

Navigating Factors Affecting Job Satisfaction Among Working Americans*

Analysis using US General Social Survey (1989 to 2016)

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*Code and data in this report are available at: https://github.com/shirleychen003/job_satisfaction.git.

1 Introduction

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2 Data

2.1 Source Data and Methodology

Based at the University of Chicago since 1972, the General Social Survey (GSS) is a project with the objective of monitoring and analyzing the intricacies of American society (1). The GSS Data Explorer makes it so that data retrieved from the project is a publicly available resource, accessible to various types of people, such as educators, policymakers, or researchers through the National Opinion Research Center (NORC). The dataset used for this paper was retrieved from The General Social Survey (GSS) Data Explorer website (citation). We retrieved survey data relating to work and job in the years of 1989, 1998, 2006, and 2016.

Majority of the GSS data was collected through face-to-face interviews with the target population of adults (18+) residing in the United States; however, starting in 2002, Computer-assisted personal interviewing methods were introduced (3). The use of manual edits and keypunching were eliminated, and training to learn how to use CAPI was included.

All the survey data used was in relation to job and work in the Work Orientation Module; the specific variable names extracted from the dataset being `intjob`, `hlpoths`, and `hlp soc`. For the years and demographic data, the specific variable names extracted were `year`, `age` and `sex`.

2.2 Data Cleaning

The open source statistical programming language (R Core Team 2023) was used to clean and analyze the data, along with producing the graphs. The main packages that supported this process included (Wickham 2023), (Wickham et al. 2023), (Xie 2023), (Firke 2023), and (Spinu, Grolemond, and Wickham 2023).

The cleaning process involved filtering the specific data variables used for our analysis from the downloaded GSS dataset, and renaming any variables with meaningful names. For example, rather than “`hlpoths`” being the column name for “importance of helping others in a job”, we renamed it to `helping_others`, as shown in Table #. Further, the numerical values representing the participants’ responses (1-5) were changed to the representative words/phrases (not important, very important, etc.). Table 1 shows the old and new variable names used in cleaning, the description of variables, and sample responses.

Table 1: GSS Dataset

Variable	New.Name	Description	Example.Response
hlpoths	helping_others	Importance of helping others in a job	Very Important
hlp soc	social_usefulness	Importance of social usefulness in a job	Not Important

2.3 Data Terminology

The response choices for each question and their respective code in brackets are as follows: Inapplicable (-100), No Answer (-99), Do Not Know/Cannot Choose (-98), Very Important (1), Important (2), Neither (3), Not important (4), and Not Important At All (5). For our graphs, we did not include the Inapplicable, No Answer, and Do Not Know/Cannot choose responses to focus on the discernible participant responses.

2.4 Respondent Demographics

Table 2 shows the number and percentage of male and female respondents for 1989, 1998, 2006, and 2016. The percentages of female participants were consistently higher than the male participants, as the female participant percentages were always above 50% while the male participant percentages ranged from low to high 40s.

Table 3 displays the number of respondents within different age groups for 1989, 1998, 2006, and 2016. The classified age groups are ‘18-24’, ‘25-34’, ‘45-54’, ‘55-64’, and ‘65+’. Further, there is a column labelled “N/A” for the respondents who did not disclose their age. As shown by the table, the 18-24 age group had the least amount of participants every year, while the age group with the most participants per year varied; however, the age range of the most participants per year stayed between 25-54.

Table 2: Respondent Gender Demographics for 1989, 1989, 2006, and 2016

Year	Sex	Count	Percentage
1989	female	789	56.40
1989	male	610	43.60
1998	female	681	58.86
1998	male	476	41.14
2006	female	808	53.51
2006	male	702	46.49
2016	female	766	52.14
2016	male	703	47.86

Table 3: Respondent Count of Participants in Age Groups by Year

Year	18-24	25-34	35-44	45-54	55-64	65+	N/A
1989	151	324	296	215	154	257	2
1998	108	255	298	188	125	182	1
2006	110	269	329	335	227	231	9
2016	112	238	275	266	268	303	7

Table 4: Respondent Age Demographics by Year

Year	Mean	Median	Mode	Min	Max
1989	45	42	28	18	89
1998	45	42	33	18	89
2006	47	46	47	18	89
2016	49	49	58	18	89

2.5 Graphs of Responses

Figure 1 and Figure 2, shows the responses to the prompt “On the following list there are various aspects of jobs. Please circle one number to show how important you personally consider it is in a job” where each graph represents one of the aspects. Respondents answered on a 1 to 5 Likert scale where 1 represents “very important” and 5 represents “not important at all”.

