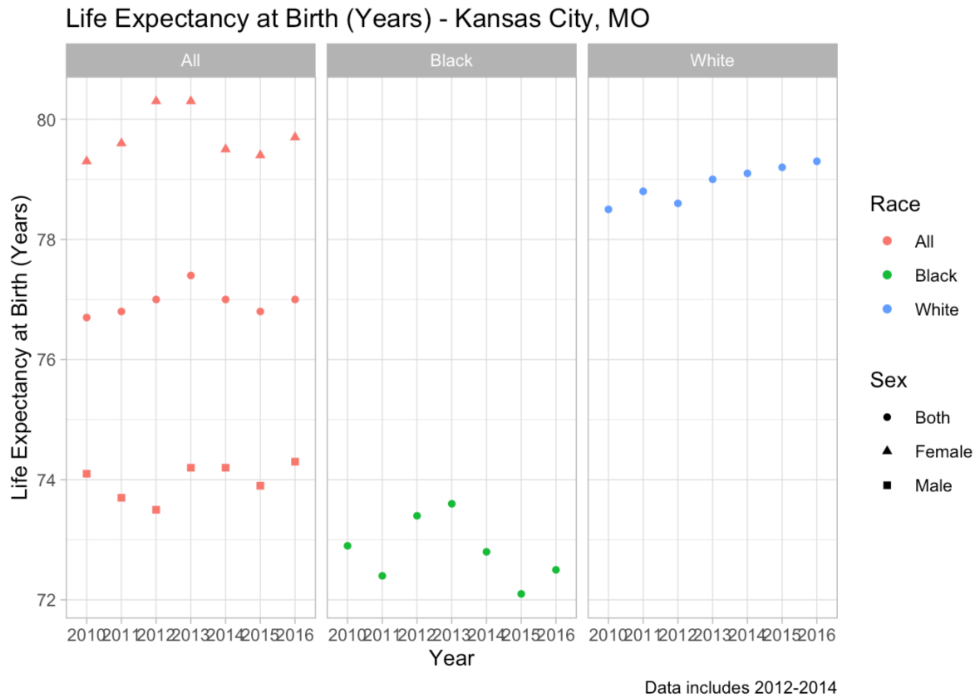

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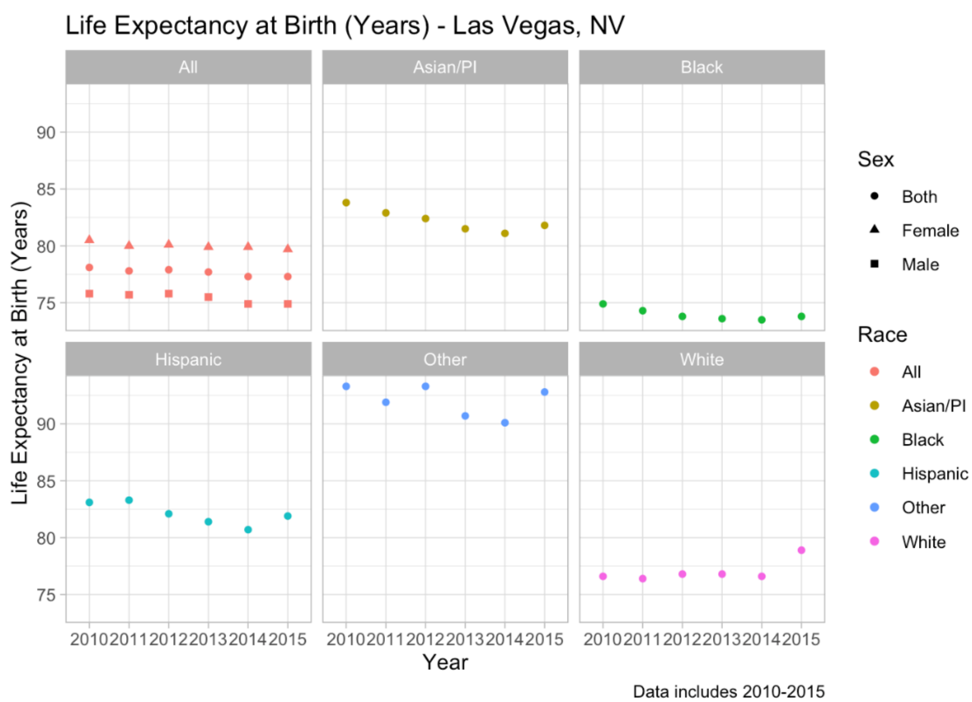

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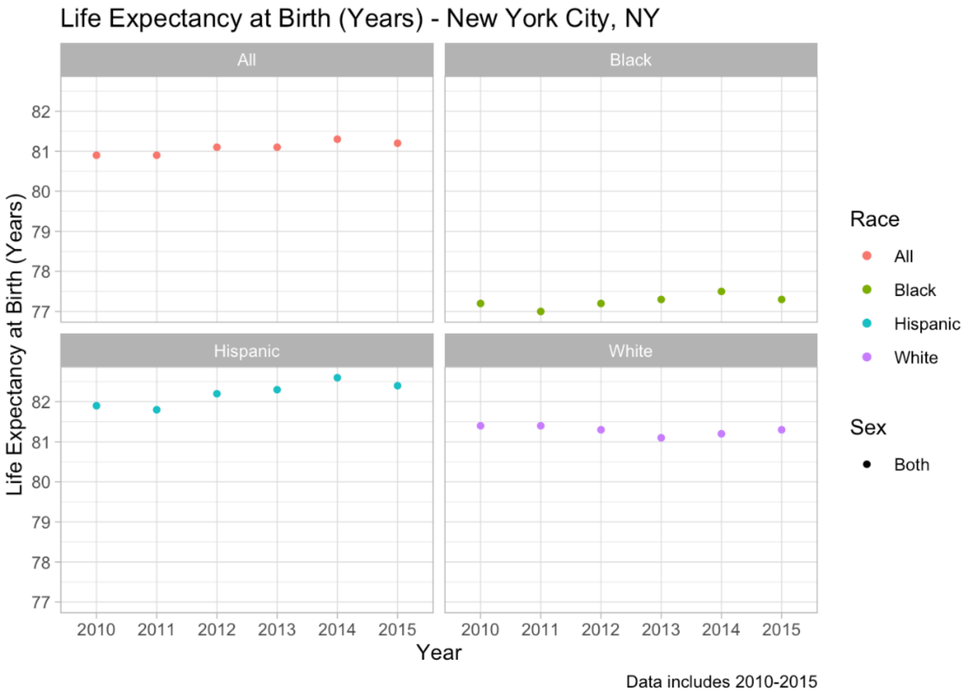


