International Research Journal of Natural and Applied Sciences
ISSN: (2349-4077)
Impact Factor 5.46 Volume 8, Issue 06, June 2021
Website- www.aarf.asia, Email : editoraarf@gmail.com

AN ASSESSMENT OF NATIONAL PRIVATE-INDUSTRY FOSSIL-FUEL WORKFORCE METRICS DURING THE ENFORCEMENT ERA OF THE CROSS-STATE AIR POLLUTION RULE

James Tanoos
Clinical Associate Professor at Purdue Polytechnic Vincennes

The Cross-State Air Pollution Rule, the United States' sweeping air pollution federal legislation, was enacted to limit carbon emissions from the fossil fuel industry to improve air quality. Critics claimed that this would be the death stroke to the fossil-fuel industry and all related stakeholders. While the positive results have come with unanticipated consequences, there has been little quantitative research on the effects of these regulations on those employed in related industries. This study aims to fill this gap by assessing the impact of the Rule on professions associated with the fossil fuel industry. Various financial metrics published annually by the US Bureau of Labor Statistics were analyzed using two-sample *t*-tests to determine the impact of the regulation on the financial health of inter-related domestic workforces.

Air pollution has been the subject of scientific study for centuries (Pott, 1775; Carson, 1962; Perkins, 1974; Stern et al., 1984). Research has shown that exposure to poor air quality results in deteriorated health. Munzel et al. (2017) concluded that air pollution, when added to usual loud noise, contributed to more than 75% of general human environmental stressors and disease in urbanized societies. The United Nations stated that poor air quality is lowering global life expectancy, causes long-term health problems, and kills 7 million people per year (UN Press Release, 2019). Governments around the world have taken action or been called on to take action to address poor air quality for decades (Taylor, 2008; Gardiner, 2019; Issitt, 2019). The United States federal government became active in regulating air pollution in the twentieth century with the enactment of the 1963 Clean Air Act (Davidson & Norbeck, 2011; Carlson & Burtraw, 2019), and international institutions have implemented broad air quality policies such as the Kyoto Protocol in 1997 and the Paris Climate Agreement in 2016.

Recently, researchers have linked long-term exposure to air pollution and contracting COVID-19 to interrelated human health deterioration. Friedman (2020, para. 17) referred to the world pandemic as having "far-reaching implications on clean-air regulations", citing those living in the American Northeast as those most adversely impacted in the United States. The COVID-19 pandemic shuttered factories across the American Rust Belt (the Midwest geographic region of the United States) and kept citizens from driving their vehicles starting in Spring 2020, prompting some positive unintended consequences. Since the Rust Belt air pollution travels east, the Northeast region witnessed a 30% drop in air pollution by the end of March 2020 (Newburger, 2020). Subsequent studies have linked COVID prevention measures such as lockdowns to decreased air pollution (Chang et al., 2020).

Furthermore, studies have shown a correlation between "long-term exposure to [air] pollution and COVID-19 deaths" (Friedman, para. 1) and the majority of health issues making people more at-risk for COVID-19 respiratory problems "are the same diseases that are affected by long-term exposure to air-pollution" (Wu et al., 2020, p. 1). In addition, 15% of COVID-related deaths have been associated with long-term exposure to air pollution (Stoye, 2020). Other studies found positive correlations between certain thresholds of poor air quality and COVID mortality rates (Coker et al., 2020; Hoang & Tran, 2020). Annesi-Maesano (2021, p. 3) stated that "researchers have rightly recognized the importance of considering the role of air pollution in the COVID-19 pandemic".

The Cross-State Air Pollution Rule (CSAPR) was specifically developed to address carbon emissions from the fossil-fuel industry in order to improve air quality. The CSAPR unofficially took effect when the EPA replaced the Clean Air Interstate Rule of 2005 on July 6, 2011. At that time, the law attempted to protect downwind (Northeast) states from soot (oxides of nitrogen and sulfur dioxide in the air) and was aimed at fossil fuel-powered plants, penalizing the Rust Belt in a so-called "good neighbor" provision. The CSAPR was enacted to limit the "ozone season nitrogen oxides emissions" (EPA Production Files, 2020, p. 25), focusing mainly on Rust Belt (Midwestern American) states "in order to attain certain ozone and fine particle air quality standards" (Alonso & Snyder, 2014, p. 88). The CSAPR rule was fully implemented in 2013 and was seen as an impetus to further anti-coal legislative action, eventually leading to the Clean Power Plan.

Through the broad executive powers of the 1963 Clean Air Act, the 2015 Clean Power Plan, which encompassed strict energy-related federal regulatory legislation limiting fossil-fuel usage, included three distinct regulations for carbon-emitting power plants "from new, modified, and existing … sources" (McCubbin, 2014, p. 60) in an attempt to shift to renewable energy sources. This law targeted power plants that rely on electric generators or coal as their main fuel. The Clean Power Plan was one of the most controversial energy-related political issues of recent times (Rosenbaum, 2016) due to its "uneven impact on the energy industry, boosting … some regions … while biting others" (Smith & Miller, 2015, p. 1). Many claimed that it would be a major setback or even the end of the national fossil-fuel private workforce and all related stakeholders. When it was enacted, critics claimed that national coal production would decrease by 242 million tons as a result (National Mining Association, 2017).

This debate escalated during the lead-up to the 2016 presidential election (DeBellis, 2015) and was one of the few policy issues on which each candidate's stance diverged diametrically (Kerrigan, 2018; Rushefsky, 2017). On the day it was enacted, then-Governor Mike Pence called the 2015

Clean Power Plan act "ill-conceived and poorly constructed" because of its stringent regulations on organizations associated with the coal industry (Shepherd & Rappeport, 2016, para. 3). The Democratic nominee for US President, Hillary Clinton, adopted the prior administration's stance regarding the Clean Power Plan (Banks, 2016; Parnes & Allen, 2017) and bluntly said, "We are going to put a lot of coal miners and coal companies out of business … we've got to move away from coal and all the other fossil-fuels" (O'Donoghue, 2016, p. 2). By the summer of 2016, Pence, then the Republican Vice-Presidential candidate, addressed the issue at the Republican National Convention, stating that Americans "don't want a president who promises to put a lot of coal miners and coal companies out of business" (Kessler et al., 2016, p. 4). Many political scholars believe that the 2016 presidential election was won in Rust Belt states as a result of campaign promises to roll back Clean Power Plan fossil-fuel regulations (Lake & Edna, 2016; Segal et al., 2016; Clinton, 2017; Parnes & Allen, 2017; Sabato et al., 2017). Kraybill (2017) cited fossil-fuels as a key issue prompting the polarizing rhetoric that shaped the 2016 campaign.

While air quality regulations were intended to produce better air quality, for the CSAPR and its successor, the Clean Power Plan, critics have levied the related impacts on the private sector of the national fossil-fuel industry as negative consequences. However, there has been little quantitative research on the effects of these pollution regulations on related stakeholders, specifically those directly employed in related industries. To fill this gap, this study will assess the impact of the CSAPR on the American workforce in the fossil-fuel industry.

Methodology/Results/Future Studies

The North American Industry Classification System (NAICS) "is the standard used by Federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. business economy" (United States Census Bureau, 2021). Its specific business classifications are utilized in this study for data mining. The 3-digit classification system includes sectors in the US economy related to specialty trade and further divides up these units based on code order in two distinct supersector categories: 1) Goods Producing and 2) Service Producing. There are 21 categories of the various goods-producing industries in the "manufacturing" category (Industries at a Glance, 2021). Of those categories, subsector 324, *Petroleum and Coal Products Manufacturing*, will be used in this study (Parkinson, 2021) to locate economic data associated with pan-labor costs within the national coal and fossil-fuel industries. From the NAICS subsector 324 description in the United States Bureau of Labor Statistics (BLS):

> *The Petroleum and Coal Products Manufacturing subsector is based on the transformation of crude petroleum and coal into usable products… "In addition, this subsector includes establishments that primarily further process refined petroleum and coal products and produce products, such as asphalt coatings and petroleum lubricating oils". (Industries at a Glance, 2021). Filtering further into this subsector are various "data series" statistics, all inter-related to the subsector.*

The BLS provides various economic subheadings under the heading "workforce statistics" by year in subsector 324; nine were selected for purposes of this study (Parkinson, 2021). Those subheadings, whose accessible monthly and annual data date back to 2009, include employment, nonsupervisory employment, hourly earnings, nonsupervisory hourly earnings, weekly hours, nonsupervisory weekly hours, labor, labor productivity index (LPI), and unit labor (whereas labor, LPI, and unit labor all measure productivity in the industry).

To increase the rigor of the analyses, monthly data were observed as the sample unit for the nine workforce statistics subheadings that provided data by month, whereas annual data were utilized in the statistical tests otherwise. This study compared trends before and after 2013, since the 2011 CSAPR, which was the impetus for further legislation directed at fossil-fuels in the federal energy sector, fully took effect in 2013 (see below).

Table 1.

Economic Metrics: Before and after the CSAPR went into effect

Labor Metrics	**Before 2013**	**After 2013**
Employment	112.00	112.76
Nonsupervisory Employment	70.38	75.57
Hourly Earnings	34.57	41.89
Nonsupervisory Hourly Earnings	32.45	38.91
Weekly Hours	43.98	42.99
Nonsupervisory Weekly Hours	45.05	45.51
Labor (Total Labor Hours)	99.61	103.18
LPI	104.13	108.75
Unit Labor	105.10	117.11

Two-sample *t*-tests with a significance level of 0.05 were performed to determine the impact of the CSAPR on the financial health of inter-related economic labor factors (BLS Handbook of Methods, 2021). The metrics in red font below (nonsupervisory employment, hourly earnings, nonsupervisory hourly earnings, and weekly earnings) were deemed to be statistically significant, whereas the means of the two groups can be confidently deemed to be different. Nonsupervisory employment as well as the coinciding hours both increased dramatically. In addition, the weekly hours for all employees actually *decreased*, along with a coinciding sharp increase in hourly earnings. The LPI represents output per hour, which signifies an increasing efficiency in this process. Future studies may assess which factors such as technological innovations allowed output to increase.

Table 2.