2.5.1 Helps Others

In Figure 1, the proportion of respondents to the prompt “A job that allows someone to help other people?” is displayed. From the first year of data collection in 1989 to 2006, “Important” was the most selected response. In 2016, “Very Important” surpassed “Important” by 1%. In general, you can see an increase in “Very Important” respondents across the years while there is little change in the proportion of “Not Important” and “Not Important At All” responses. Further, there is a general decrease in “Neither” responses from 1989 - 2006 which is interrupted when there is a slight increase in 2016.

2.5.2 Social Usefulness

Figure 2 displays the proportion of responses for the prompt “A job that is useful to society?”. There is a large increase in the proportion of “Very Important” responses from 1989 to 2016.

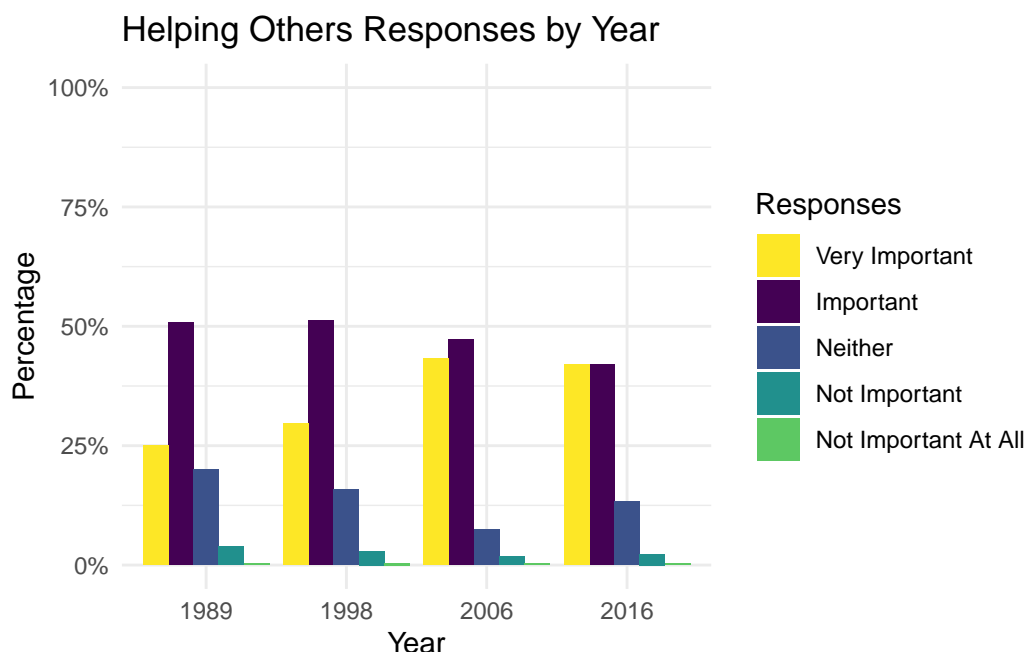


Figure 1: Q1 - “A job that allows someone to help other people?”

In contrast, there is a gradual decline for both “Important” and “Neither”. There is little change in “Not Important” and “Not Important At All”. Compared to the other figures, this graph has the most varying change in the “neutral” response.

3 Results

3.1 Overall Trends

Table 5 summarizes the average responses per year for each question, where 1 represents “Very Important” and 5 represents “Not Important At All”. There is a general decrease in scores, meaning importance increased, each year. The largest change from 1989 to 2016 was “Social Usefulness”, with an average response decrease of 0.311. Overall, interesting work was consistently more important than helping others and social usefulness with an average of 0.264 points lower. As time passed, interesting work became rated more similarly with the other two factors, and in 2016 the average difference was only 0.144 points.