Figure 14G

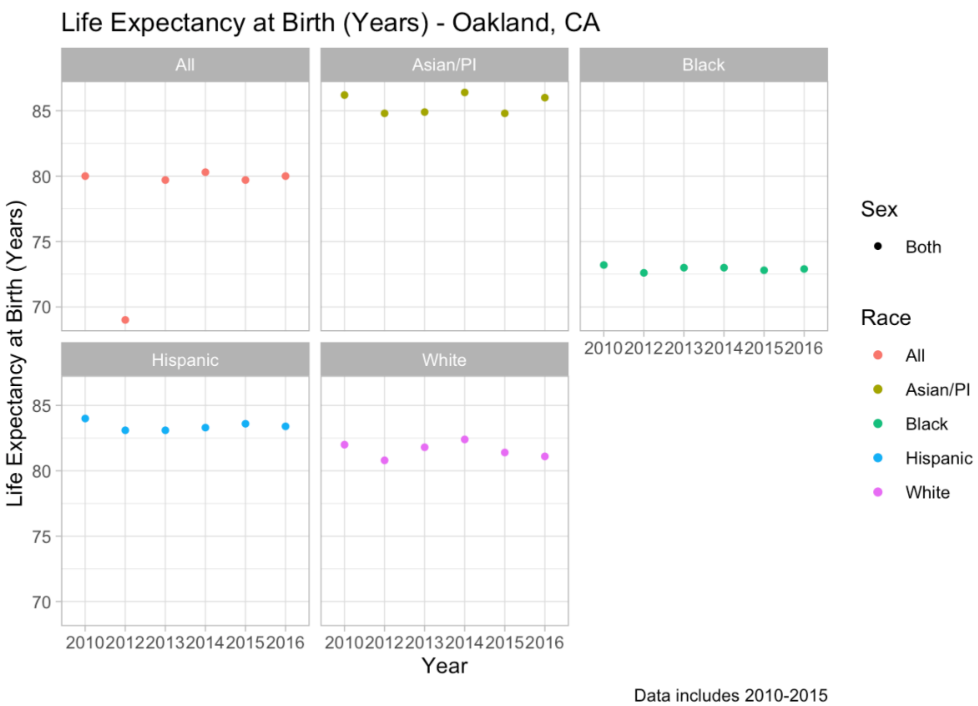


Figure 14H

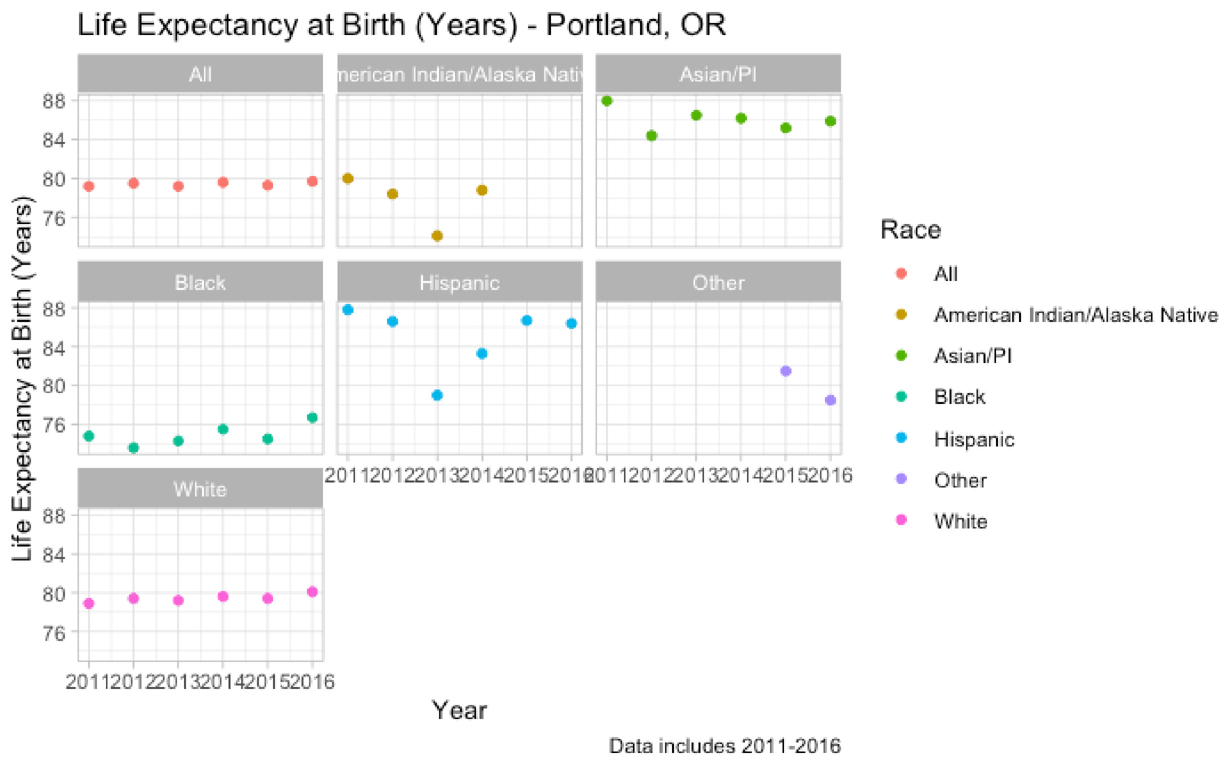


Figure 14I

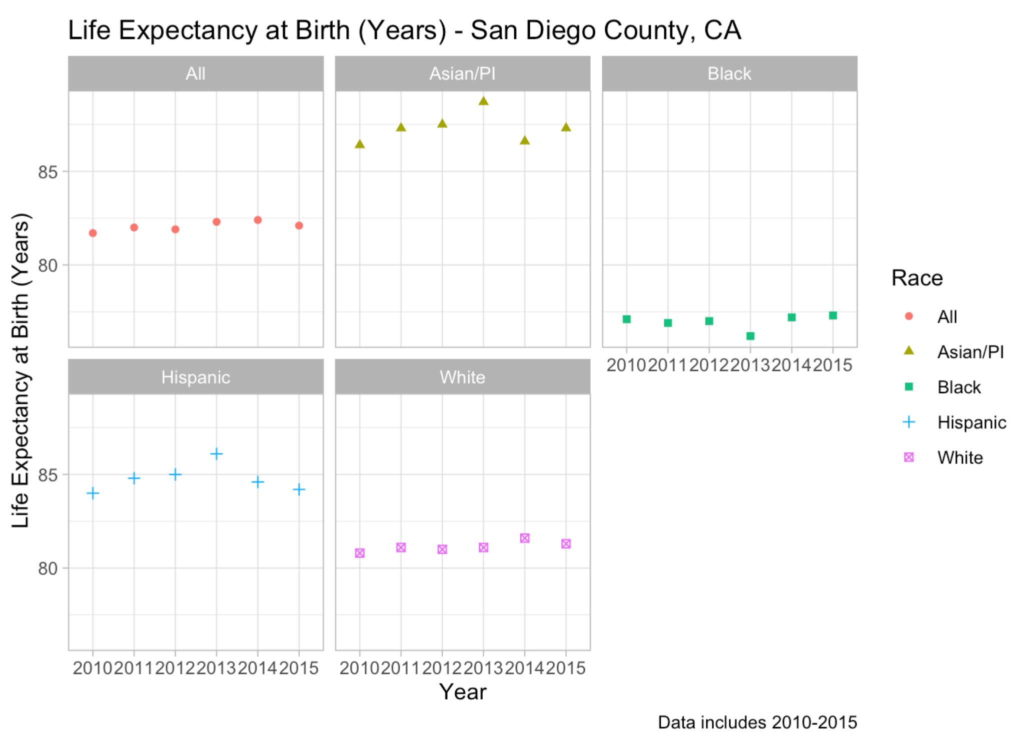


Figure 14J

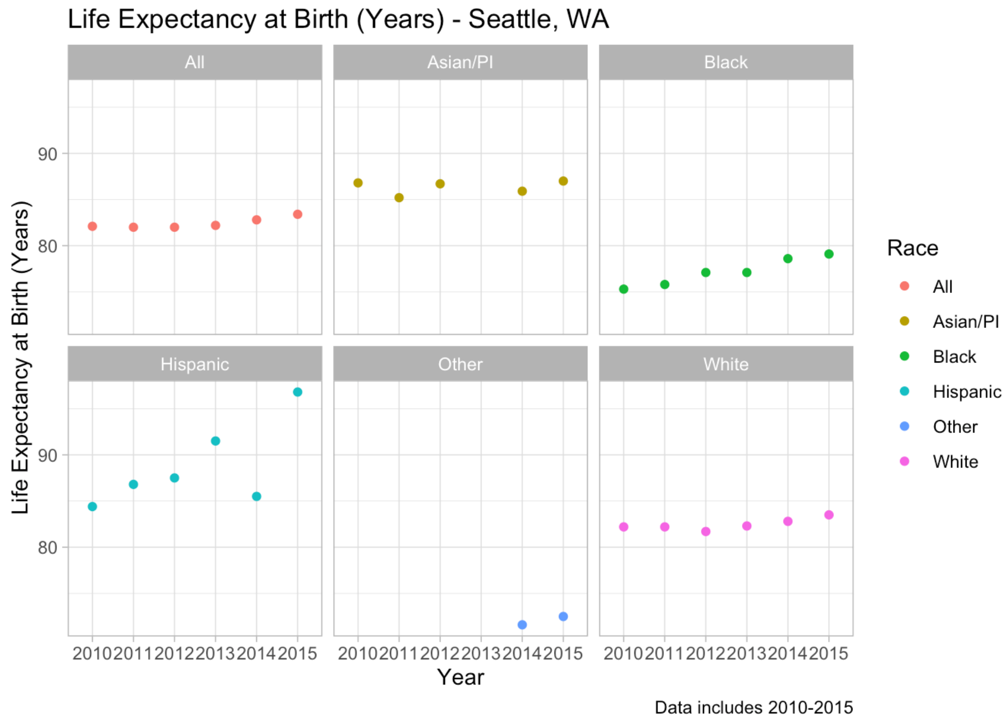


Figure 15A

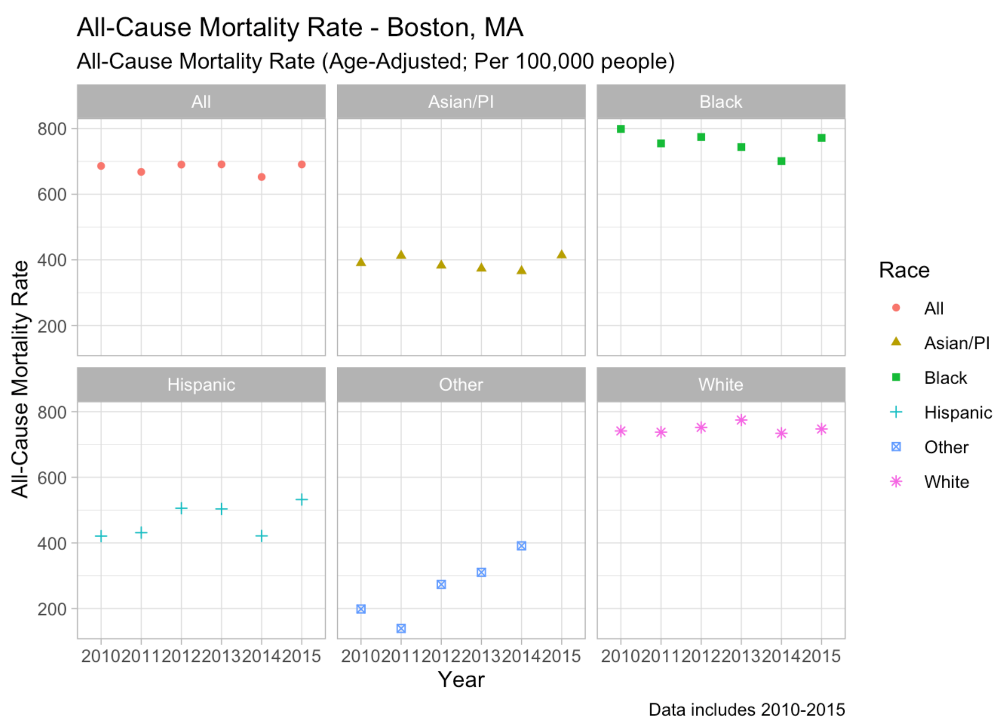


Figure 15B

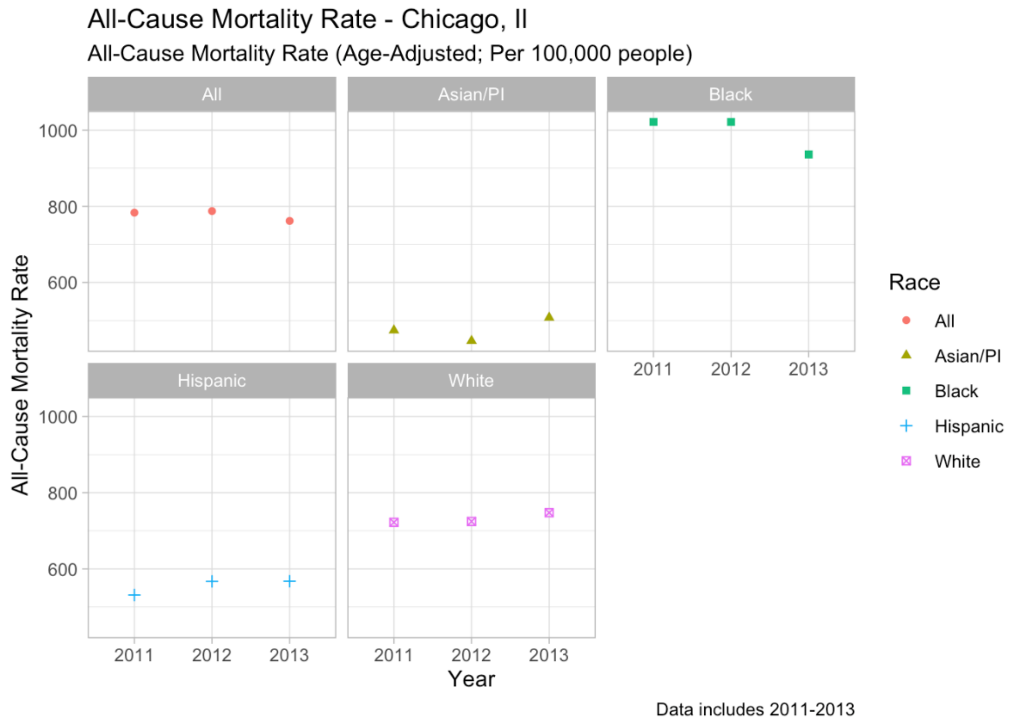


Figure 15C

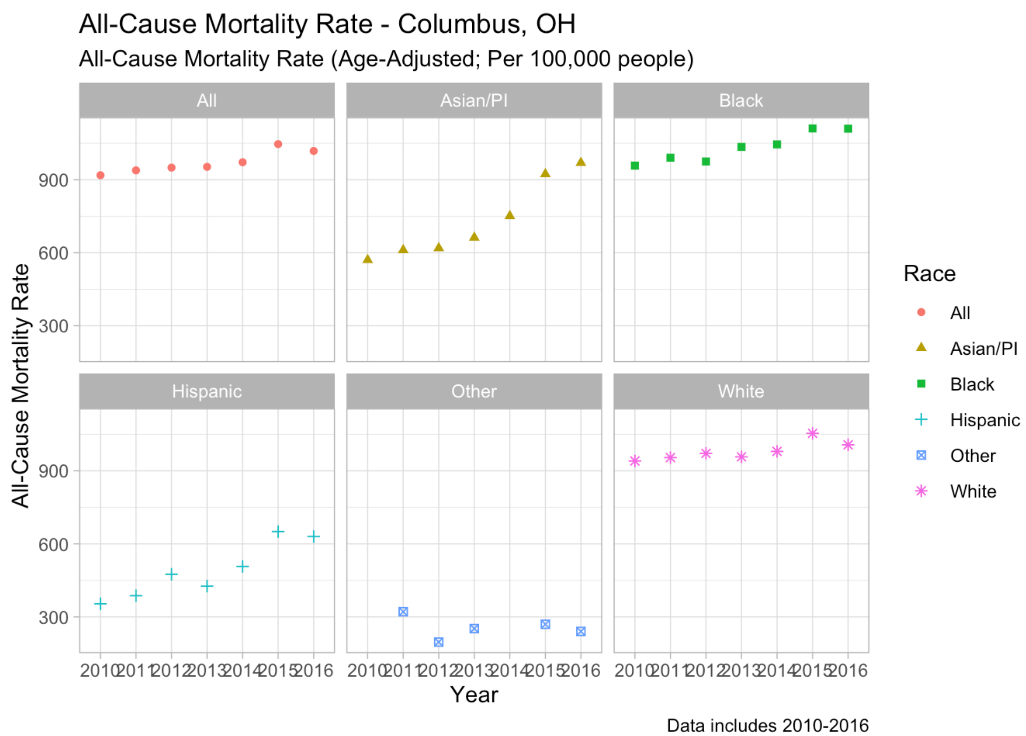


Figure 15D