Economic Metrics: p-values before and after the CSAPR went into effect

Labor Metrics	***p*-values from the two-sample t-tests**
Employment	0.1174
Nonsupervisory Employment	$< 0.05 = 2.2 \times 10^{-16}$
Hourly Earnings	$< 0.05 = 2.2 \times 10^{-16}$
Nonsupervisory Hourly Earnings	$< 0.05 = 2.2 \times 10^{-16}$
Weekly Hours	$< 0.05 = 7.729 \times 10^{-5}$
Nonsupervisory Weekly Hours	0.1464
Labor (Total Labor Hours)	0.1808
LPI (Labor Productivity, 2007=100)	0.0755
Unit Labor	0.0060

Nonsupervisory employees include those in "private, service-providing industries who are not above the working-supervisor level" (BLS Handbook of Methods, 2021, p. 2). As such, the dramatic increase after 2013 for total nonsupervisory employment and nonsupervisory hourly earnings is worthy of additional focus. In particular, these increases may translate into higher overall costs to the consumer for energy in the fossil-fuel industry. The statistically significant *decrease* in total weekly hours, which the BLS Handbook of Methods defines as "the total weekly hours divided by the employees paid for those hours" (2021, p. 3) as well as the *increase* in hourly earnings (which takes into consideration overtime hourly earnings) after 2013 may indicate more part-time workers in this industry. While not statistically significant, the increases in labor, LPI, and unit labor should be noted because these categories measure labor productivity and costs, or output given the number of hours worked to produce the output. Extraneous variables prompting these increases in output such as technological innovations may be worthy of subsequent inquiry in this industry.

A key takeaway is that while overall employment remained flat, the number of nonsupervisory workers and their hourly earnings increased at a statistically significant rate. Weekly hours of all employees actually decreased (at a statistically significant rate), even though weekly hours of nonsupervisory employees remained flat. Future studies should analyze the factors that led the weekly hours of all employees to decrease and determine whether the increases in LPI such as technological innovations caused overall weekly hours to decrease. The stark increases in both nonsupervisory employees and their pay may also require additional scrutiny, considering that productivity increased and overall hours decreased. This scrutiny may reveal whether the higherups are manipulating increases in their own pay through across-the-board increases in nonsupervisory hourly earnings as a means of rationalizing their own increased pay.

References

Alonso, R., & Snyder, S. (2014, June). With Victory on the Cross State Air Pollution Rule, EPA Continues Campaign Against Coal. *The Electricity Journal, 27*(5), 88-89.

Annesi-Maesano, I., & D'Amatto, G. (2021). Pros and Cons for the Role of Air Pollution on COVID-19 Development. Retrieved from https://onlinelibrarywiley.com.ezproxy.lib.purdue.edu/doi/pdfdirect/10.1111/all.14818.

Banks, G. (2016, September 13). Why a Price on Carbon Is Unlikely in the U.S. Anytime Soon. *Wall St. Journal*, business/energy section.

BLS Handbook of Methods. (2021). Chapter 2: Employment, hours, and earnings from the establishment survey. Retrieved from https://www.bls.gov/opub/hom/pdf/ces-20110307.pdf.

Carlson, A., & Burtraw, D. (2019). Lessons from the Clean Air Act: Building durability and adaptability into US climate and energy policy. New York, NY: Cambridge University Press.

Carson, R. (1962). *Silent Spring*. Boston, MA: Houghton Mifflin Company.

Chang, H., Meyerhoefer, C., & Yang, F. (2020, July). COVID-19 Prevention and Air Pollution in the Absence of a Lockdown. National Bureau of Economic Research. Working Paper 27604.

Clinton, H. R. (2017). *What Happened*. London, UK: Simon & Schuster Ltd.

Coker, E., Cavalli, L., Fabrizi, E., Guastella, G., Lippo, E., Parisi, M., Pontarollo, N., Rizzati, M., Varacca, A., & Vergalli, S. (2020). The Effects of Air Pollution on COVID-19 Related Mortality in Northern Italy. *Environmental & Resource Economics, 76*(4), 611-634.

Davidson, J., & Norbeck, J. (2011). *An Interactive History of the Clean Air Act: Scientific and policy perspectives.* Philadelphia, PA: Elsevier Publishing.

DeBellis, E. (2015, November). In Defense of the Clean Power Plan. *Ecology Law Quarterly, 42*(2), 235-261.

EPA Production Files. (2020). Regulatory Impact Analysis for the Proposed Revised Cross-State Air Pollution Rule: Update for the 2008 Ozone NAAQS. Retrieved from https://www.epa.gov/sites/production/files/202010/documents/revised_csapr_update_ria_pr posal.pdf

Friedman, L. (2020, April 7). New Research Links Air Pollution to Higher Coronavirus Death Rates. *New York Times.* Retrieved from https://www.nytimes.com/2020/04/07/climate/air-pollution-coronavirus-covid.html.

Gardiner, B. (2019). *Choked: Life and breath in the age of air pollution.* Chicago, IL: University of Chicago Press.

Hoang, T., & Tran, T. (2020, June). Ambient Air Pollution, Meteorology, and COVID-19 Infection in Korea. *Journal of Medical Virology*, *26*(4), 478-491.

Industries at a Glance. (2021). US Bureau of Labor Statistics. Petroleum and Coal Products Manufacturing: NAICS 324.

Issitt, M. (2019). *Opinions Throughout History: The environment*. Amenia, NY: Gray House Publishing.

Kerrigan, H. (2017). *Historic Documents of 2017-Current Events that Chronicle the Year: Introductory essays that build understanding primary sources that aid research*. Thousand Oaks, CA: CQ Press.

Kessler, G., & Ye Hee Lee, M. (2016, July 21). *Fact Check: Pence misses mark by taking Clinton quotes out of context.* Retrieved from http://www.chicagotribune.com/news/nationworld/politics/ct-republican-national-convention-fact-check-20160720-story.html.

Kraybill, J. (2017). *Unconventional, Partisan, and Polarizing Rhetoric: How the 2016 election shaped the way candidates strategize, engage, and communicate.* Lanham, MD: Lexington Books.

McCubbin, P. (2014, March). Regulation of Greenhouse Gases and Other Air Pollutants in the First Obama Administration and Major Air Issues for the Second Term. *Buffalo Environmental Law Journal*.

Munzel, T., Sorensen, M., Gori, T., Schmidt, F., Rao, X., Brook, J., Chen, L., Brook, R., & Rajagopalan, S. (2017, February). Environmental Stressors and Cardio-metabolic Disease: Part I–epidemiologic evidence supporting a role for noise and air pollution and effects of mitigation strategies. *European Heart Journal*, *38*(8), 550-556.

Newburger, E. (2020, April 9). Air Pollution Drops 30% in Northeast US as coronavirus lockdown slows travel: NASA. *CNBC*. Retrieved from https://www.cnbc.com/2020/04/09/coronavirus-air-pollution-plummets-30percent-in northeast-us-amid-lockdowns.html.

O'Donoghue, A. (2016, August). How Coal, Energy Could Tip the Scales for Presidential Candidates in Battleground States. *Deseret News: Salt Lake City.*

Parkinson, C. (2021, January-April). *US Bureau of Labor Statistics.* Division of Information and Marketing Services. Email conversation.

Parnes, A., & Allen, J. (2017). *Shattered: Inside Hillary Clinton's doomed campaign.* New York, NY: Crown.

Perkins, H. (1974). *Air Pollution, International Edition*. New York, NY: McGraw-Hill Publishing.

Pott, P. (1775). *Chirurgical Observations: Cancer…* Farmington, Hills, MI: Gale ECCO, Print Editions.

Rosenbaum, W. R. (2016). *Environmental Politics and Policy*. Washington, D.C.: Congressional quarterly Inc.

Rushefsky, M. (2017). *Public Policy in the United States: Challenges, Opportunities, and Changes.* London, UK: Routledge Publishing.

Sabato, L., Kondik, K., & Skelley, G. (2017). *Trumped: The 2016 election that broke Aal the rules*. Lanham, MD: Rowman & Littlefield.

Segal, S., Maisano, F., Zelermyer, S. (2016, November 11). *Post-Election Update 2016*: *Environment.* Retrieved from: http://www.bracewelllaw.com/newspublications/updates/post-election-update-2016.

Shepherd, K., & Rappeport, A. (2016, July 15). How Mike Pence and Donald Trump Compare on the Issues. *New York Times.* Retrieved from https://www.nytimes.com/2016/07/16/us/politics/mike-pence-issues.html.

Smith, R., & Miller, J. (2015, August 03). Impact of EPA's Emissions Rule on Industry to Vary. *Wall St. Journal*, US section.

Stern, A., Turner, B., Boubel, R., Vallero, D., & Fox, D. (1984). *Fundamentals of Air Pollution.* Cambridge, MA: Academic Press.

Stoye, E. (2020). Daily Briefing: Air pollution linked to COVID deaths. Nature.com (London). Retrieved from https://www.nature.com/articles/d41586-020-03039-0.

Taylor, T. (2008, May). From Georgia v. Tennessee Copper Co. to Massachusetts v EPA: An overview of America's history of air pollution regulation and its effect on future remedies to climate change. *The University of Memphis Law Review, 38*(3), 763-797.

United Nations Press Release. (2019, May). UN Secretary-General António Guterres' message for World Environment Day. Retrieved from https://www.un.org/press/en/2019/sgsm19607.doc.htm.

United States Census Bureau. (2021). North American Industry Classification System: Introduction to NAICS. Retrieved from https://www.census.gov/naics/.

Wu, X., Nethery, R., Sabath, M., Braun, D., & Dominici, F. (2020). Exposure to Air Pollution and COVID 19 Mortality in the United States: A nationwide cross-sectional study. Harvard T.H. Chan School of Public Health. *Science Advances, 6*(45), 1-36

Appendix A.