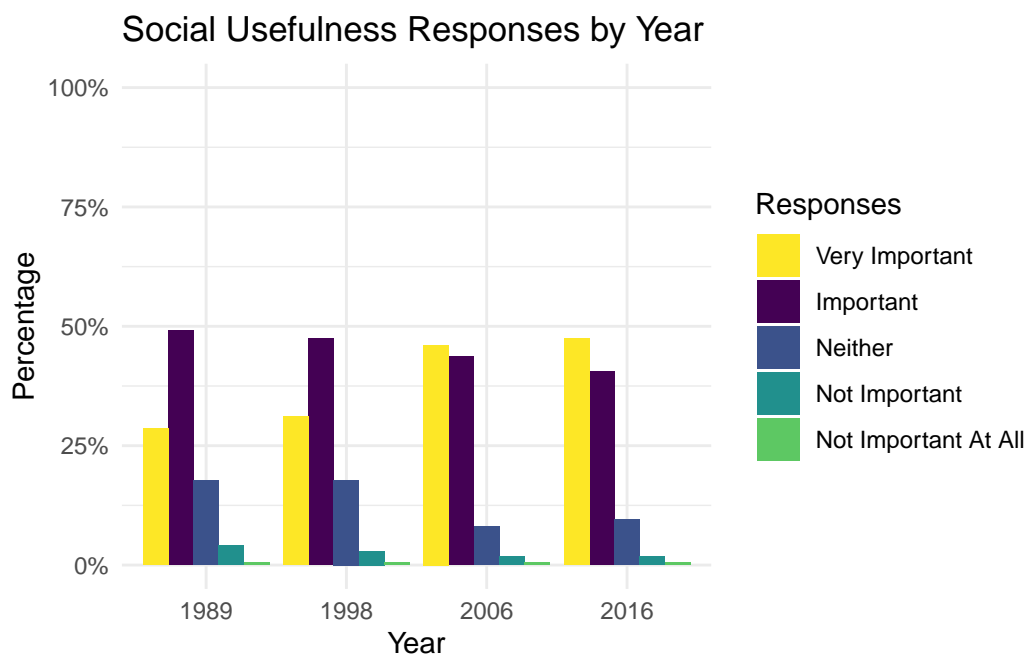


Figure 2: Q3 - “A job that is useful to society?”

Table 5: Average of Responses by Year

Year	Helping Others	Social Usefulness
1989	2.034	1.988
1998	1.932	1.943
2006	1.687	1.670
2016	1.767	1.675

3.1.1 Gender

In Table 6 and Table 7, we see the percentage distribution of responses by respondent sex for the importance of helping others. In 1989, female respondents took the more extremes, and had much higher percentages for “very important” compared to their male counterparts. In 2016, the trend continues but at a lesser scale, with the proportions evening more.

Table 6: Helping Others Response Proportions 1989

Response	Sex	Count	Percentage
very important	female	210	59.83

Response	Sex	Count	Percentage
very important	male	141	40.17
important	female	419	58.93
important	male	292	41.07
neither	female	133	47.67
neither	male	146	52.33
not important	female	24	44.44
not important	male	30	55.56
not important at all	female	3	75.00
not important at all	male	1	25.00

Table 7: Helping Others Response Proportions 2016

Response	Sex	Count	Percentage
very important	female	350	56.63
very important	male	268	43.37
important	female	324	52.43
important	male	294	47.57
neither	female	80	41.03
neither	male	115	58.97
not important	female	11	32.35
not important	male	23	67.65
not important at all	female	1	25.00
not important at all	male	3	75.00

In Table 8 and Table 9, the previous trend continues, with more women favouring importance and a decrease in gender differences in 2016. Social usefulness and interesting work had similar differences in proportions, while 1989 helping others had the largest disparity.

Table 8: Social Usefulness Response Proportions 1989

Response	Sex	Count	Percentage
very important	female	223	55.61
very important	male	178	44.39
important	female	401	58.45
important	male	285	41.55
neither	female	135	54.66
neither	male	112	45.34
not important	female	25	43.10

Response	Sex	Count	Percentage
not important	male	33	56.90
not important at all	female	5	71.43
not important at all	male	2	28.57

Table 9: Social Usefulness Response Proportions 2016

Response	Sex	Count	Percentage
very important	female	379	54.38
very important	male	318	45.62
important	female	314	52.68
important	male	282	47.32
neither	female	58	41.13
neither	male	83	58.87
not important	female	11	42.31
not important	male	15	57.69
not important at all	female	4	44.44
not important at all	male	5	55.56

3.1.2 Age

Table 10

Table 10: Helping Others Response Percentages (%) by Age

Response	18-24	25-34	35-44	45-54	55-64	65+
important	4.08	9.00	9.68	8.74	6.58	9.36
very important	2.80	7.05	8.04	6.68	5.29	5.49

Table 11

Table 11: Social Usefulness Response Percentages (%) by Age

Response	18-24	25-34	35-44	45-54	55-64	65+
important	3.6	8.64	9.65	8.00	6.05	9.00
very important	3.5	7.59	8.40	7.24	6.07	5.89

3.2 Change in importance over time

Figure 3 demonstrates the changing proportion of responses to how important is it for a job to help others.