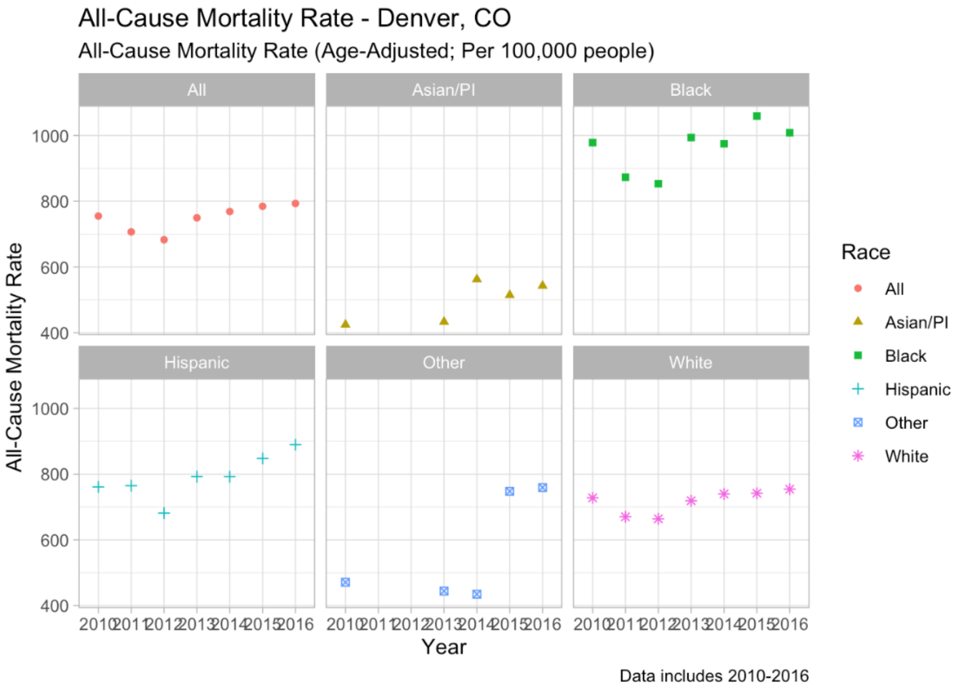


Figure 15E

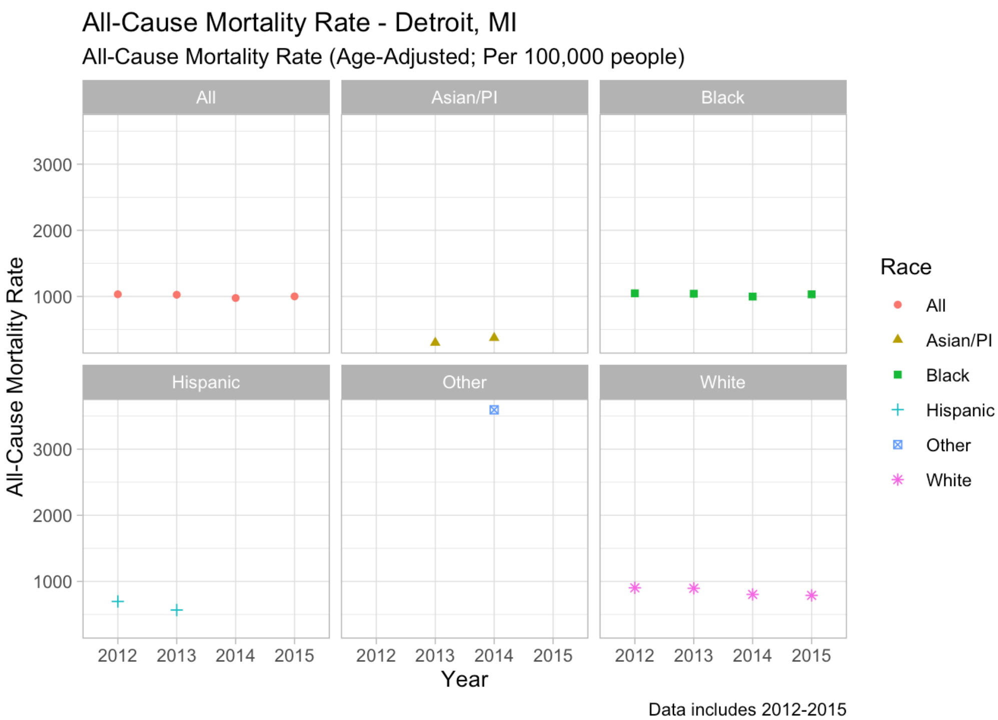


Figure 15F

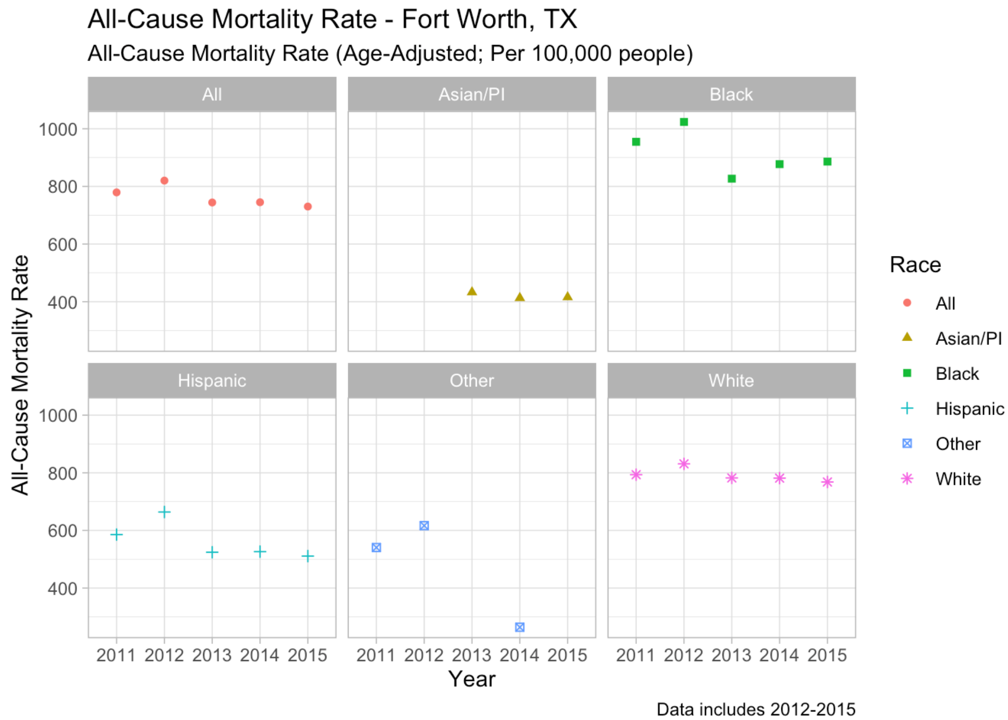


Figure 15G

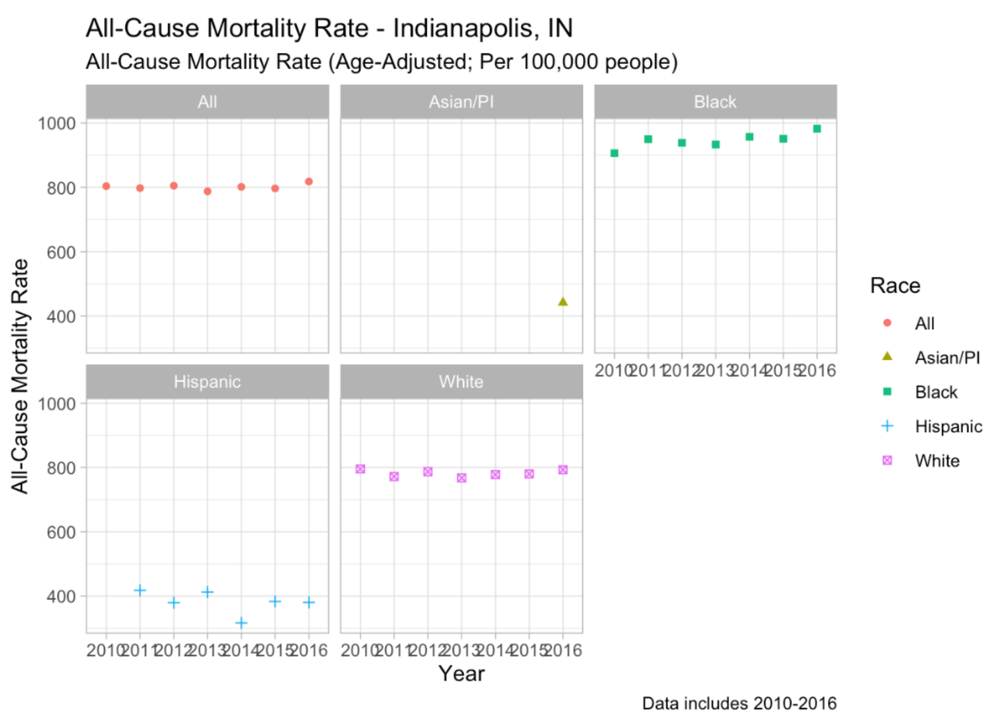


Figure 15H

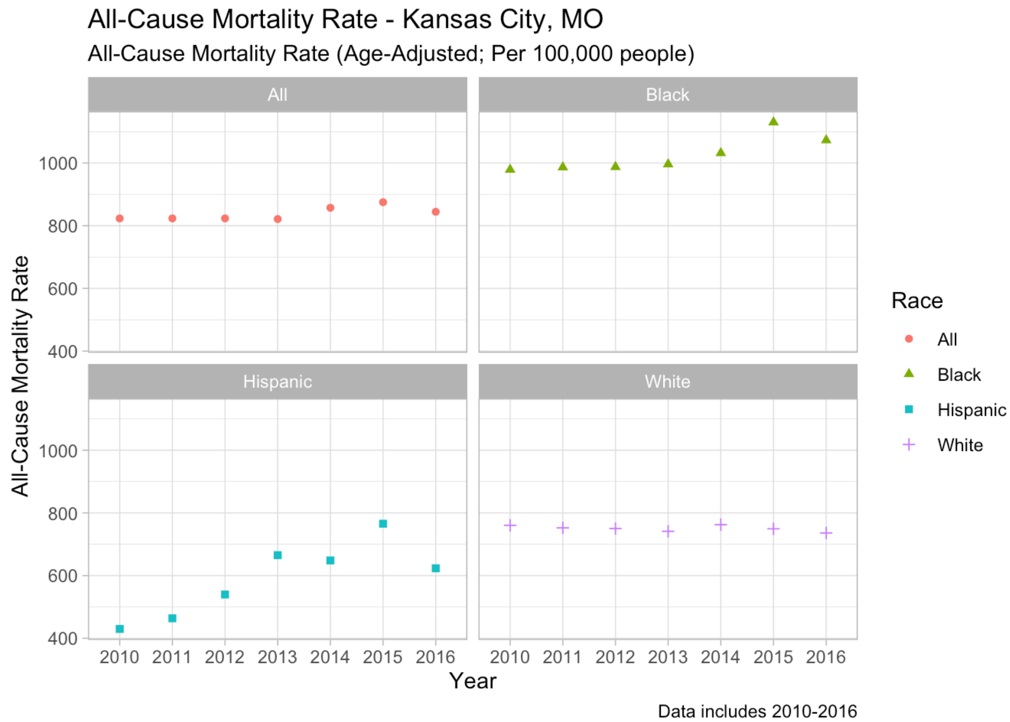


Figure 15I

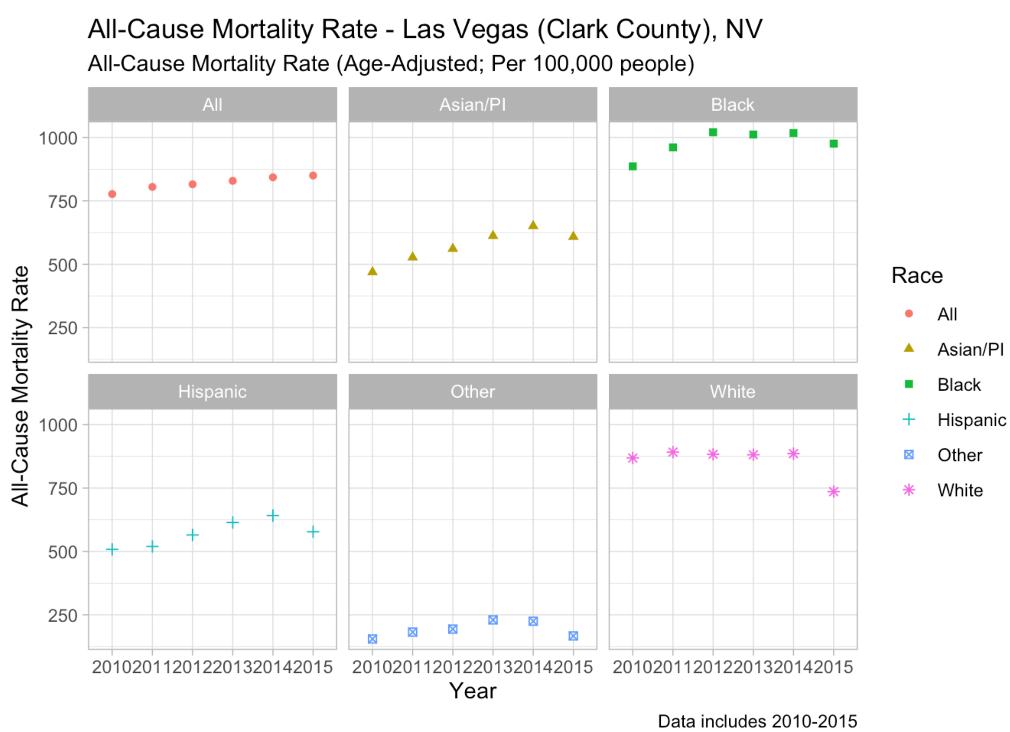


Figure 15J

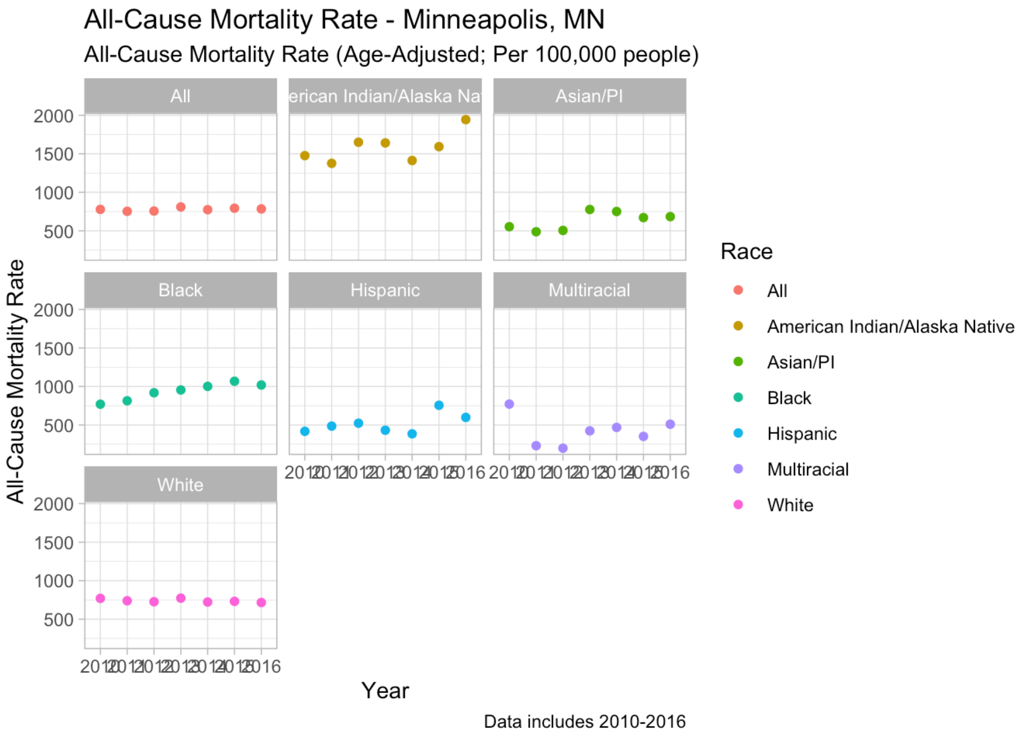


Figure 15K