Industries by Supersector

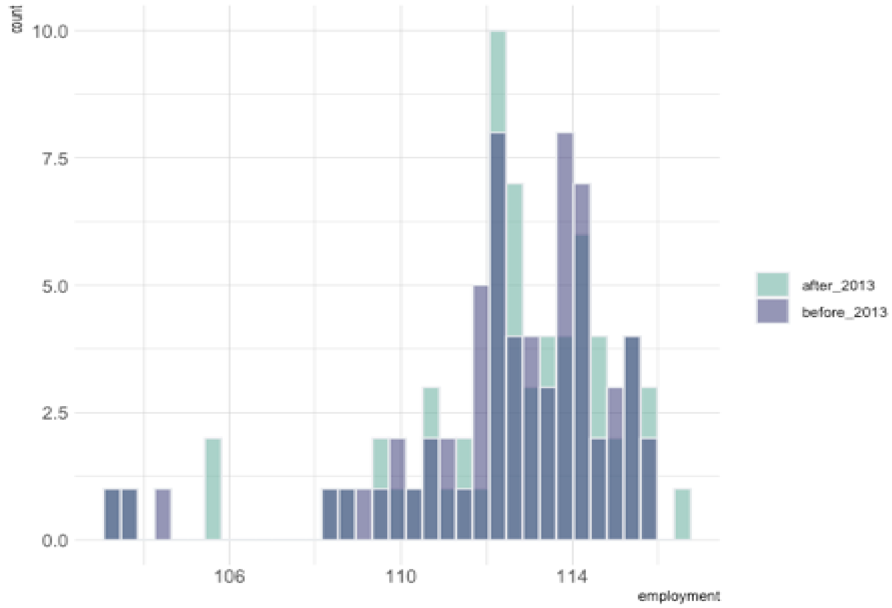
• Goods-Producing Industries
• Natural Resources and Mining
• Agriculture, Forestry, Fishing and Hunting (NAICS 11)
• Crop Production (NAICS 111)
• Animal Production (NAICS 112)
• Forestry and Logging (NAICS 113)
• Fishing, Hunting and Trapping (NAICS 114)
• Support Activities for Agriculture and Forestry (NAICS 115)
• Mining, Quarrying, and Oil and Gas Extraction (NAICS 21)
• Oil and Gas Extraction (NAICS 211)
• Mining (except Oil and Gas) (NAICS 212)
• Support Activities for Mining (NAICS 213)
• Construction
• Construction (NAICS 23)
• Construction of Buildings (NAICS 236)
• Heavy and Civil Engineering Construction (NAICS 237)
• Specialty Trade Contractors (NAICS 238)
• Manufacturing
• Manufacturing (NAICS 31-33)
• Food Manufacturing (NAICS 311)
• Beverage and Tobacco Product Manufacturing (NAICS 312)
• Textile Mills (NAICS 313)
• Textile Product Mills (NAICS 314)
• Apparel Manufacturing (NAICS 315)
• Leather and Allied Product Manufacturing (NAICS 316)
• Wood Product Manufacturing (NAICS 321)
• Paper Manufacturing (NAICS 322)
• Printing and Related Support Activities (NAICS 323)
• Petroleum and Coal Products Manufacturing (NAICS 324)
• Chemical Manufacturing (NAICS 325)
• Plastics and Rubber Products Manufacturing (NAICS 326)
• Nonmetallic Mineral Product Manufacturing (NAICS 327)
• Primary Metal Manufacturing (NAICS 331)
• Fabricated Metal Product Manufacturing (NAICS 332)
• Machinery Manufacturing (NAICS 333)
• Computer and Electronic Product Manufacturing (NAICS 334)
• Electrical Equipment, Appliance, and Component Manufacturing (NAICS 335)
• Transportation Equipment Manufacturing (NAICS 336)
• Furniture and Related Product Manufacturing (NAICS 337)
• Miscellaneous Manufacturing (NAICS 339)

• Service-Providing Industries
• Trade, Transportation, and Utilities
• Wholesale Trade (NAICS 42)
• Merchant Wholesalers, Durable Goods (NAICS 423)
• Merchant Wholesalers, Nondurable Goods (NAICS 424)
• Wholesale Electronic Markets and Agents and Brokers (NAICS 425)
• Retail Trade (NAICS 44-45)
• Motor Vehicle and Parts Dealers (NAICS 441)
• Furniture and Home Furnishings Stores (NAICS 442)
• Electronics and Appliance Stores (NAICS 443)
• Building Material and Garden Equipment and Supplies Dealers (NAICS 444)
• Food and Beverage Stores (NAICS 445)
• Health and Personal Care Stores (NAICS 446)
• Gasoline Stations (NAICS 447)
• Clothing and Clothing Accessories Stores (NAICS 448)
• Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)
• General Merchandise Stores (NAICS 452)
• Miscellaneous Store Retailers (NAICS 453)
• Nonstore Retailers (NAICS 454)
• Transportation and Warehousing (NAICS 48-49)
• Air Transportation (NAICS 481)
• Rail Transportation (NAICS 482)
• Water Transportation (NAICS 483)
• Truck Transportation (NAICS 484)
• Transit and Ground Passenger Transportation (NAICS 485)
• Pipeline Transportation (NAICS 486)
• Scenic and Sightseeing Transportation (NAICS 487)
• Support Activities for Transportation (NAICS 488)
• Postal Service (NAICS 491)
• Couriers and Messengers (NAICS 492)
• Warehousing and Storage (NAICS 493)
• Utilities (NAICS 22)
• Information
• Information (NAICS 51)
• Publishing Industries (except Internet) (NAICS 511)
• Motion Picture and Sound Recording Industries (NAICS 512)
• Broadcasting (except Internet) (NAICS 515)
• Internet Publishing and Broadcasting (NAICS 516)
• Telecommunications (NAICS 517)
• Data Processing, Hosting, and Related Services (NAICS 518)
• Other Information Services (NAICS 519)
• Financial Activities
• Finance and Insurance (NAICS 52)

• Monetary Authorities - Central Bank (NAICS 521)
• Credit Intermediation and Related Activities (NAICS 522)
• Securities, Commodity Contracts, and Other Financial Investments and Related Activities (NAICS 523)
• Insurance Carriers and Related Activities (NAICS 524)
• Funds, Trusts, and Other Financial Vehicles (NAICS 525)
• Real Estate and Rental and Leasing (NAICS 53)
• Real Estate (NAICS 531)
• Rental and Leasing Services (NAICS 532)
• Lessors of Nonfinancial Intangible Assets (except Copyrighted Works) (NAICS 533)
• Professional and Business Services
• Professional, Scientific, and Technical Services (NAICS 54)
• Management of Companies and Enterprises (NAICS 55)
• Administrative and Support and Waste Management and Remediation Services (NAICS 56)
• Administrative and Support Services (NAICS 561)
• Waste Management and Remediation Services (NAICS 562)
• Education and Health Services
• Educational Services (NAICS 61)
• Health Care and Social Assistance (NAICS 62)
• Ambulatory Health Care Services (NAICS 621)
• Hospitals (NAICS 622)
• Nursing and Residential Care Facilities (NAICS 623)
• Social Assistance (NAICS 624)
• Leisure and Hospitality
• Arts, Entertainment, and Recreation (NAICS 71)
• Performing Arts, Spectator Sports, and Related Industries (NAICS 711)
• Museums, Historical Sites, and Similar Institutions (NAICS 712)
• Amusement, Gambling, and Recreation Industries (NAICS 713)
• Accommodation and Food Services (NAICS 72)
• Accommodation (NAICS 721)
• Food Services and Drinking Places (NAICS 722)
• Other Services (except Public Administration)
• Other Services (except Public Administration) (NAICS 81)
• Repair and Maintenance (NAICS 811)
• Personal and Laundry Services (NAICS 812)
• Religious, Grantmaking, Civic, Professional, and Similar Organizations (NAICS 813)
• Private Households (NAICS 814)

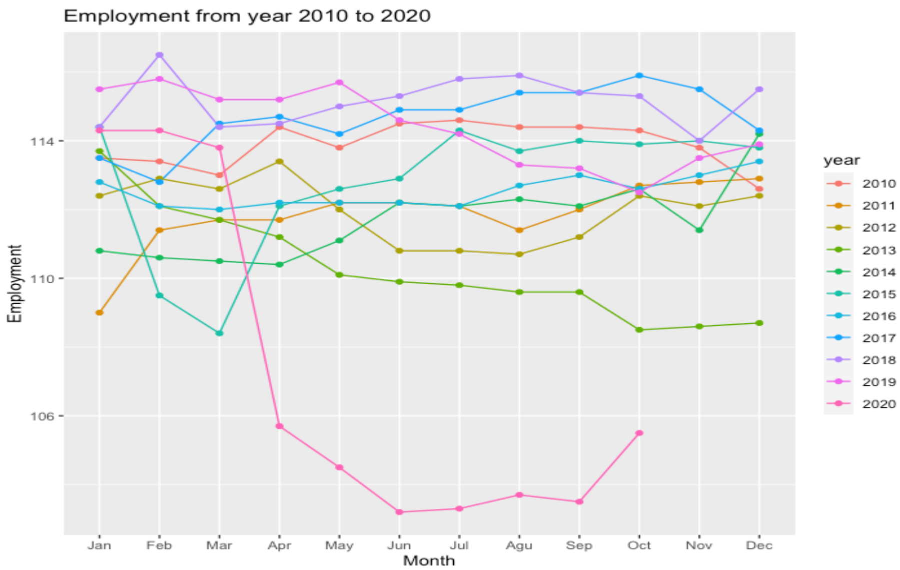
Appendix B.

Histogram for "Employment" workforce statistics metric, subsector 324



Appendix C.