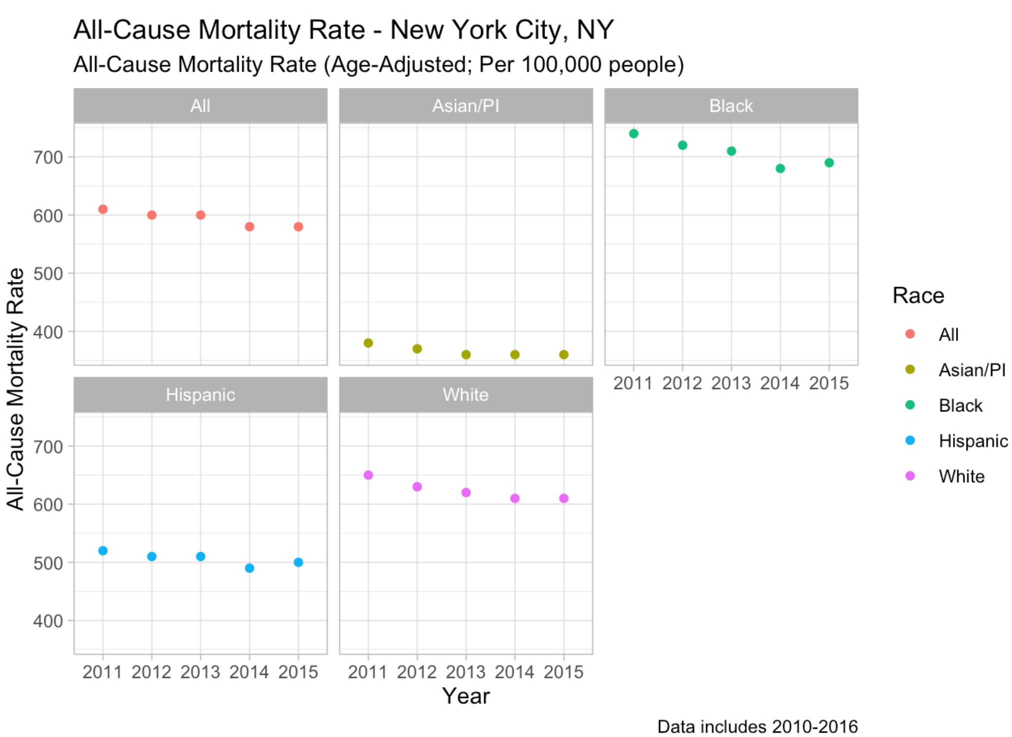


Figure 15L

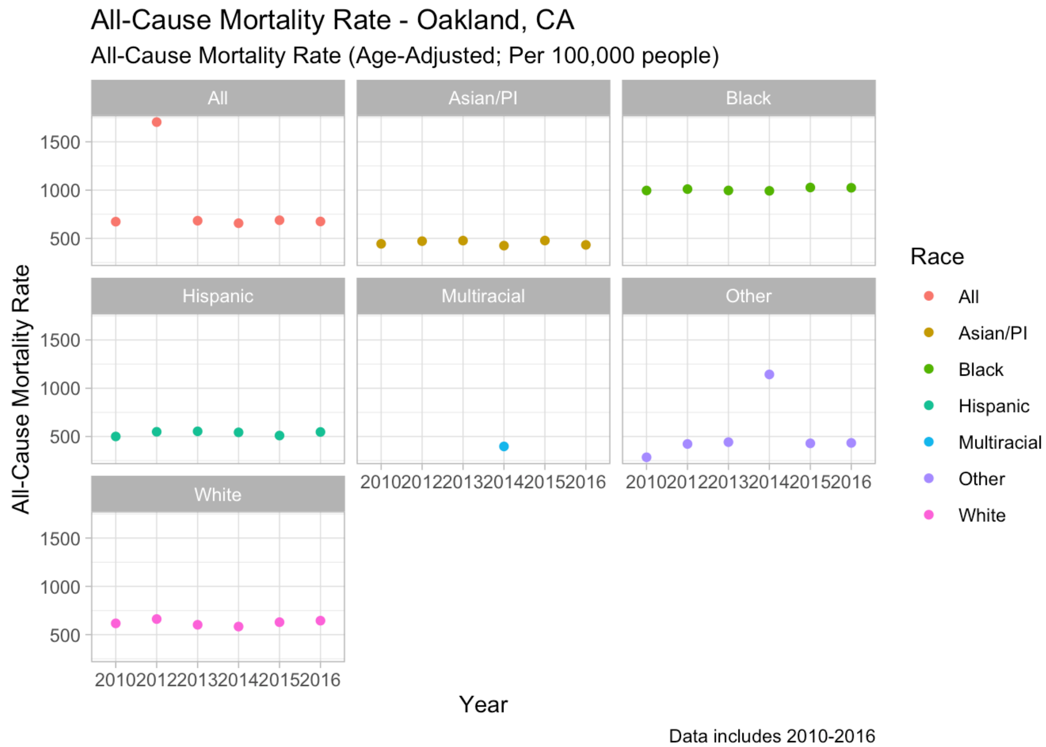


Figure 16A

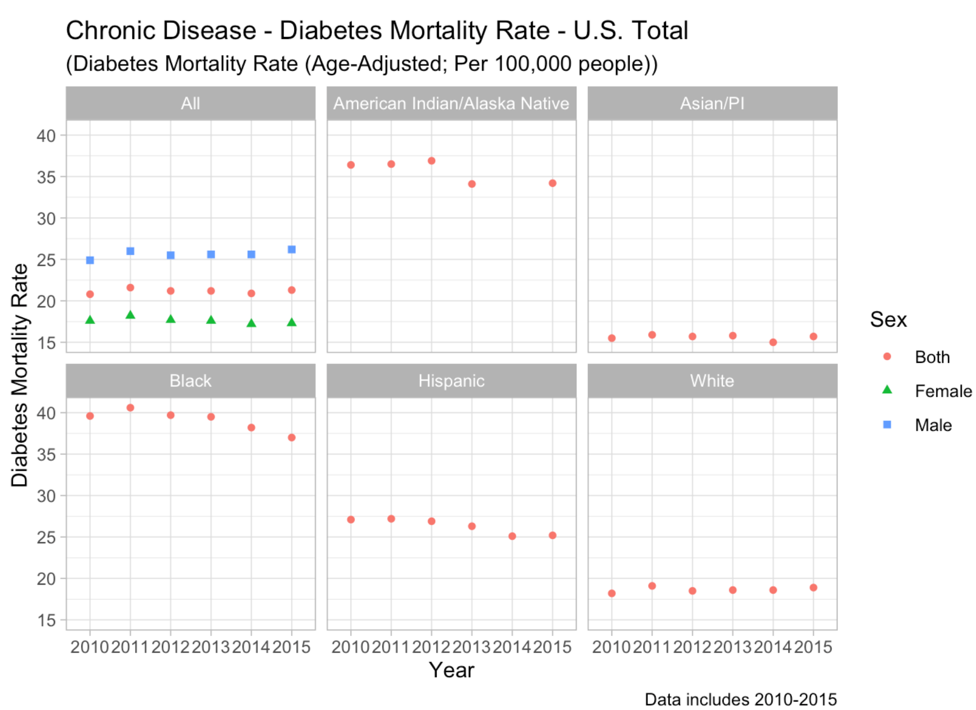


Figure 16B

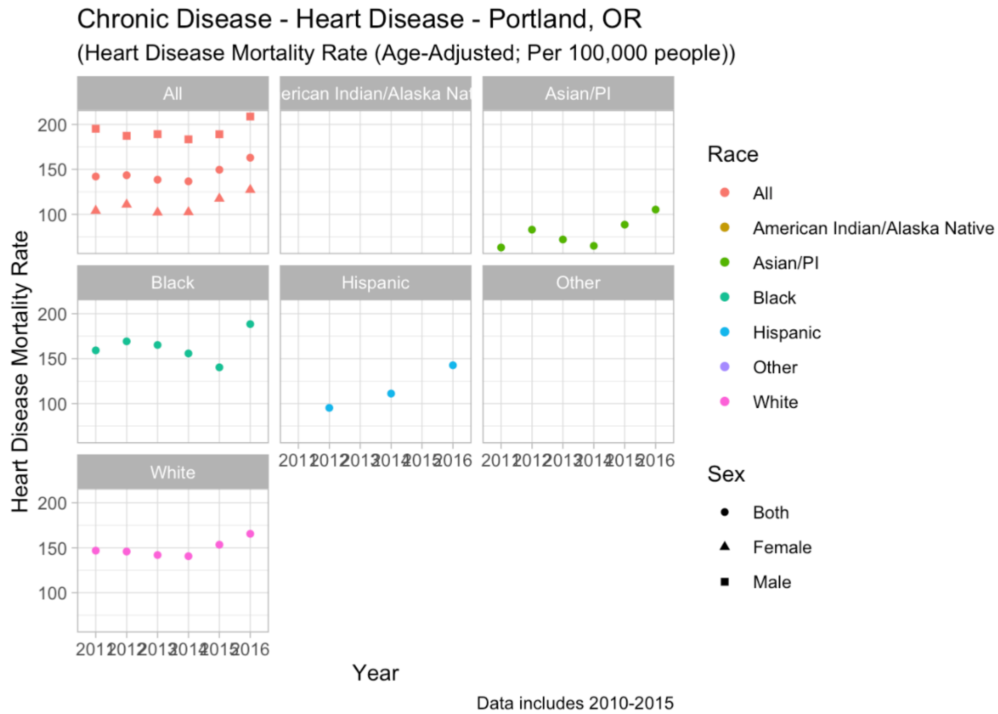


Figure 16C

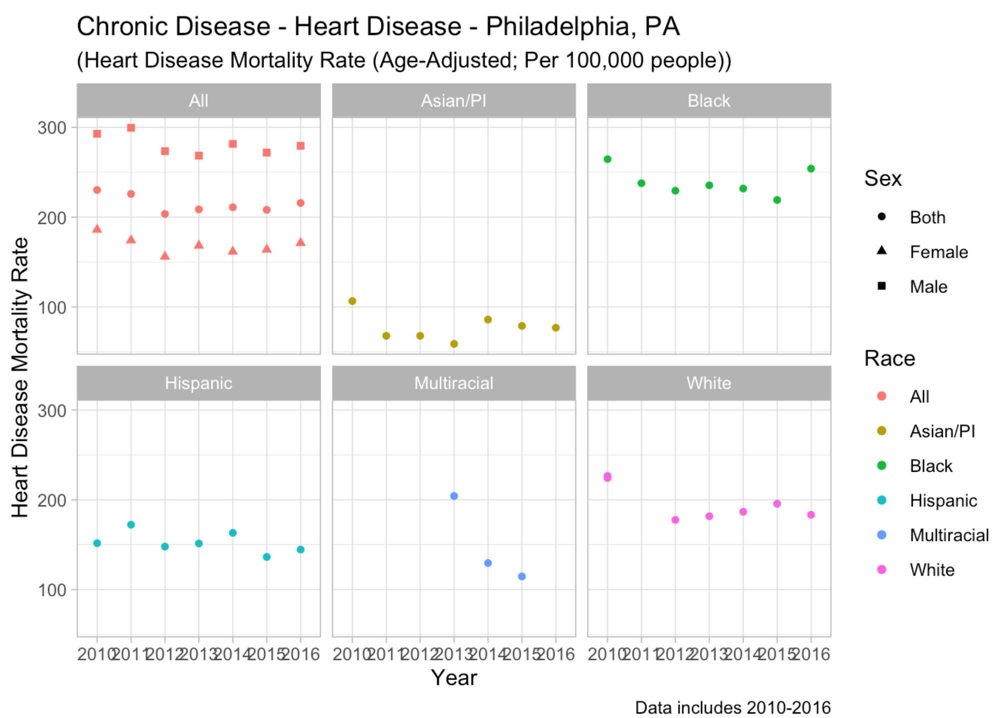


Figure 16D

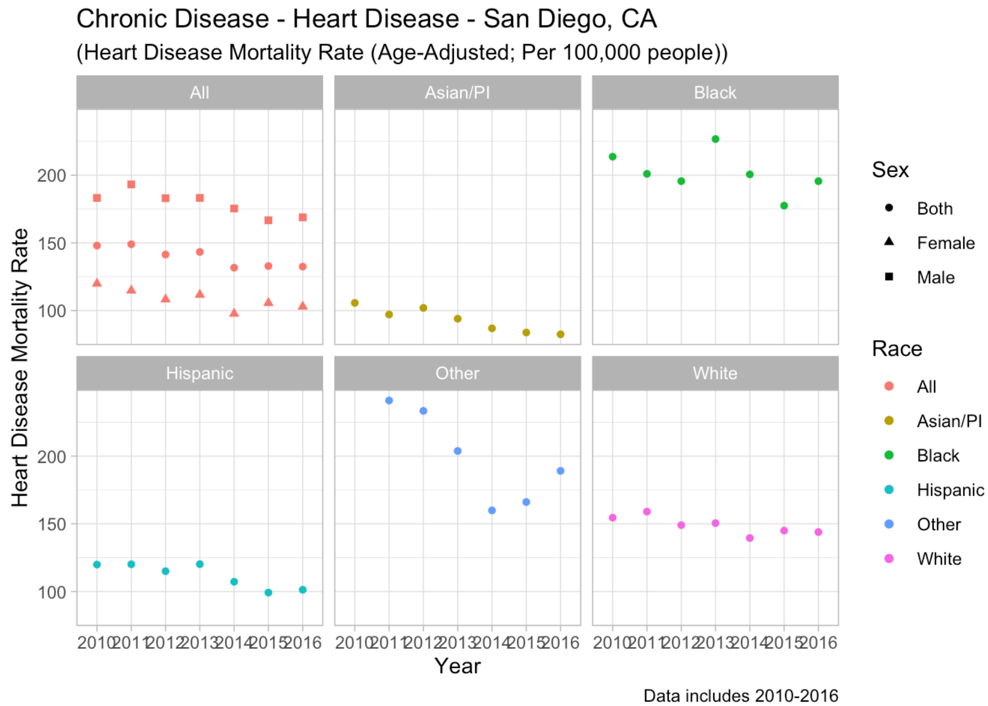


Figure 16E

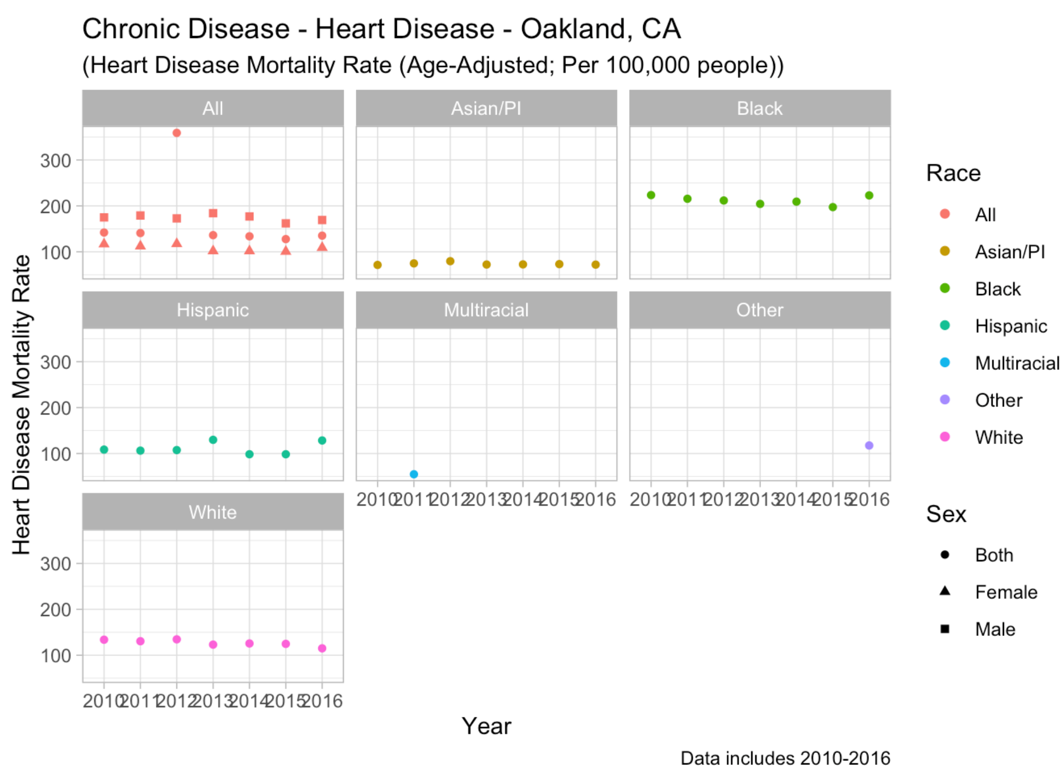


Figure 16F

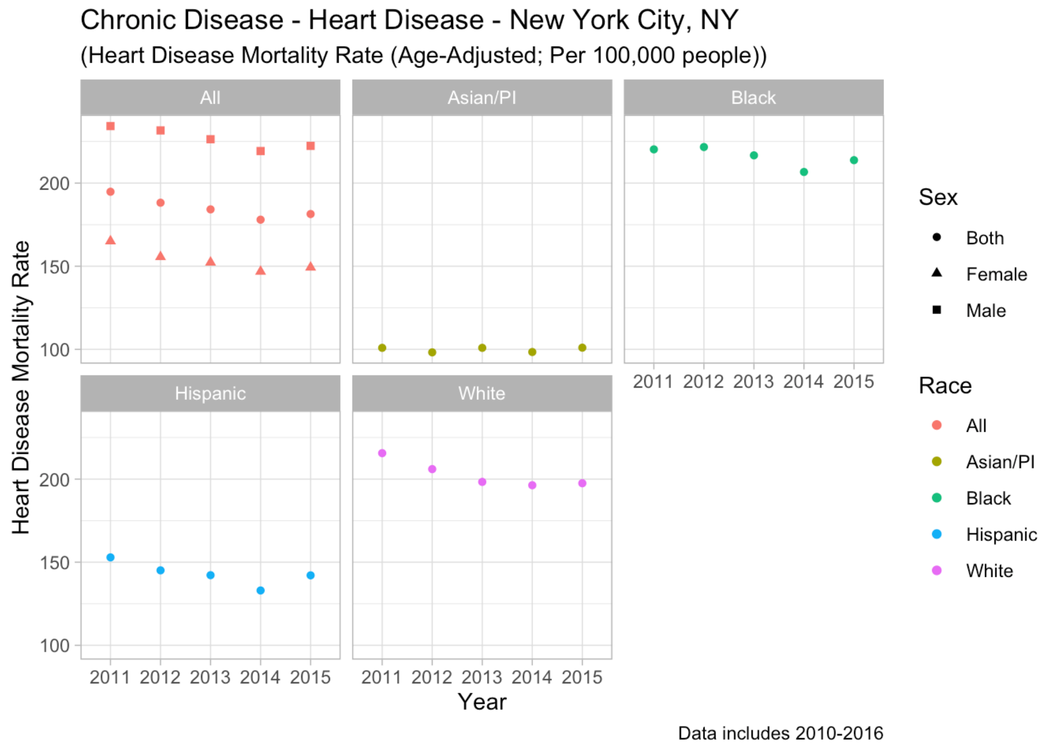


Figure 16G

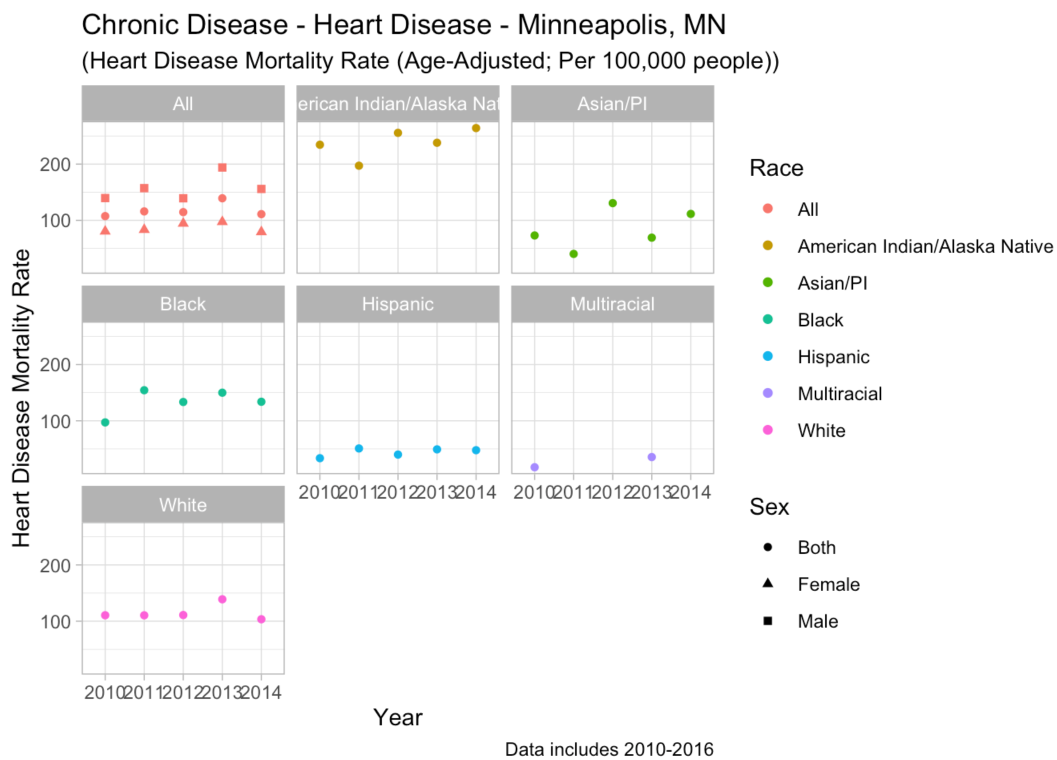


Figure 16H

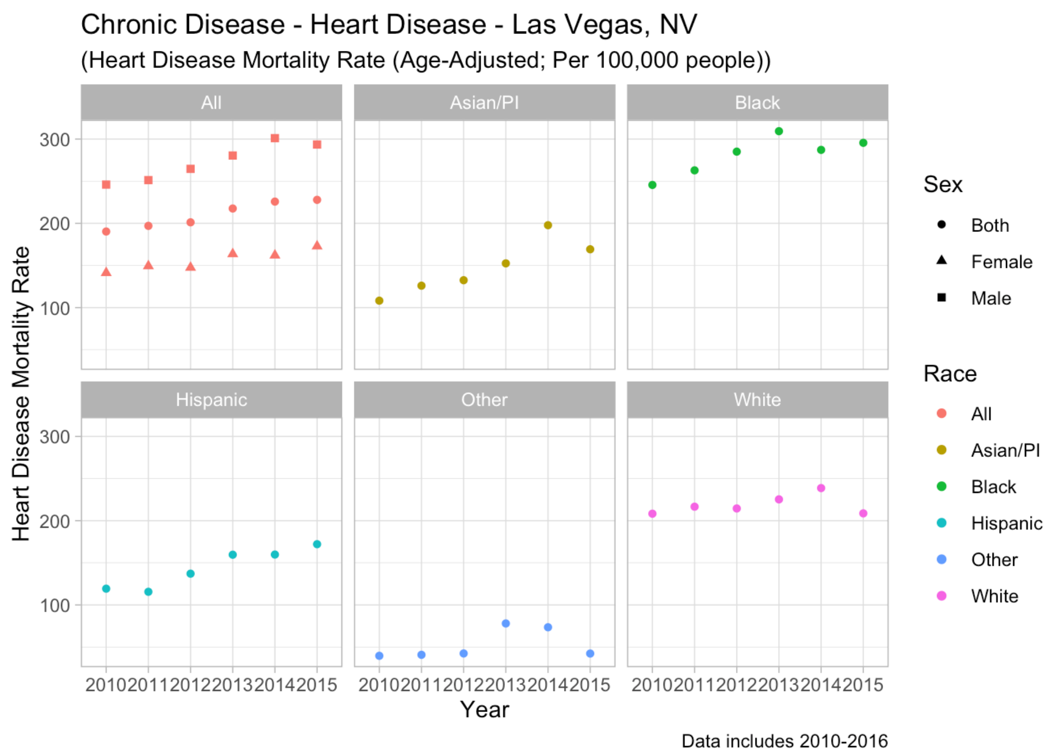
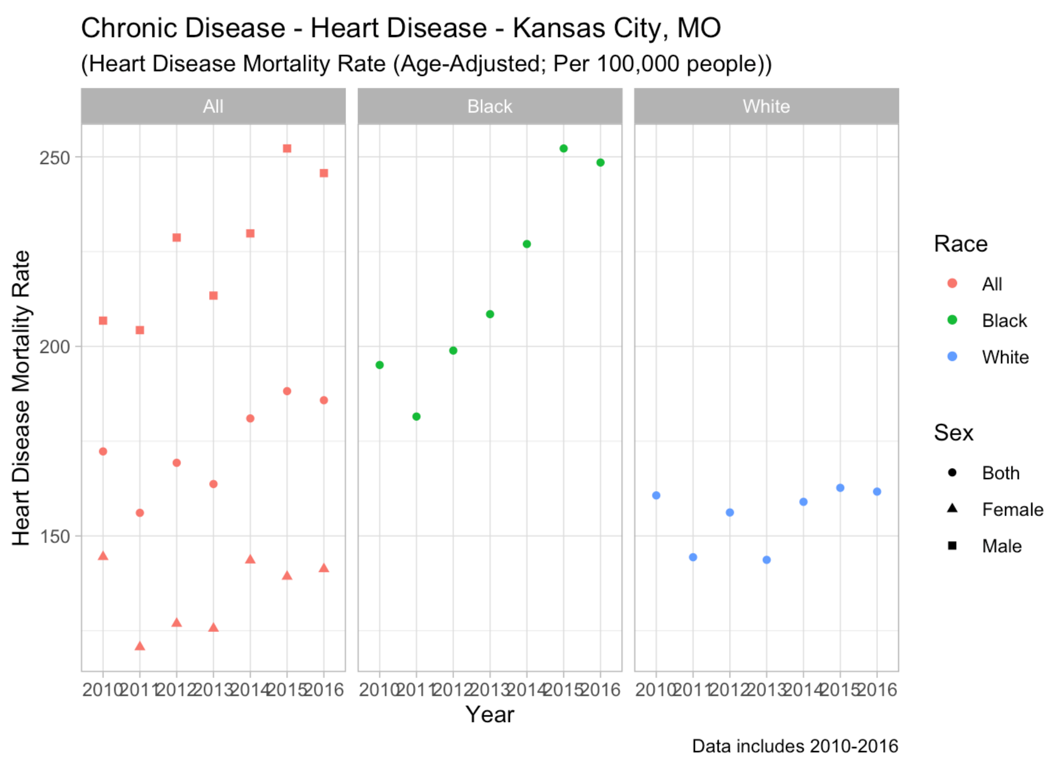


Figure 16I



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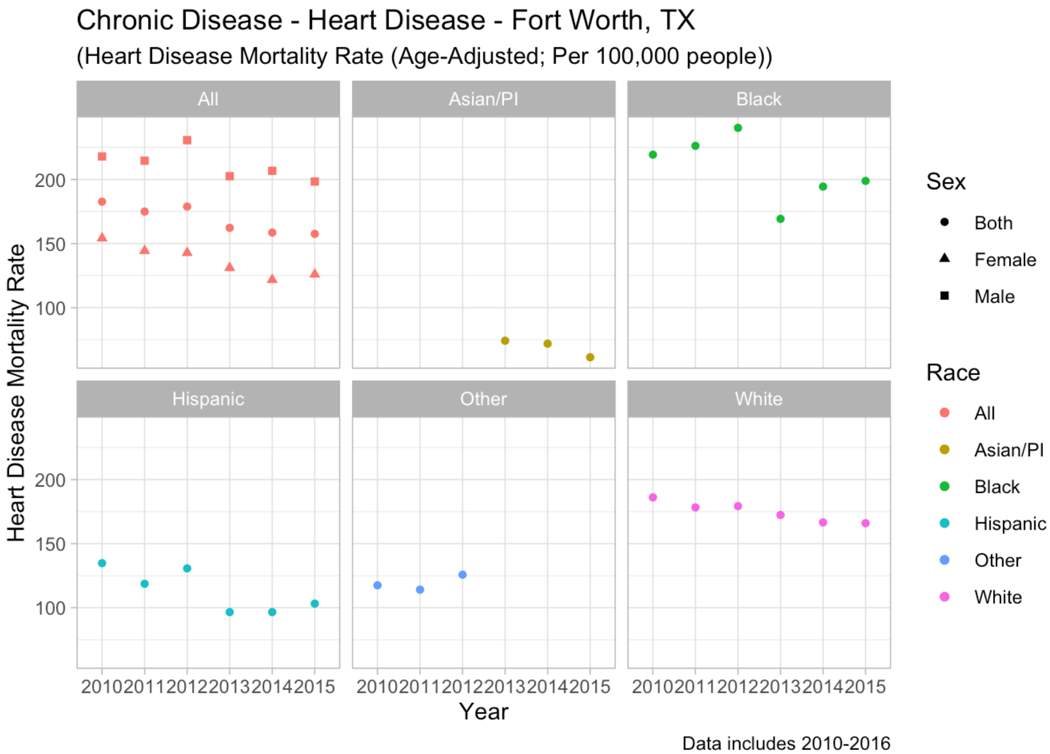

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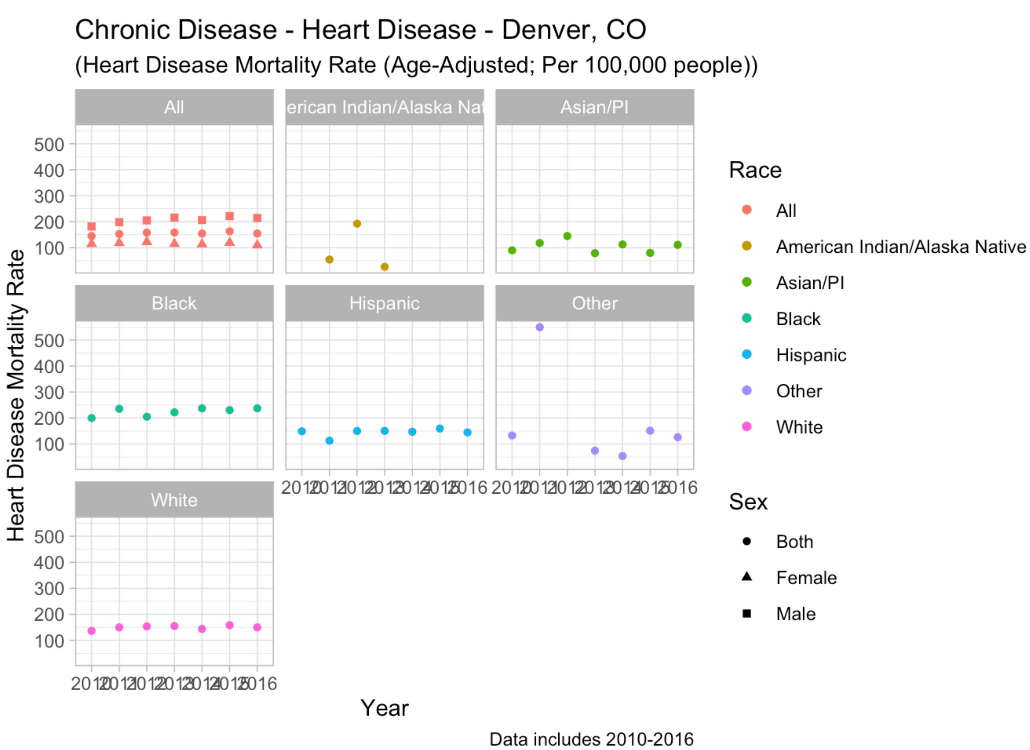