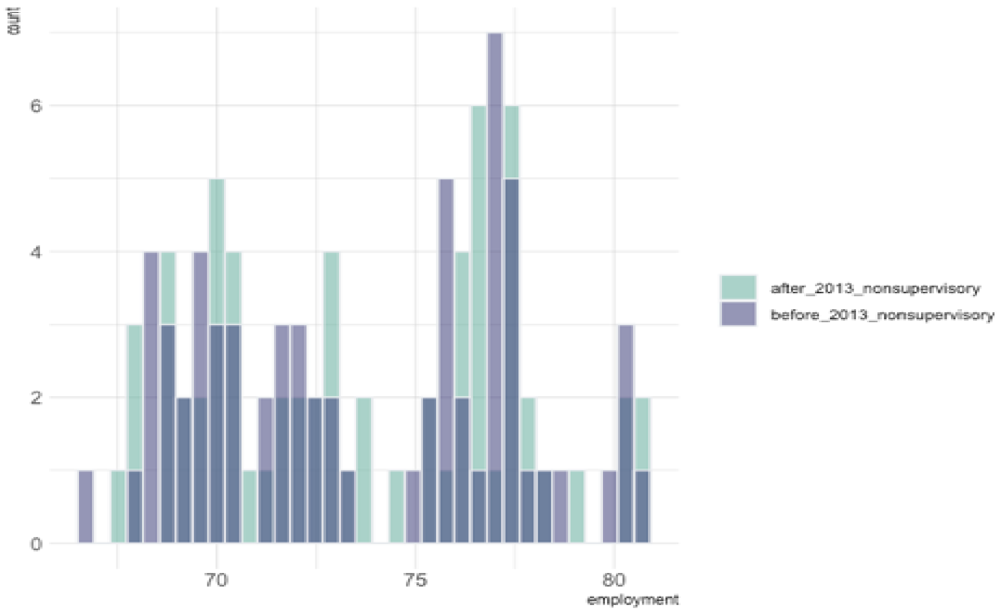
Graph & Code Output for "Employment" workforce statistics metric, subsector 324



```r
##### all employment
# read in data
before_2013 <- c(113.5,113.4,113.0,114.4,113.8,114.5,114.6,114.4,114.4,114.3,113.8,112.6,109.0,
111.4,111.7,111.7,112.2,112.2,112.1,111.4,112.0,112.7,112.8,112.9,112.4,112.9,
112.6,113.4,112.0,110.8,110.8,110.7,111.2,112.4,112.1,112.4,113.7,112.1,111.7,
111.2,110.1,109.9,109.8,109.6,109.6,108.5,108.6,108.7)
after_2013 <- c(110.8,110.6,110.5,110.4,111.1,112.2,112.1,112.3,112.1,112.6,111.4,114.2,114.4,109.5,
108.4,112.1,112.6,112.9,114.3,113.7,114.0,113.9,114.0,113.8,112.8,112.1,112.0,112.2,112.2,112.2,112.1,
112.7,113.0,112.6,113.0,113.4,113.5,112.8,114.5,114.7,114.2,114.9,114.9,115.4,115.4,115.9,115.5,114.3,
114.4,116.5,114.4,114.5,115.0,115.3,115.8,115.9,115.4,115.3,114.0,115.5,115.5,115.8,115.2,115.2,115.7,
114.6,114.2,113.3,113.2,112.5,113.5,113.9,114.,114.3,113.8,105.7,104.5,103.2,103.3,103.7,103.5,105.5)
my_data <- data.frame(
  group=rep(c("before_2013","after_2013")),
  employment = c(before_2013, after_2013)
)
#draw histogram
p0 <- my_data %>%
  ggplot(aes(x=employment, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")
# draw boxplot
boxplot(before_2013,after_2013,names=c("employment before 2013", "employment after 2013"))
# test for normality
with(my_data, shapiro.test(employment[group == "before_2013"]))
with(my_data, shapiro.test(employment[group == "after_2013"]))
## both of these two sample groups are not normal, but since the sample size is fairly large, we can still use the t test

# compute t test
res <- t.test(before_2013, after_2013, var.equal = TRUE)
res #p-value=0.1174 cannot reject the null hypothesis and thus there is no difference in the two means
# the mean for before 2013 is 112 and the mean for after 2013 is 112.7598, which are really close
# therefore it is not surprising that there is no difference in the two means

## line graph
my_data_a <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value=c(113.5,113.4,113.0,114.4,113.8,114.5,114.6,114.4,114.4,114.3,113.8,112.6,109.0,

         111.4,111.7,111.7,112.2,112.2,112.1,111.4,112.0,112.7,112.8,112.9,112.4,112.9,
         112.6,113.4,112.0,110.8,110.8,110.7,111.2,112.4,112.1,112.4,113.7,112.1,111.7,
         111.2,110.1,109.9,109.8,109.6,109.6,108.5,108.6,108.7,110.8,110.6,110.5,110.4,111.1,112.2,112.1,112.3,112.1,112.6,111.4,114.2,114.4,109.5,
         108.4,112.1,112.6,112.9,114.3,113.7,114.0,113.9,114.0,113.8,112.8,112.1,112.0,112.2,112.2,112.2,112.1,
         112.7,113.0,112.6,113.0,113.4,113.5,112.8,114.5,114.7,114.2,114.9,114.9,115.4,115.4,115.9,115.5,114.3,
         114.4,116.5,114.4,114.5,115.0,115.3,115.8,115.9,115.4,115.3,114.0,115.5,115.5,115.8,115.2,115.2,115.7,
         114.6,114.2,113.3,113.2,112.5,113.5,113.9,114.3,114.3,113.8,105.7,104.5,103.2,103.3,103.7,103.5,105.5,NA,NA))
month_order <- c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec')
ggplot(my_data_a, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Employment from year 2010 to 2020",x="Month", y = "Employment")
```

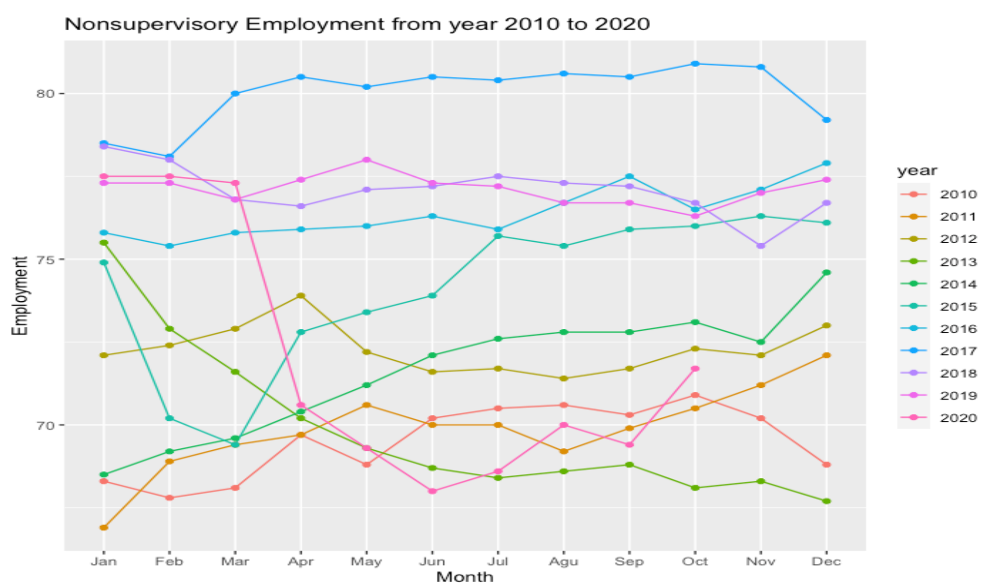
Appendix D.

Histogram for "Nonsupervisory Employment" workforce statistics metric, subsector 324



Appendix E.

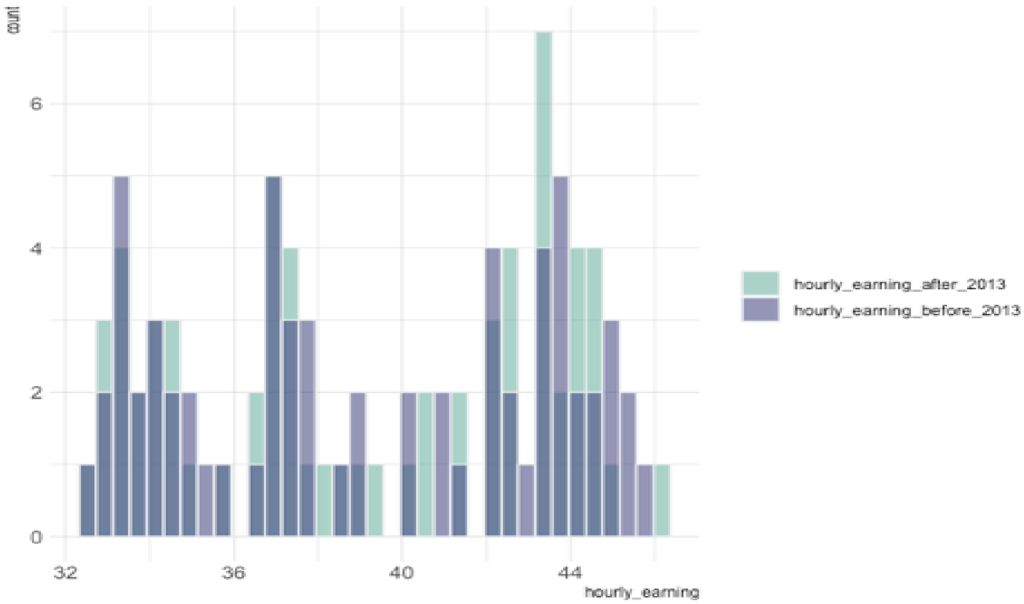
Graph & Code Output for "Nonsupervisory Employment" workforce statistics metric, subsector 324



```
#### nonsupervisory employment
## read in data
before_2013non <- c(68.3,67.8,68.1,69.7,68.8,70.2,70.5,70.6,70.3,70.9,70.2,68.8,66.9,68.9,69.4,69.7,70.6,
70.0,70.0,69.2,69.9,70.5,71.2,72.1,72.1,72.4,72.9,73.9,72.2,71.6,71.7,71.4,71.7,72.3,72.1,73.0,75.5,72.9,
71.6,70.2,69.3,68.7,68.4,68.6,68.8,68.1,68.3,67.7)
after_2013non <- c(68.5,69.2,69.6,70.4,71.2,72.1,72.6,72.8,72.8,73.1,72.5,74.6,74.9,70.2,69.4,72.8,73.4,73.9,75.7,
75.4,75.9,76.0,76.3,76.1,75.8,75.4,75.8,75.9,76.0,76.3,75.9,76.7,77.5,76.5,77.1,77.9,78.5,78.1,80.0,80.5,80.2,80.5,
80.4,80.6,80.5,80.9,80.8,79.2,78.4,78.0,76.8,76.6,77.1,77.2,77.5,77.3,77.2,76.7,75.4,76.7,77.3,77.3,76.8,77.4,78.0,
77.3,77.2,76.7,76.7,76.3,77.0,77.4,77.5,77.5,77.3,70.6,69.3,68.0,68.6,70.0,69.4,71.7)
my_data1 <- data.frame(
  group=rep(c("before_2013_nonsupervisory","after_2013_nonsupervisory")),
  employment = c(before_2013non, after_2013non)
)
# draw histogram
p1 <- my_data1 %>%
  ggplot(aes(x=employment, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")

## draw boxplot
boxplot(before_2013non,after_2013non, names=c("nonsupervisory employment before 2013","nonsupervisory employment after 2013"))
# test for normality
with(my_data1, shapiro.test(employment[group == "before_2013_nonsupervisory"]))
with(my_data1, shapiro.test(employment[group == "after_2013_nonsupervisory"]))
## both of these two samples are not normal
# compute t test
res1 <- t.test(before_2013non, after_2013non, var.equal = TRUE)
res1
## the p-value of the t test is less than 0.05, therefore the two means are different from each other

## line graph
my_data_b <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value = c(68.3,67.8,68.1,69.7,68.8,70.2,70.5,70.6,70.3,70.9,70.2,68.8,

          66.9,68.9,69.4,69.7,70.6,70.0,70.0,69.2,69.9,70.5,71.2,72.1,
          72.1,72.4,72.9,73.9,72.2,71.6,71.7,71.4,71.7,72.3,72.1,73.0,
          75.5,72.9,71.6,70.2,69.3,68.7,68.4,68.6,68.8,68.1,68.3,67.7,
          68.5,69.2,69.6,70.4,71.2,72.1,72.6,72.8,72.8,73.1,72.5,74.6,
          74.9,70.2,69.4,72.8,73.4,73.9,75.7,75.4,75.9,76.0,76.3,76.1,
          75.8,75.4,75.8,75.9,76.0,76.3,75.9,76.7,77.5,76.5,77.1,77.9,
          78.5,78.1,80.0,80.5,80.2,80.5,80.4,80.6,80.5,80.9,80.8,79.2,
          78.4,78.0,76.8,76.6,77.1,77.2,77.5,77.3,77.2,76.7,75.4,76.7,
          77.3,77.3,76.8,77.4,78.0,77.3,77.2,76.7,76.7,76.3,77.0,77.4,
          77.5,77.5,77.3,70.6,69.3,68.0,68.6,70.0,69.4,71.7,NA,NA))

ggplot(my_data_b, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Nonsupervisory Employment from year 2010 to 2020",x="Month", y = "Employment")
```