Figure 16L

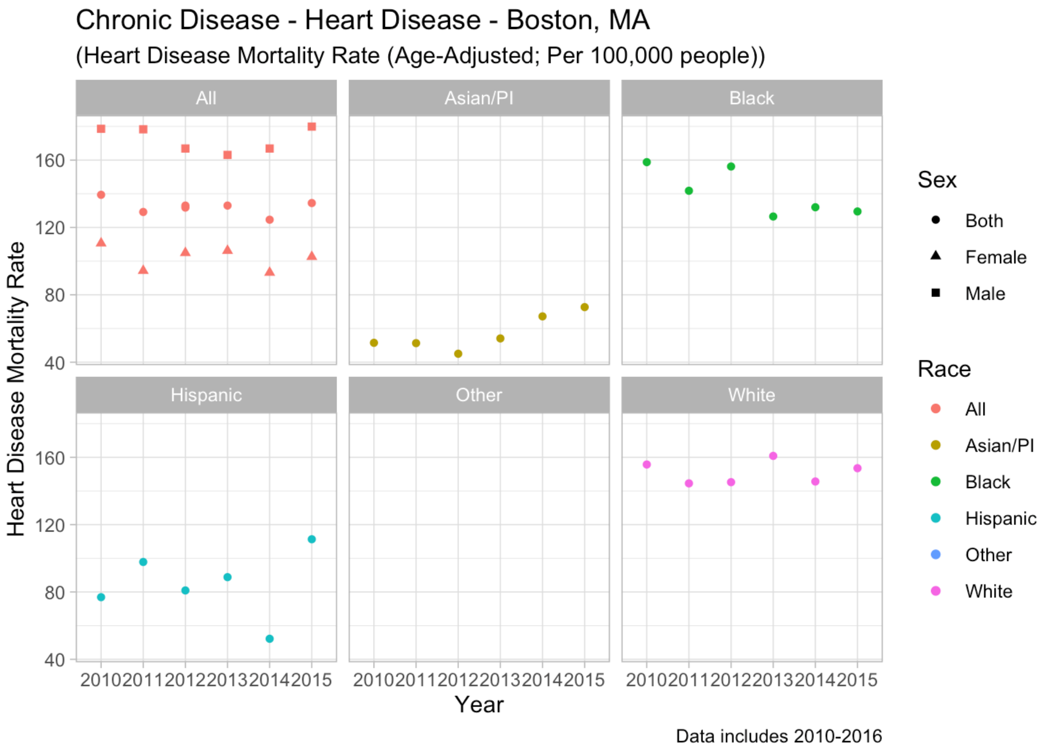


Figure 17A

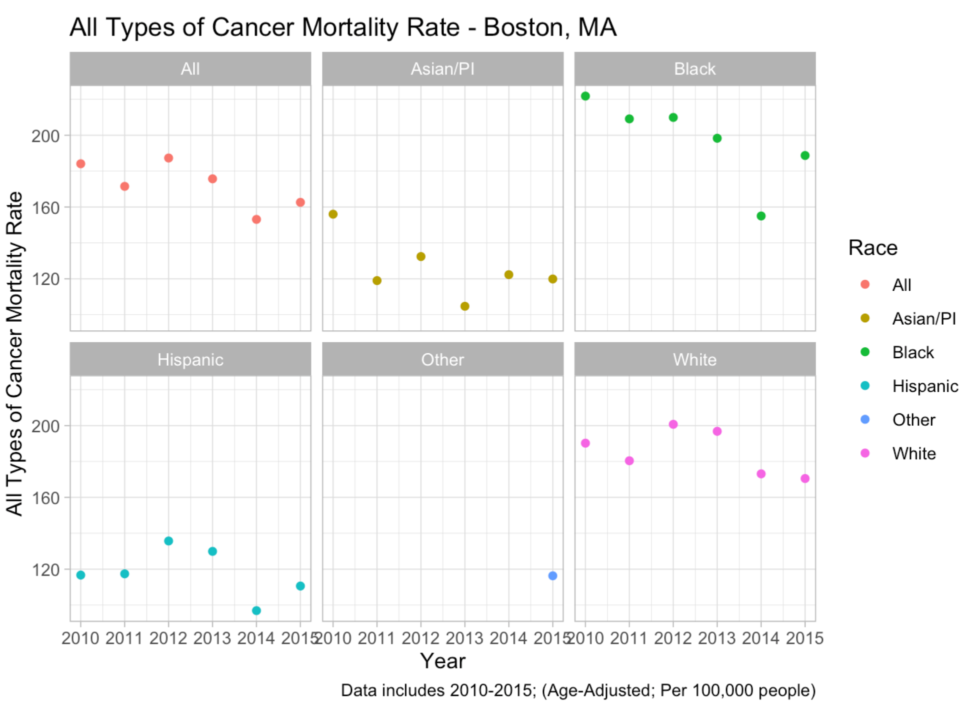


Figure 17B

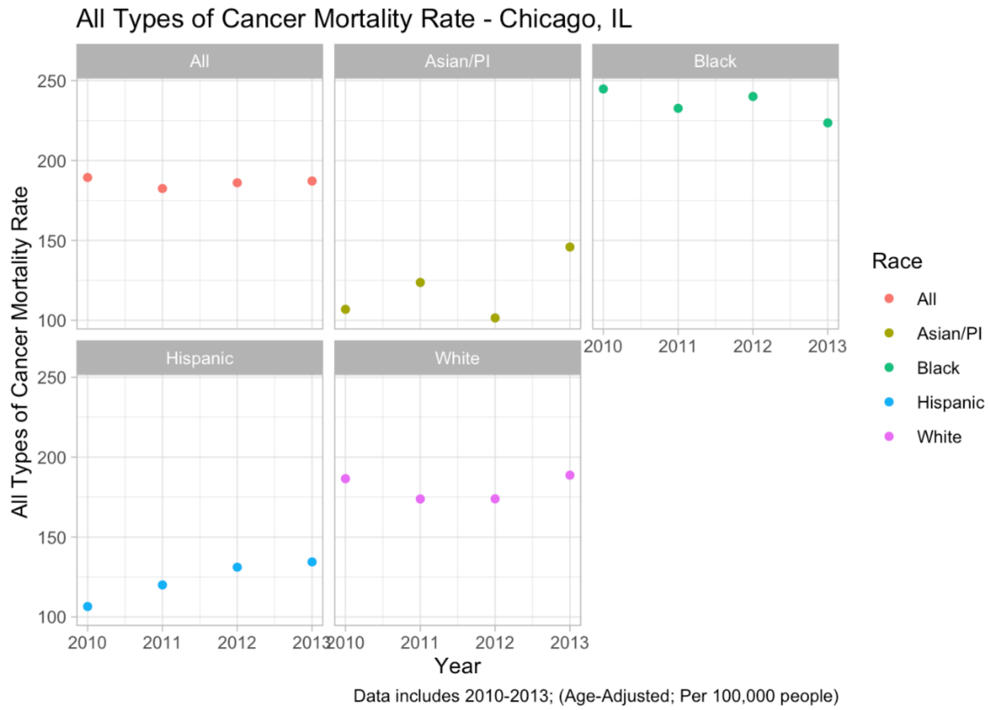


Figure 17C

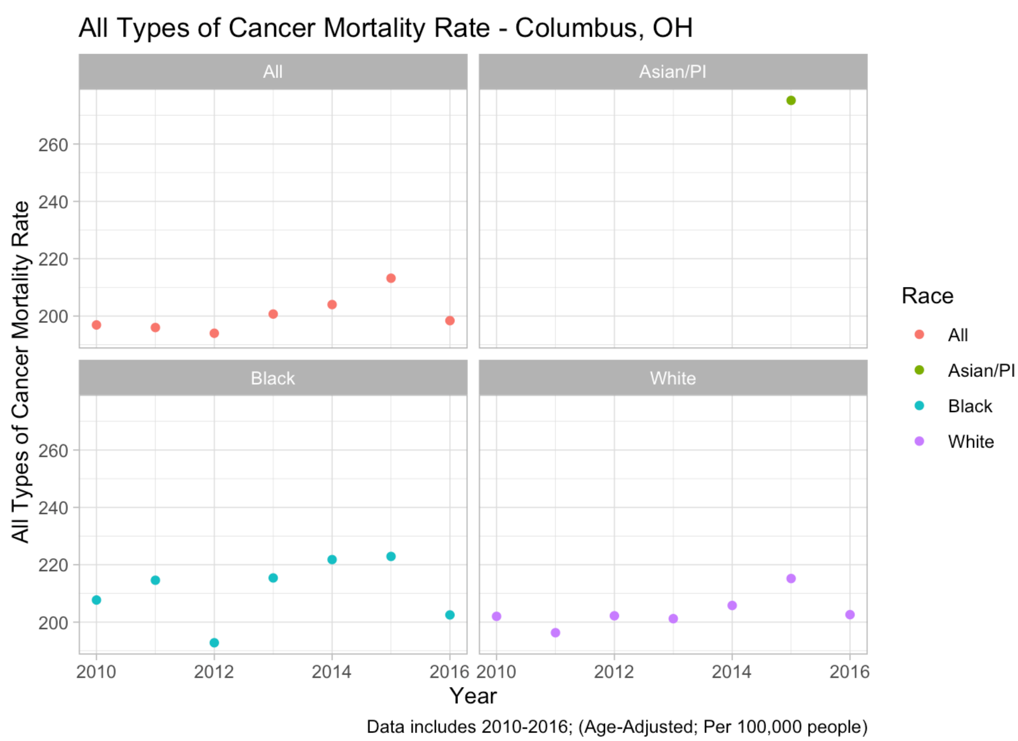


Figure 17D

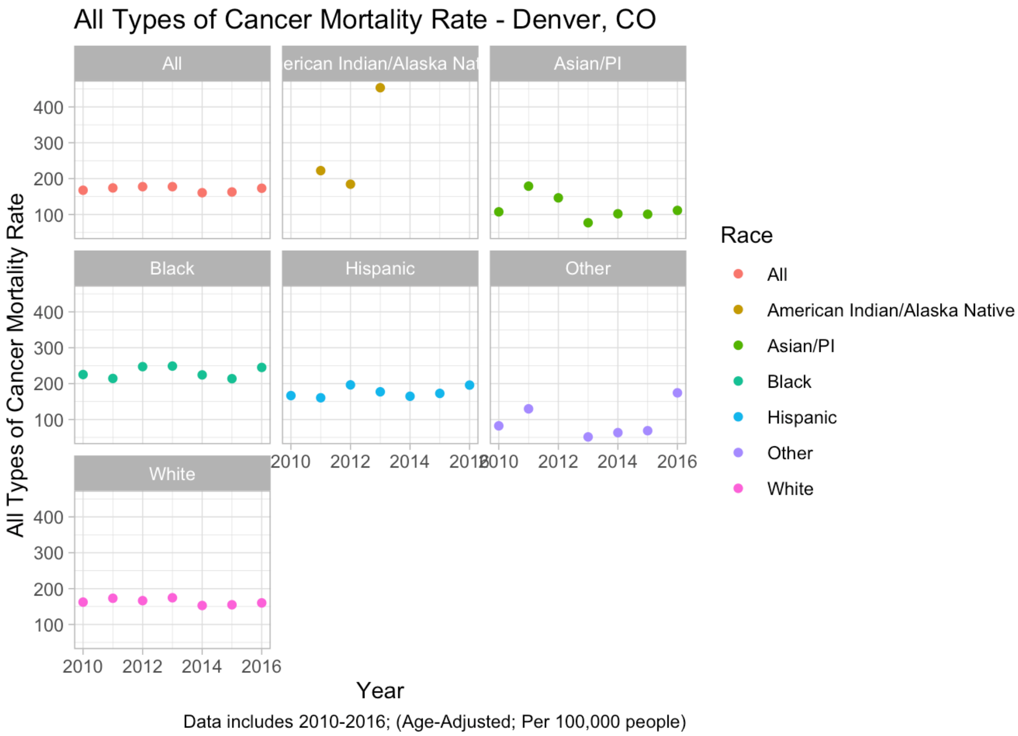


Figure 17E

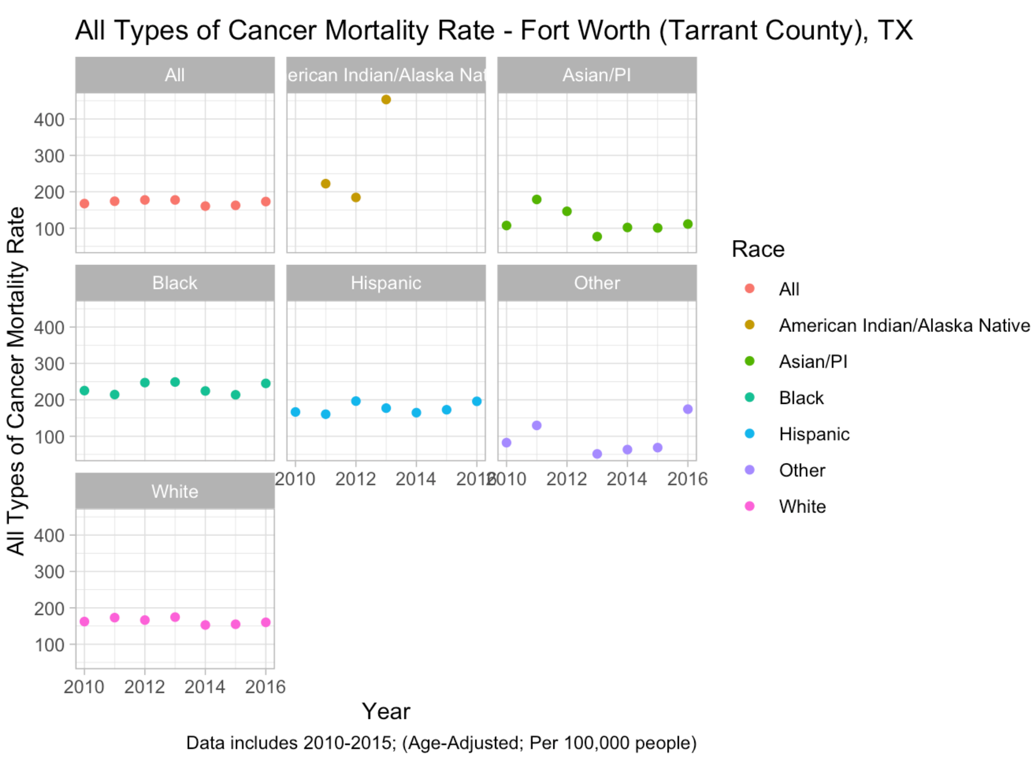


Figure 17F

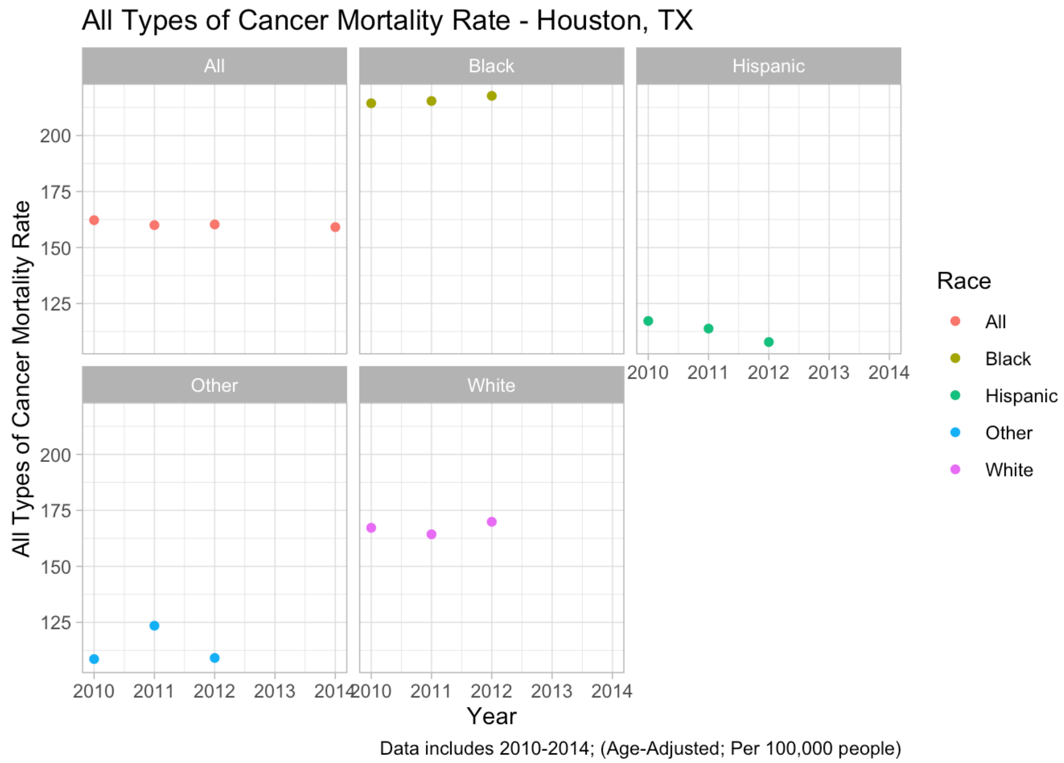


Figure 17G

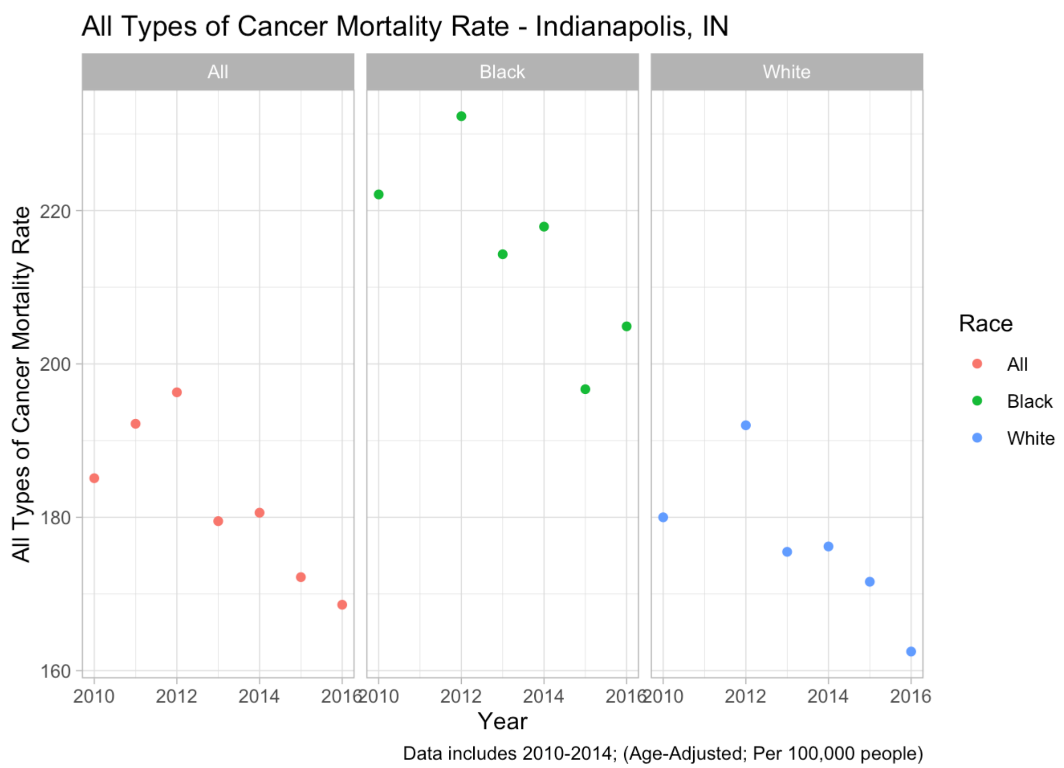


Figure 17H

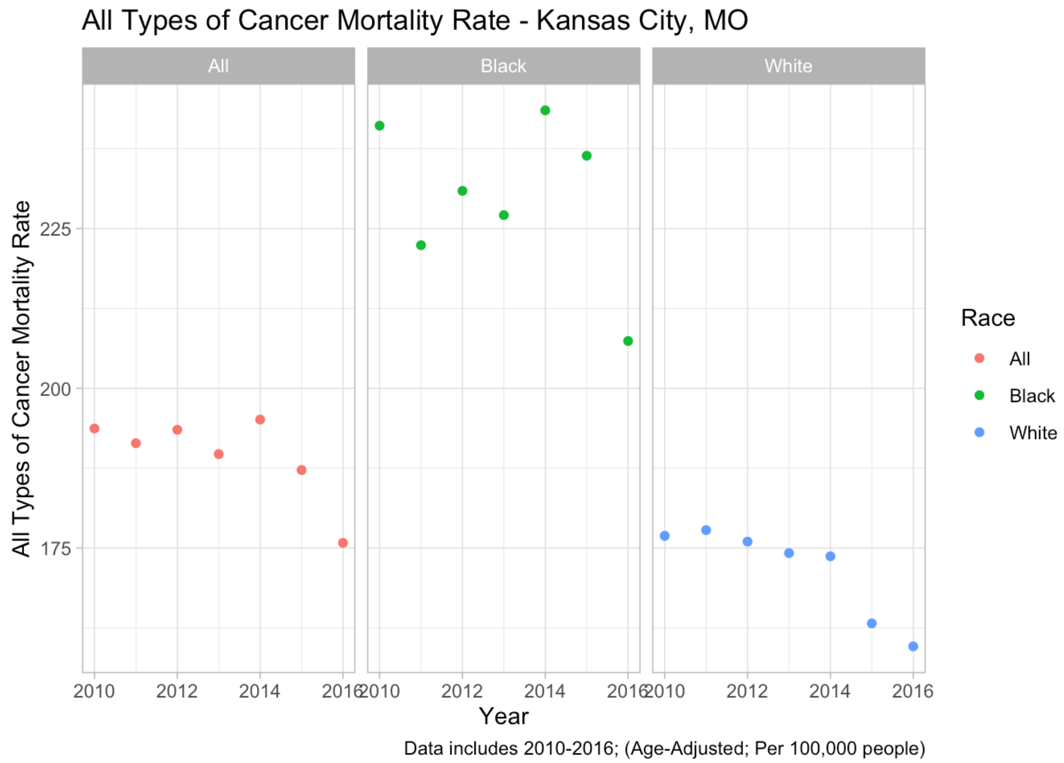


Figure 17I

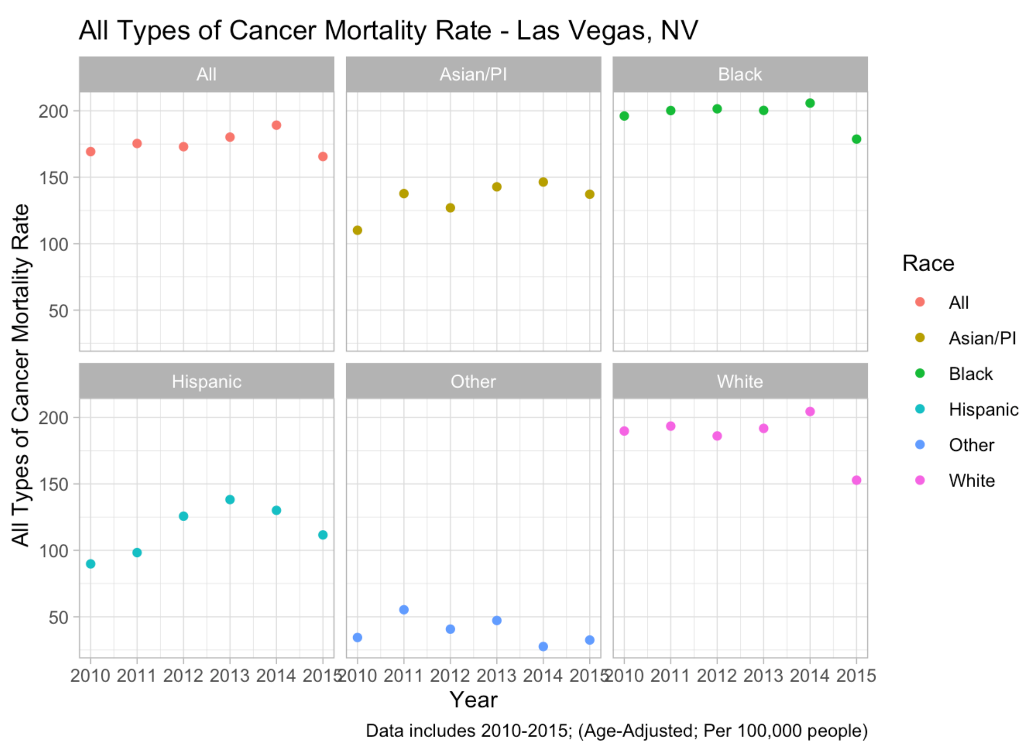
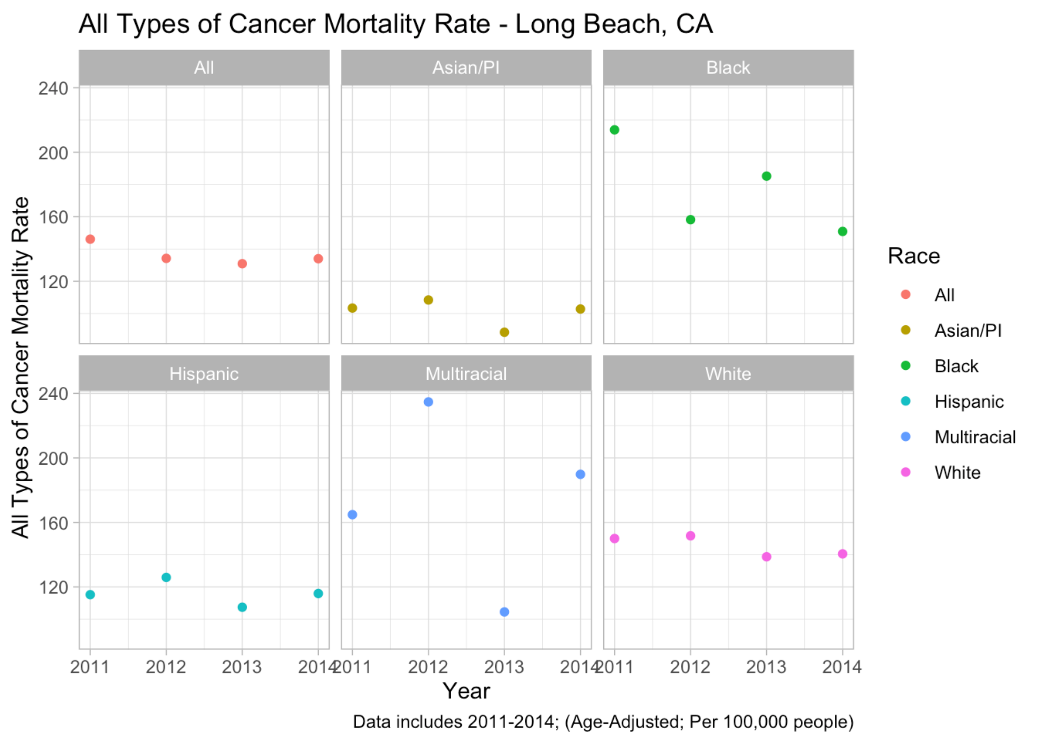