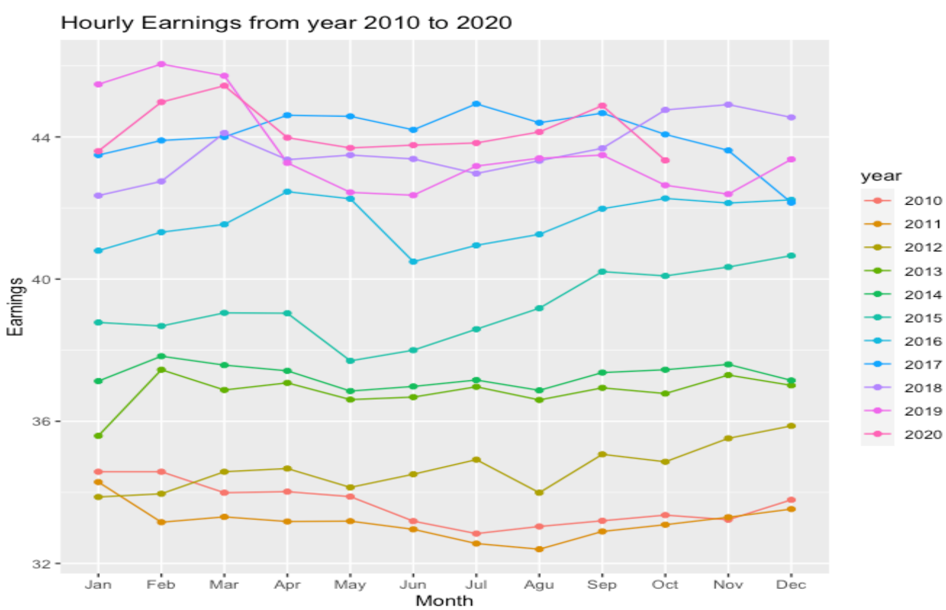
Appendix F.

Histogram for "Hourly earnings" workforce statistics metric, subsector 324



Appendix G.

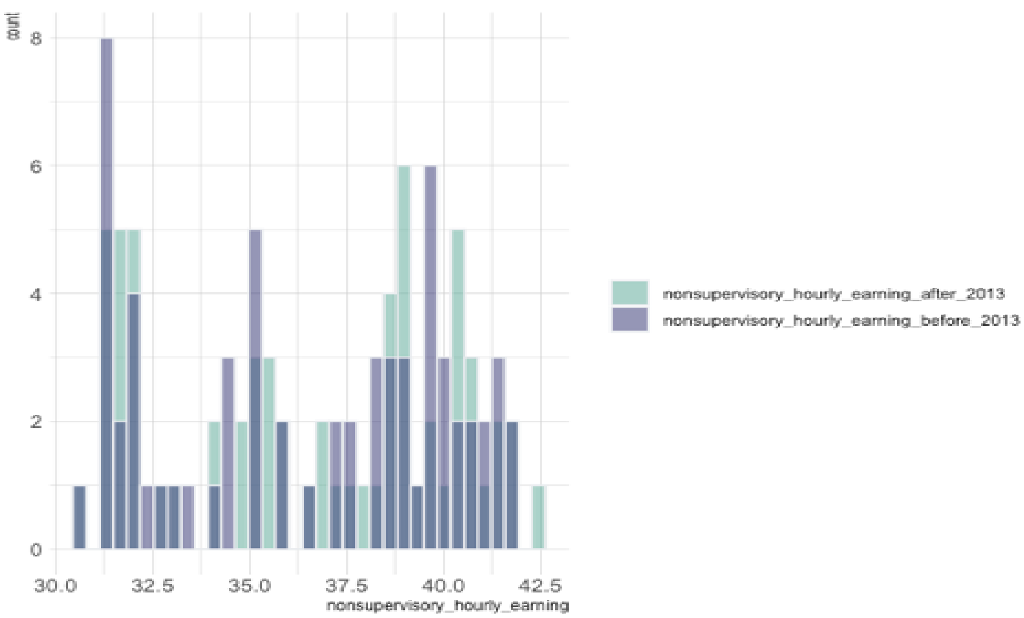
Graph & Code Output for "Hourly earnings" workforce statistics metric, subsector 324



```
#### hourly earnings
## read in data
before_2013_earning <- c(34.58,34.58,33.99,34.02,33.88,33.19,32.84,33.04,33.20,33.36,33.23,33.79,34.29,33.16,33.31,33.18,33.19,
32.96,32.56,32.40,32.90,33.09,33.30,33.53,33.87,33.96,34.58,34.67,34.14,34.51,34.92,33.99,35.07,34.86,35.52,35.87,35.59,37.45,
36.88,37.08,36.61,36.68,36.97,36.60,36.94,36.78,37.30,37.01)
after_2013_earning <- c(37.13,37.83,37.58,37.42,36.85,36.98,37.16,36.87,37.37,37.45,37.60,37.15,38.78,38.68,39.05,39.04,37.70,
38.00,38.59,39.18,40.21,40.09,40.34,40.66,40.80,41.32,41.54,42.46,42.26,40.49,40.95,41.26,41.98,42.27,42.14,42.23,43.49,43.90,
44.00,44.61,44.58,44.20,44.93,44.40,44.67,44.07,43.62,42.15,42.35,42.75,44.11,43.36,43.49,43.38,42.97,43.33,43.68,44.76,44.91,
44.55,45.48,46.05,45.72,43.27,42.44,42.36,43.18,43.40,43.49,42.64,42.39,43.37,43.60,44.98,45.44,43.98,43.69,43.77,43.83,44.14,
44.88,43.34)
my_data4 <- data.frame(
  group=rep(c("hourly_earning_before_2013","hourly_earning_after_2013")),
  hourly_earning = c(before_2013_earning, after_2013_earning)
)
## draw histogram
p4 <- my_data4 %>%
  ggplot(aes(x=hourly_earning, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")

## draw boxplot
boxplot(before_2013_earning, after_2013_earning,names=c("hourly earning before 2013", "hourly earning after 2013"))
# compute t test
res4 <- t.test(before_2013_earning, after_2013_earning, var.equal = TRUE)
res4
# p-value is less thna 0.05, there is a difference between the two means

## line graph
my_data_e <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value = c(34.58,34.58,33.99,34.02,33.88,33.19,32.84,33.04,33.20,33.36,33.23,33.79,

            34.29,33.16,33.31,33.18,33.19,32.96,32.56,32.40,32.90,33.09,33.30,33.53,
            33.87,33.96,34.58,34.67,34.14,34.51,34.92,33.99,35.07,34.86,35.52,35.87,
            35.59,37.45,36.88,37.08,36.61,36.68,36.97,36.60,36.94,36.78,37.30,37.01,
            37.13,37.83,37.58,37.42,36.85,36.98,37.16,36.87,37.37,37.45,37.60,37.15,
            38.78,38.68,39.05,39.04,37.70,38.00,38.59,39.18,40.21,40.09,40.34,40.66,
            40.80,41.32,41.54,42.46,42.26,40.49,40.95,41.26,41.98,42.27,42.14,42.23,
            43.49,43.90,44.00,44.61,44.58,44.20,44.93,44.40,44.67,44.07,43.62,42.15,
            42.35,42.75,44.11,43.36,43.49,43.38,42.97,43.33,43.68,44.76,44.91,44.55,
            45.48,46.05,45.72,43.27,42.44,42.36,43.18,43.40,43.49,42.64,42.39,43.37,
            43.60,44.98,45.44,43.98,43.69,43.77,43.83,44.14,44.88,43.34,NA,NA))
ggplot(my_data_e, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Hourly Earnings from year 2010 to 2020",x="Month", y = "Earnings")
```