Figure 17J



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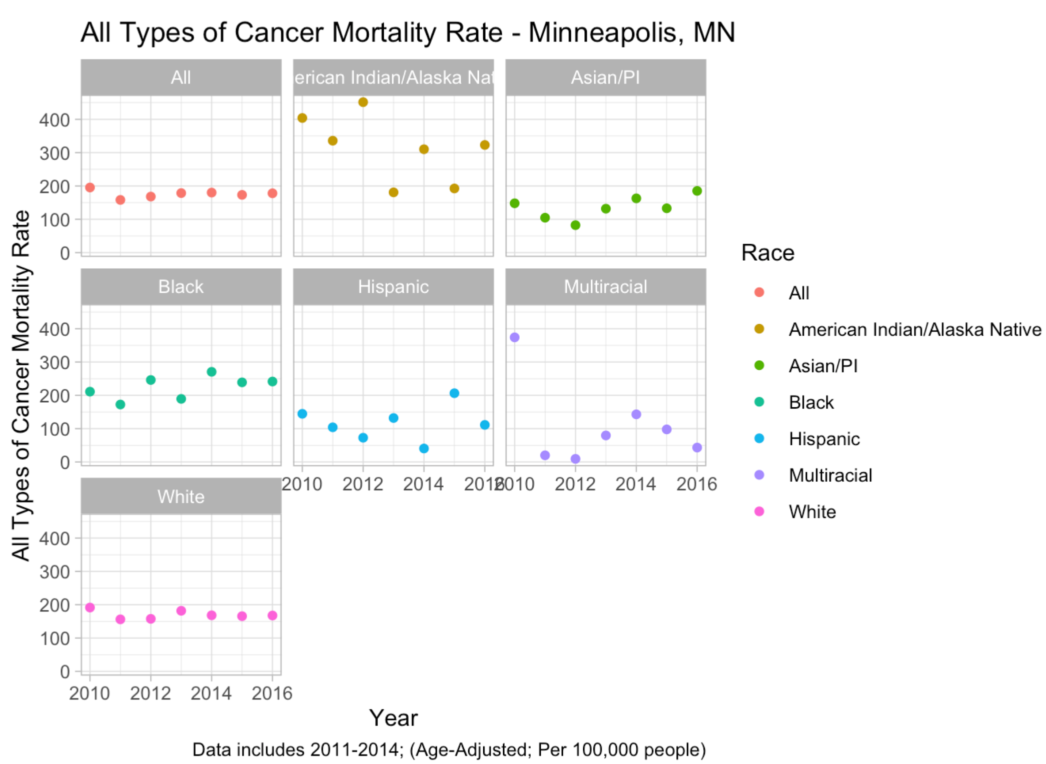

Figure 17L

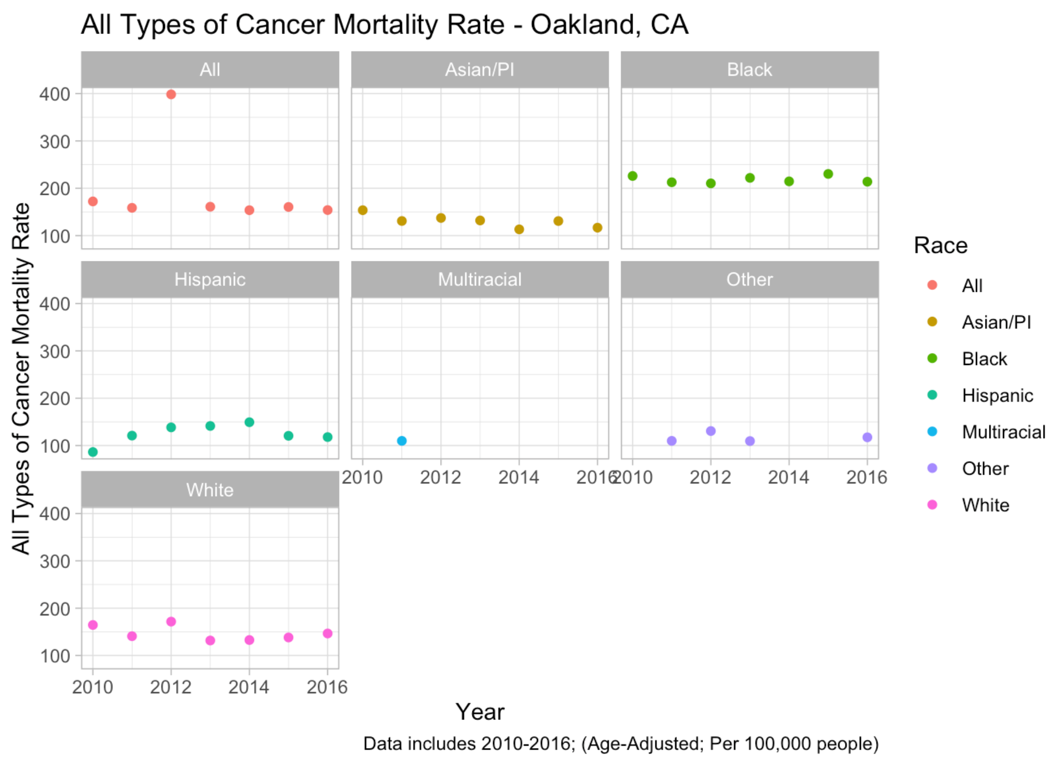

Figure 17M

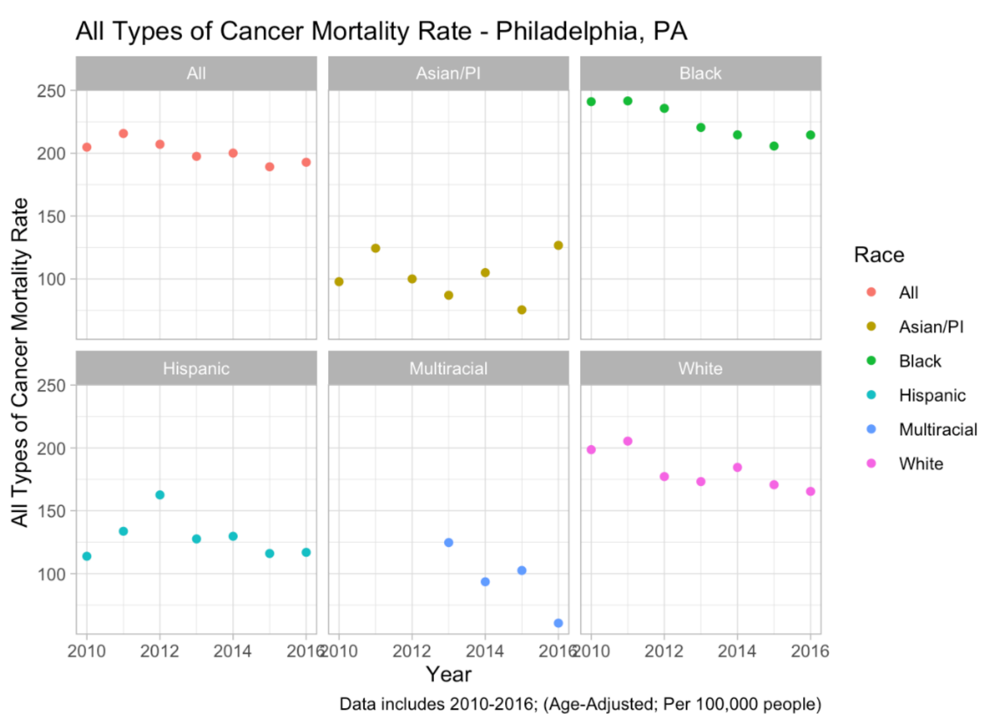

Figure 17N

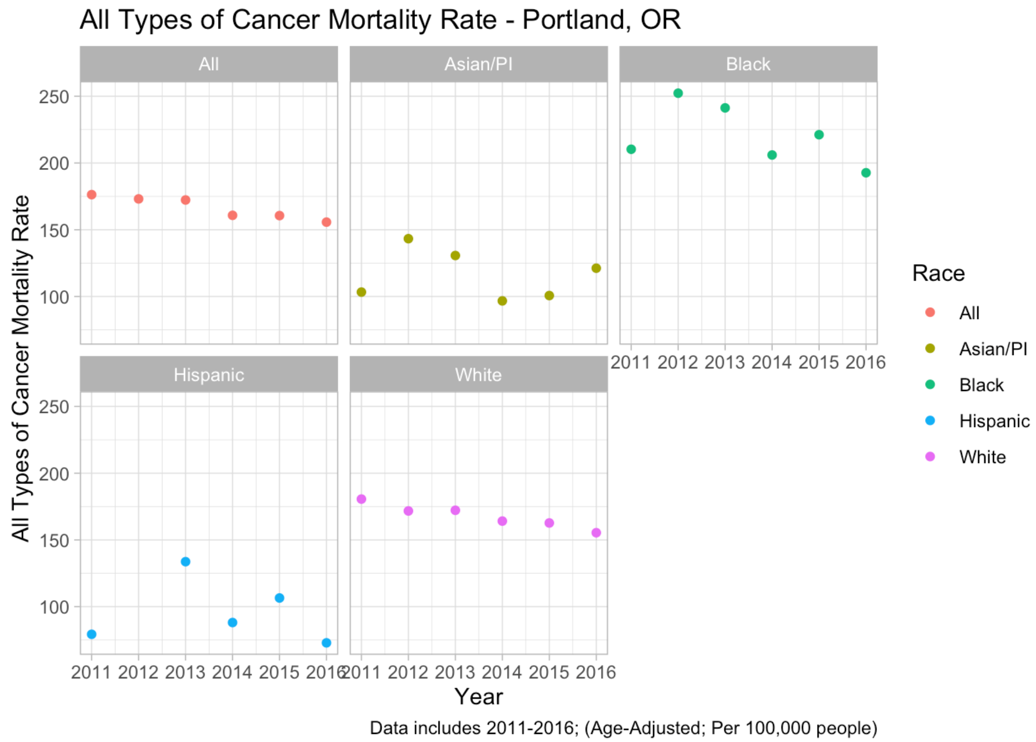

Figure 17O

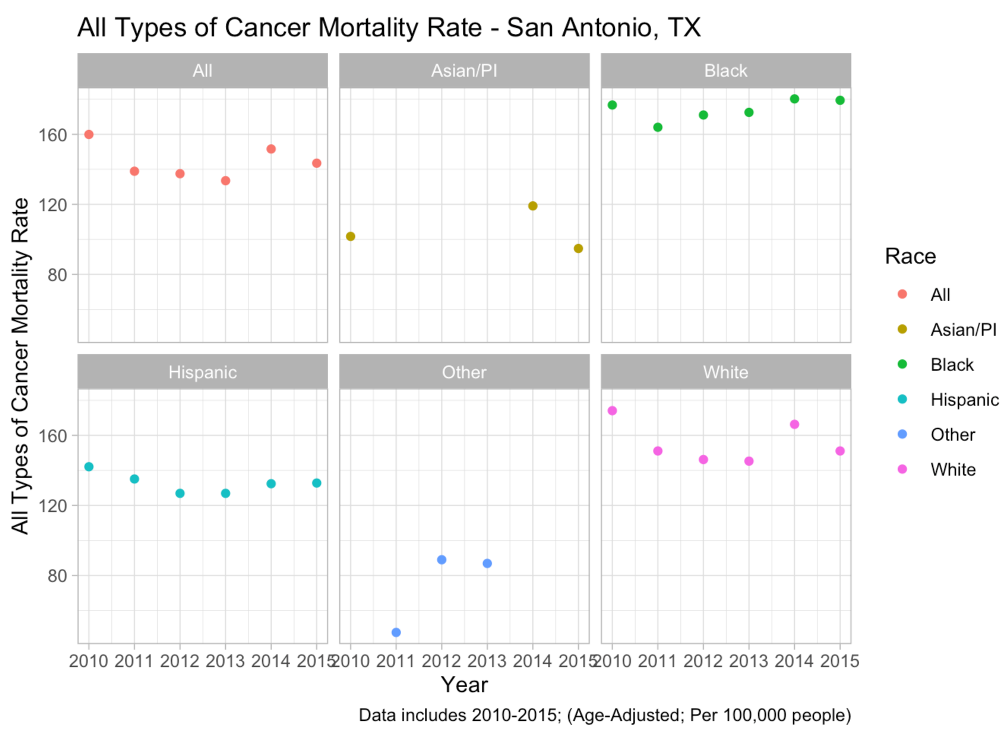

Figure 17P

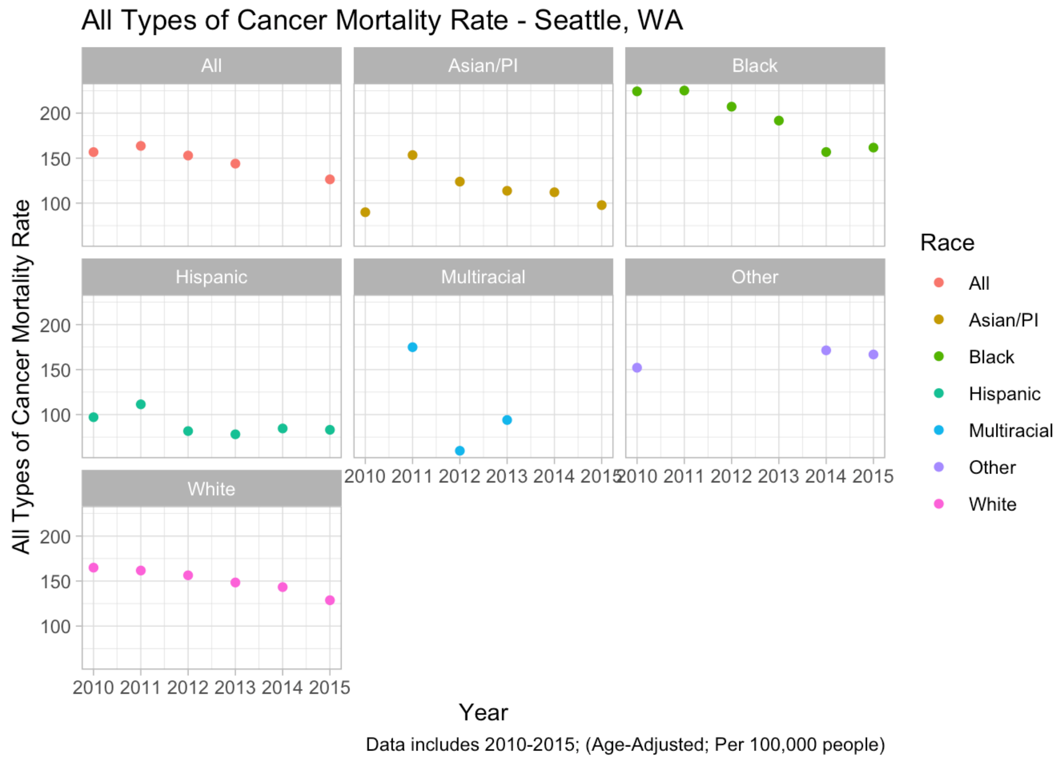

Figure 17Q