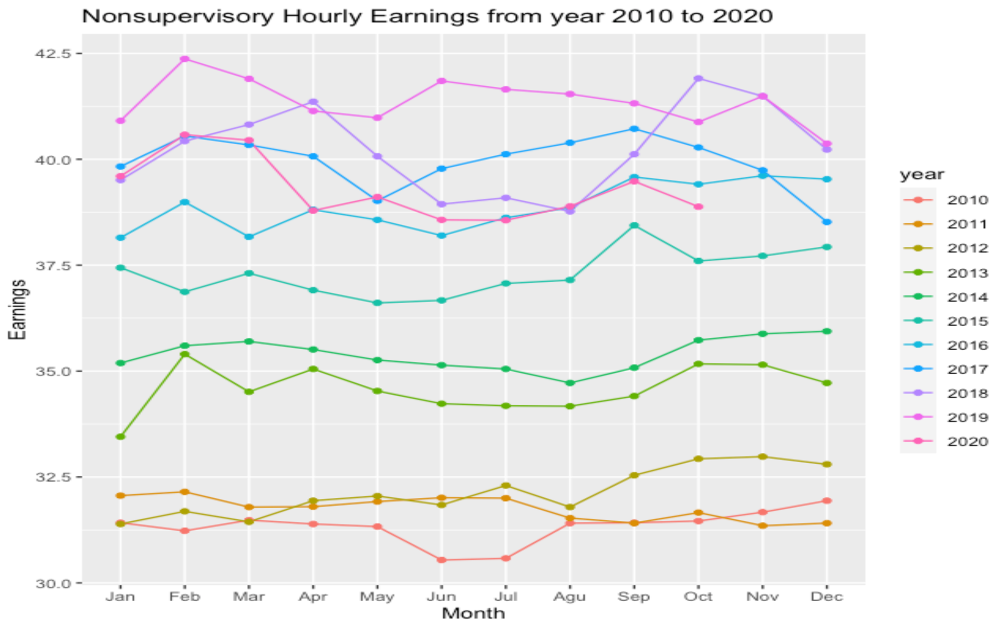
Appendix H.

Histogram for "Nonsupervisory Hourly earnings" workforce statistics metric, subsector 324



Appendix I.

Graph & Code Output for "Nonsupervisory Hourly earnings" workforce statistics metric, subsector 324

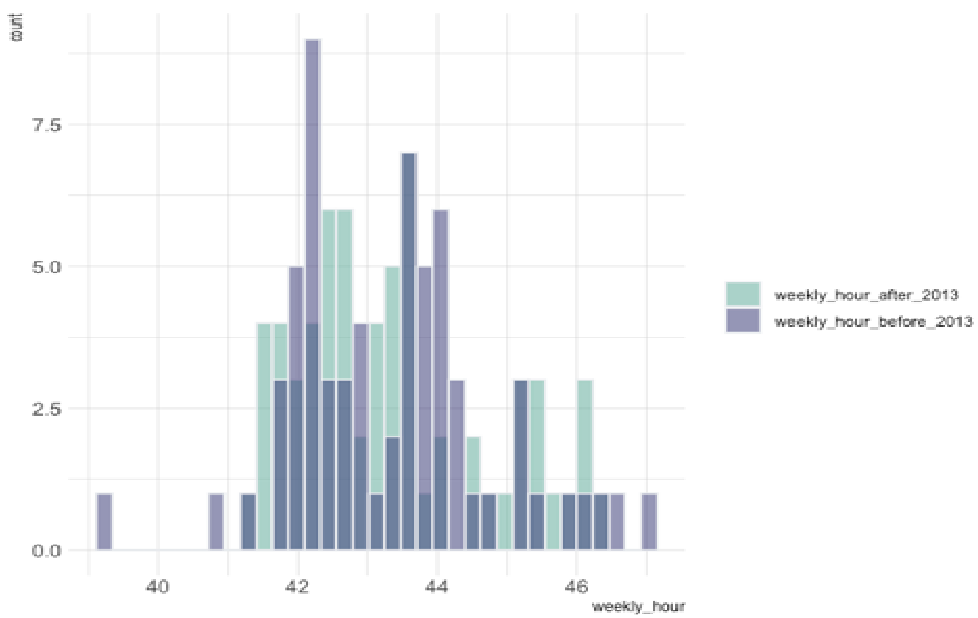



```
#### hourly earnings(nonsupervisory)
## read in data
before_2013_earning_non <-c(31.42,31.23,31.48,31.39,31.33,30.54,30.58,31.41,31.42,31.46,31.67,31.94,32.06,32.15,31.79,31.80,
31.92,32.01,32.00,31.53,31.41,31.66,31.35,31.41,31.39,31.69,31.44,31.94,32.05,31.84,32.30,31.79,32.54,32.93,32.98,32.80,33.45,
35.40,34.51,35.05,34.53,34.23,34.18,34.17,34.41,35.17,35.15,34.72)
after_2013_earning_non <- c(35.19,35.60,35.70,35.51,35.26,35.14,35.05,34.72,35.08,35.73,35.88,35.94,37.44,36.87,37.31,36.91,36.61,
36.67,37.07,37.15,38.44,37.60,37.72,37.93,38.15,38.99,38.17,38.81,38.57,38.20,38.62,38.86,39.58,39.41,39.61,39.53,39.83,40.55,
40.34,40.07,39.02,39.78,40.12,40.39,40.72,40.28,39.74,38.52,39.51,40.43,40.82,41.36,40.07,38.94,39.09,38.77,40.12,41.91,41.49,
40.23,40.91,42.37,41.90,41.14,40.98,41.85,41.65,41.54,41.32,40.88,41.49,40.37,39.60,40.58,40.45,38.79,39.11,38.57,38.56,38.89,39.48,38.88)
my_data5 <- data.frame(
  group=rep(c("nonsupervisory_hourly_earning_before_2013","nonsupervisory_hourly_earning_after_2013")),
  nonsupervisory_hourly_earning = c(before_2013_earning_non, after_2013_earning_non)
)
## draw histogram
p5 <- my_data5 %>%
  ggplot(aes(x=nonsupervisory_hourly_earning, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")
## draw boxplot
boxplot(before_2013_earning_non, after_2013_earning_non,names=c("nonsupervisory hourly earning before 2013", "nonsupervisory hourly earning after 2013
# compute t test
res5<- t.test(before_2013_earning_non, after_2013_earning_non, var.equal = TRUE)
res5
# p-value is less thna 0.05, there is a difference between the two means

## line graph
my_data_f <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value = c(31.42,31.23,31.48,31.39,31.33,30.54,30.58,31.41,31.42,31.46,31.67,31.94,
```

```
            32.06,32.15,31.79,31.80,31.92,32.01,32.00,31.53,31.41,31.66,31.35,31.41,
            31.39,31.69,31.44,31.94,32.05,31.84,32.30,31.79,32.54,32.93,32.98,32.80,
            33.45,35.40,34.51,35.05,34.53,34.23,34.18,34.17,34.41,35.17,35.15,34.72,
            35.19,35.60,35.70,35.51,35.26,35.14,35.05,34.72,35.08,35.73,35.88,35.94,
            37.44,36.87,37.31,36.91,36.61,36.67,37.07,37.15,38.44,37.60,37.72,37.93,
            38.15,38.99,38.17,38.81,38.57,38.20,38.62,38.86,39.58,39.41,39.61,39.53,
            39.83,40.55,40.34,40.07,39.02,39.78,40.12,40.39,40.72,40.28,39.74,38.52,
            39.51,40.43,40.82,41.36,40.07,38.94,39.09,38.77,40.12,41.91,41.49,40.23,
            40.91,42.37,41.90,41.14,40.98,41.85,41.65,41.54,41.32,40.88,41.49,40.37,
            39.60,40.58,40.45,38.79,39.11,38.57,38.56,38.89,39.48,38.88,NA,NA))
ggplot(my_data_f, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Nonsupervisory Hourly Earnings from year 2010 to 2020",x="Month", y = "Earnings")
```

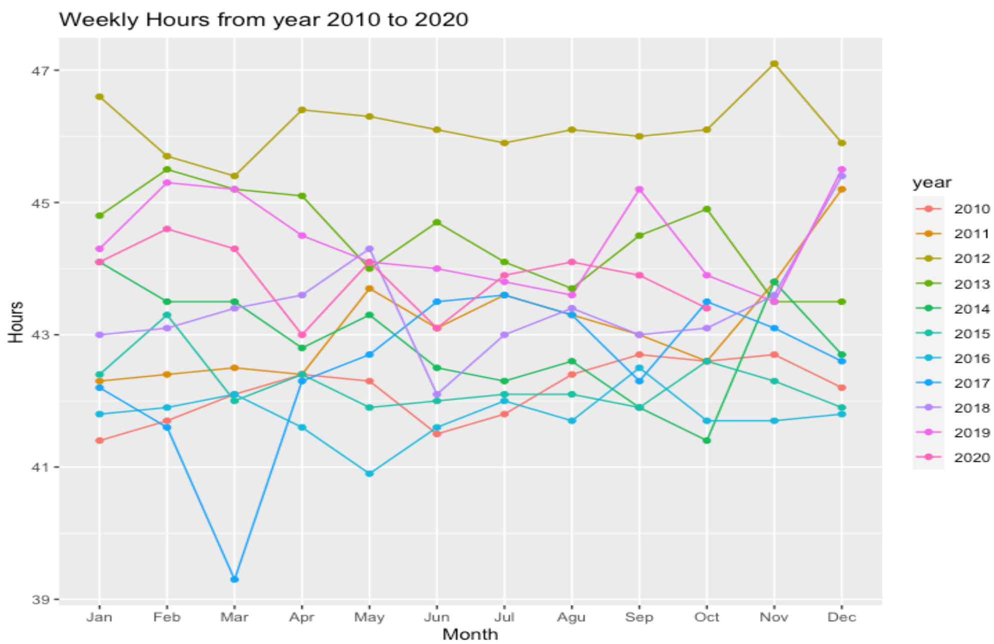
Appendix J.

Histogram for "Weekly Hours" workforce statistics metric, subsector 324



Appendix K.

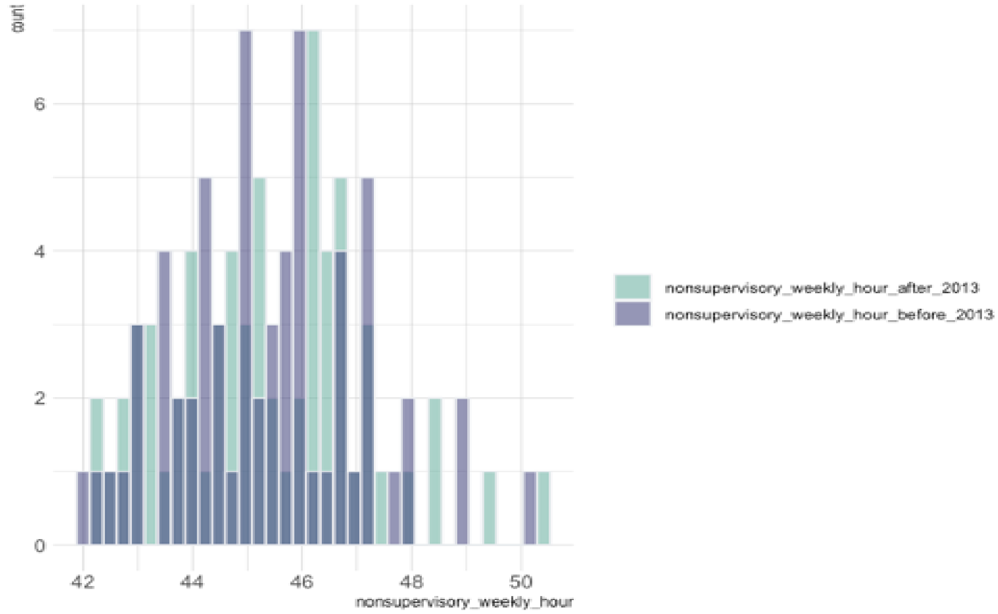
Graph & Code Output for "Weekly Hours" workforce statistics metric, subsector 324




```
              42.3,42.4,42.5,42.4,43.7,43.1,43.6,43.3,43.0,42.6,43.8,45.2,
              46.6,45.7,45.4,46.4,46.3,46.1,45.9,46.1,46.0,46.1,47.1,45.9,
              44.8,45.5,45.2,45.1,44.0,44.7,44.1,43.7,44.5,44.9,43.5,43.5,
              44.1,43.5,43.5,42.8,43.3,42.5,42.3,42.6,41.9,41.4,43.8,42.7,
              42.4,43.3,42.0,42.4,41.9,42.0,42.1,42.1,41.9,42.6,42.3,41.9,
              41.8,41.9,42.1,41.6,40.9,41.6,42.0,41.7,42.5,41.7,41.7,41.8,
              42.2,41.6,39.3,42.3,42.7,43.5,43.6,43.3,42.3,43.5,43.1,42.6,
              43.0,43.1,43.4,43.6,44.3,42.1,43.0,43.4,43.0,43.1,43.6,45.4,
              44.3,45.3,45.2,44.5,44.1,44.0,43.8,43.6,45.2,43.9,43.5,45.5,
              44.1,44.6,44.3,43.0,44.1,43.1,43.9,44.1,43.9,43.4,NA,NA))
ggplot(my_data_h, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Weekly Hours from year 2010 to 2020",x="Month", y = "Hours")
#### weekly hours
## read in data
before_2013_weekly <-c(41.4,41.7,42.1,42.4,42.3,41.5,41.8,42.4,42.7,42.6,42.7,42.2,42.3,42.4,42.5,42.4,43.7,43.1,43.6,43.3,43.0,42.6,
43.8,45.2,46.6,45.7,45.4,46.4,46.3,46.1,45.9,46.1,46.0,46.1,47.1,45.9,44.8,45.5,45.2,45.1,44.0,44.7,44.1,43.7,44.5,44.9,43.5,43.5)
after_2013_weekly <-c(44.1,43.5,43.5,42.8,43.3,42.5,42.3,42.6,41.9,41.4,43.8,42.7,42.4,43.3,42.0,42.4,41.9,42.0,42.1,42.1,41.9,42.6,
42.3,41.9,41.8,41.9,42.1,41.6,40.9,41.6,42.0,41.7,42.5,41.7,41.7,41.8,42.2,41.6,39.3,42.3,42.7,43.5,43.6,43.3,42.3,43.5,43.1,42.6,43.0,
43.1,43.4,43.6,44.3,42.1,43.0,43.4,43.0,43.1,43.6,45.4,44.3,45.3,45.2,44.5,44.1,44.0,43.8,43.6,45.2,43.9,43.5,45.5,44.1,44.6,44.3,43.0,
44.1,43.1,43.9,44.1,43.9,43.4)
my_data7 <- data.frame(
  group=rep(c("weekly_hour_before_2013","weekly_hour_after_2013")),
  weekly_hour = c(before_2013_weekly, after_2013_weekly)
)
## draw histogram
p7 <- my_data7 %>%
  ggplot(aes(x=weekly_hour, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")
## draw boxplot
boxplot(before_2013_weekly, after_2013_weekly,names=c("Weekly Hours before 2013", "Weekly Hours after 2013"))
# compute t test
res7<- t.test(before_2013_weekly, after_2013_weekly, var.equal = TRUE)
res7
# p-value is less thna 0.05, there is a difference between the two means

## line graph
my_data_h <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value = c(41.4,41.7,42.1,42.4,42.3,41.5,41.8,42.4,42.7,42.6,42.7,42.2,
```

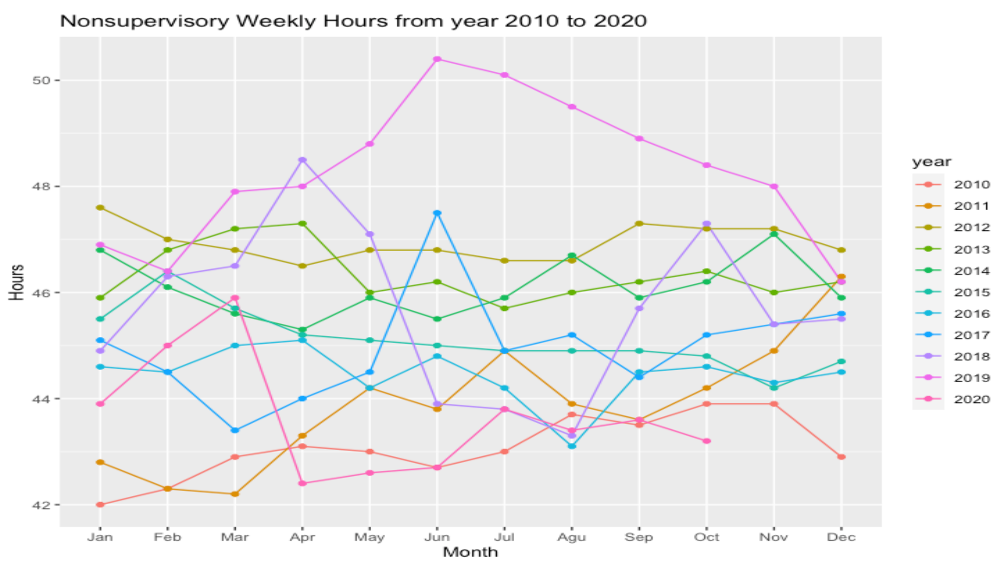
Appendix L.

Histogram for "Nonsupervisory Weekly Hours" workforce statistics metric, subsector 324



Appendix M.

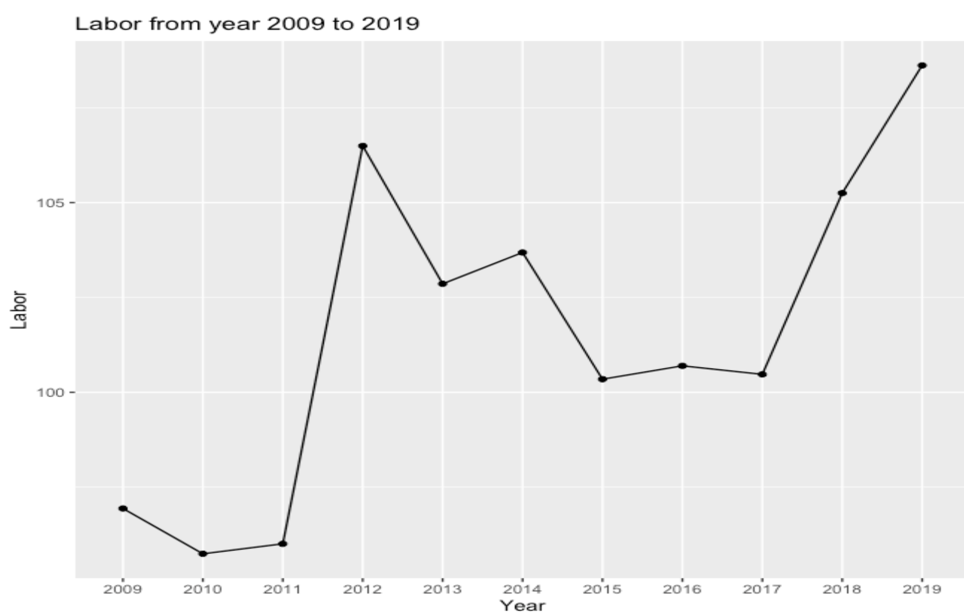
Graph & Code Output for "Nonsupervisory Weekly Hours" workforce statistics metric, subsector 324



```
#### weekly hours nonsupervisory
## read in data
before_2013_weekly_non <-c(42.0,42.3,42.9,43.1,43.0,42.7,43.0,43.7,43.5,43.9,43.9,42.9,42.8,42.3,42.2,43.3,44.2,43.8,44.9,43.9,43.6,44.2,
44.9,46.3,47.6,47.0,46.8,46.5,46.8,46.8,46.6,46.6,47.3,47.2,47.2,46.8,45.9,46.8,47.2,47.3,46.0,46.2,45.7,46.0,46.2,46.4,46.0,46.2)
after_2013_weekly_non <-c(46.8,46.1,45.6,45.3,45.9,45.5,45.9,46.7,45.9,46.2,47.1,45.9,45.5,46.4,45.7,45.2,45.1,45.0,44.9,44.9,44.9,44.8,
44.2,44.7,44.6,44.5,45.0,45.1,44.2,44.8,44.2,43.1,44.5,44.6,44.3,44.5,45.1,44.5,43.4,44.0,44.5,47.5,44.9,45.2,44.4,45.2,45.4,45.6,44.9,
46.3,46.5,48.5,47.1,43.9,43.8,43.3,45.7,47.3,45.4,45.5,46.9,46.4,47.9,48.0,48.8,50.4,50.1,49.5,48.9,48.4,48.0,46.2,43.9,45.0,45.9,42.4,
42.6,42.7,43.8,43.4,43.6,43.2)
my_data8 <- data.frame(
  group=rep(c("nonsupervisory_weekly_hour_before_2013","nonsupervisory_weekly_hour_after_2013")),
  nonsupervisory_weekly_hour = c(before_2013_weekly_non, after_2013_weekly_non)
)
## draw histogram
p8 <- my_data8 %>%
  ggplot(aes(x=nonsupervisory_weekly_hour, fill=group)) + geom_histogram(color="#e9ecef", alpha=0.6, position = 'identity',bins=35) +
  scale_fill_manual(values=c("#69b3a2", "#404080")) +
  theme_ipsum() +
  labs(fill="")
## draw boxplot
boxplot(before_2013_weekly_non, after_2013_weekly_non,names=c("Nonsupervisory Weekly Hours before 2013", "Nonsupervisory Weekly Hours after 2013"))
# compute t test
res8<- t.test(before_2013_weekly_non, after_2013_weekly_non, var.equal = TRUE)
res8  ##p-value=0.1464
# the p-value is larger than 0.05, there is no difference between these two means

## line graph
my_data_i <- data.frame(
  year=rep(c("2010","2011","2012","2013","2014","2015","2016","2017","2018","2019","2020"),each=12),
  month = rep(c('Jan','Feb','Mar','Apr','May','Jun','Jul','Agu','Sep','Oct','Nov','Dec'),11),
  value = c(42.0,42.3,42.9,43.1,43.0,42.7,43.0,43.7,43.5,43.9,43.9,42.9,

            42.8,42.3,42.2,43.3,44.2,43.8,44.9,43.9,43.6,44.2,44.9,46.3,
            47.6,47.0,46.8,46.5,46.8,46.8,46.6,46.6,47.3,47.2,47.2,46.8,
            45.9,46.8,47.2,47.3,46.0,46.2,45.7,46.0,46.2,46.4,46.0,46.2,
            46.8,46.1,45.6,45.3,45.9,45.5,45.9,46.7,45.9,46.2,47.1,45.9,
            45.5,46.4,45.7,45.2,45.1,45.0,44.9,44.9,44.9,44.8,44.2,44.7,
            44.6,44.5,45.0,45.1,44.2,44.8,44.2,43.1,44.5,44.6,44.3,44.5,
            45.1,44.5,43.4,44.0,44.5,47.5,44.9,45.2,44.4,45.2,45.4,45.6,
            44.9,46.3,46.5,48.5,47.1,43.9,43.8,43.3,45.7,47.3,45.4,45.5,
            46.9,46.4,47.9,48.0,48.8,50.4,50.1,49.5,48.9,48.4,48.0,46.2,
            43.9,45.0,45.9,42.4,42.6,42.7,43.8,43.4,43.6,43.2,NA,NA))
ggplot(my_data_i, aes(x=factor(month, level=month_order), y=value, group=year)) +
  geom_line(aes(color=year))+
  geom_point(aes(color=year))+
  labs(title="Nonsupervisory Weekly Hours from year 2010 to 2020",x="Month", y = "Hours")
```

Appendix N.

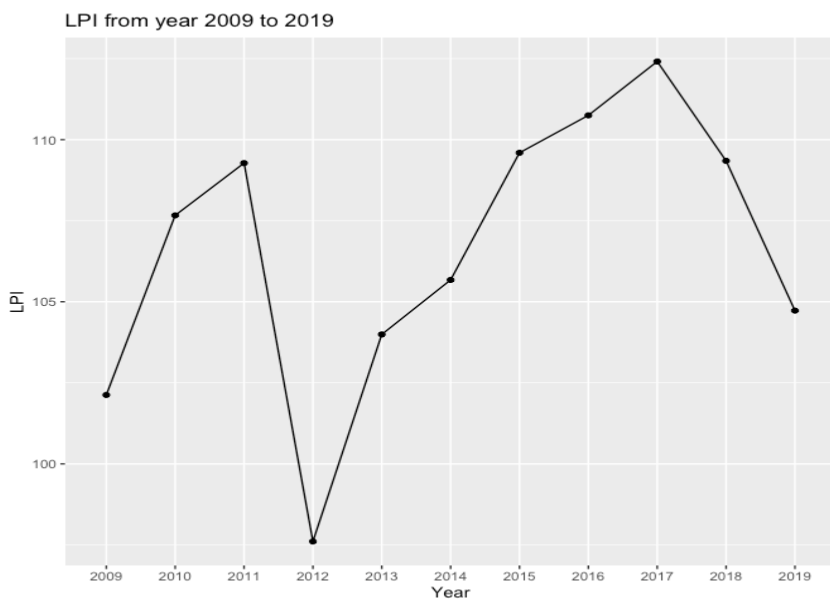
Graph & Code Output for "Labor" workforce statistics metric, subsector 324



```
#### Labor
## read in data
before_2013_labor <-c(96.937,95.743,96.006,106.493,102.859)
after_2013_labor <-c(103.685,100.345,100.697,100.473,105.250,108.616)
my_data9 <- data.frame(
  group=rep(c("labor_before_2013","labor_after_2013")),
  labor = c(before_2013_labor, after_2013_labor)
)

## draw boxplot
boxplot(before_2013_labor, after_2013_labor,names=c("Labor Cost before 2013", "Labor Cost after 2013"))
# compute t test
res9<- t.test(before_2013_labor, after_2013_labor, var.equal = TRUE)
res9
# the p-value is larger than 0.05, indicating no difference in the two means
# but the sample sizes are really small, this may be the reason for the low accuracy

## line graph
my_data_j <- data.frame(
  year=rep(c("2009","2010","2011","2012","2013","2014","2015","2016","2017","2018","2019"),each=1),
  value = c(96.937,95.743,96.006,106.493,102.859,103.685,100.345,100.697,100.473,105.250,108.616)
)
ggplot(my_data_j, aes(x=year, y=value,group=1)) +
  geom_line()+
  geom_point()+
  labs(title="Labor from year 2009 to 2019",x="Year", y = "Labor")
```

Appendix O.

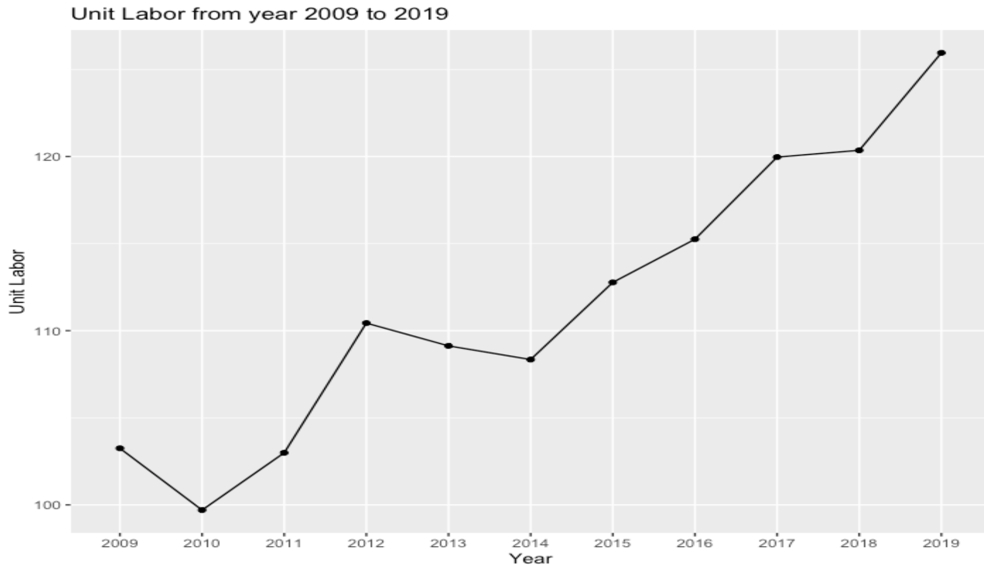
Graph & Code Output for "LPI" workforce statistics metric, subsector 324




```
####Output
## read in the data
before_2013_output <- c(98.999,103.081,104.913,103.947,106.967)
after_2013_output <- c(109.569,109.974,111.522,112.944,115.087,113.751)
## draw boxplot
boxplot(before_2013_output, after_2013_output,names=c("Output before 2013", "Output after 2013"))
# compute t test
res11<- t.test(before_2013_output, after_2013_output, var.equal = TRUE)
res11
# p-value is less than 0.05, there is a difference between the two means

## line graph
my_data_l <- data.frame(
  year=rep(c("2009","2010","2011","2012","2013","2014","2015","2016","2017","2018","2019"),each=1),
  value = c(98.999,103.081,104.913,103.947,106.967,109.569,109.974,111.522,112.944,115.087,113.751)
)
ggplot(my_data_l, aes(x=year, y=value,group=1)) +
  geom_line()+
  geom_point()+
  labs(title="Output from year 2009 to 2019",x="Year", y = "Output")
```

Appendix P.

Graph & Code Output for "Unit Labor" workforce statistics metric, subsector 324




```
#### 13: Unit Labor
## read in data
before_2013_unit_labor <- c(103.247,99.701,102.990,110.436,109.128)
after_2013_unit_labor <- c(108.344,112.772,115.250,119.966,120.354,125.951)
## draw boxplot
boxplot(before_2013_unit_labor, after_2013_unit_labor,names=c("Unit Labor before 2013", "Unit Labor after 2013"))
# compute t test
res12<- t.test(before_2013_unit_labor, after_2013_unit_labor, var.equal = TRUE)
res12
# p-value is less than 0.05, there is a difference between the two means

## line graph
my_data_m <- data.frame(
  year=rep(c("2009","2010","2011","2012","2013","2014","2015","2016","2017","2018","2019"),each=1),
  value = c(103.247,99.701,102.990,110.436,109.128,108.344,112.772,115.250,119.966,120.354,125.951)
)
ggplot(my_data_m, aes(x=year, y=value,group=1)) +
  geom_line()+
  geom_point()+
  labs(title="Unit Labor from year 2009 to 2019",x="Year", y = "Unit Labor")
```