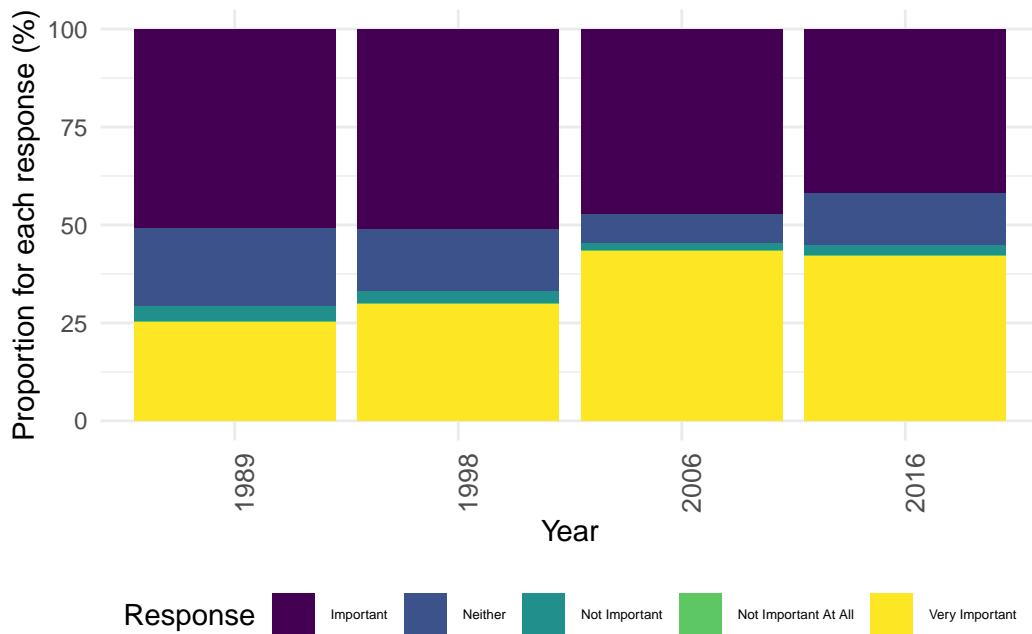


Figure 3: Proportion of Responses to Importance of Job that Helps Other

```
<ggproto object: Class ScaleDiscrete, Scale, gg>
  aesthetics: fill
  axis_order: function
  break_info: function
  break_positions: function
  breaks: waiver
  call: call
  clone: function
  dimension: function
  drop: TRUE
  expand: waiver
  get_breaks: function
  get_breaks_minor: function
  get_labels: function
  get_limits: function
  guide: legend
```

```

is_discrete: function
is_empty: function
labels: waiver
limits: NULL
make_sec_title: function
make_title: function
map: function
map_df: function
n.breaks.cache: NULL
na.translate: TRUE
na.value: NA
name: waiver
palette: function
palette.cache: NULL
position: left
range: environment
rescale: function
reset: function
scale_name: viridis_d
train: function
train_df: function
transform: function
transform_df: function
super: <ggproto object: Class ScaleDiscrete, Scale, gg>

```

4 Discussion

4.1 Economic Factors

In the early 1990s, much of the Western world, including the United States, entered a recession (Wikipedia 2024). The 1980s had a very slow productivity growth at 1.5 each year and at the end of the early 90s recession, the Federal budget had a \$298 billion deficit (Su 2001). In 2000, the U.S. had their highest unemployment rate in three decades at 4.0% (Su 2001). The low employment rates from late 1989 to 1992 possibly contributed to the lower amount of importance workers placed on their occupation being one which helps others, is interesting, and is useful to society; at the time, workers may have prioritized pay and stability. In contrast, the 2010s had the lowest unemployment rate, low inflation rates, and low interest (“What Trends Distinguished the u.s. Economy over the Past Decade?” 2019). The decade was the first since the 1850s to skip a recession and low unemployment broke a 50-year record. These factors may have contributed to participants putting higher value on occupation factors outside of stability and pay.

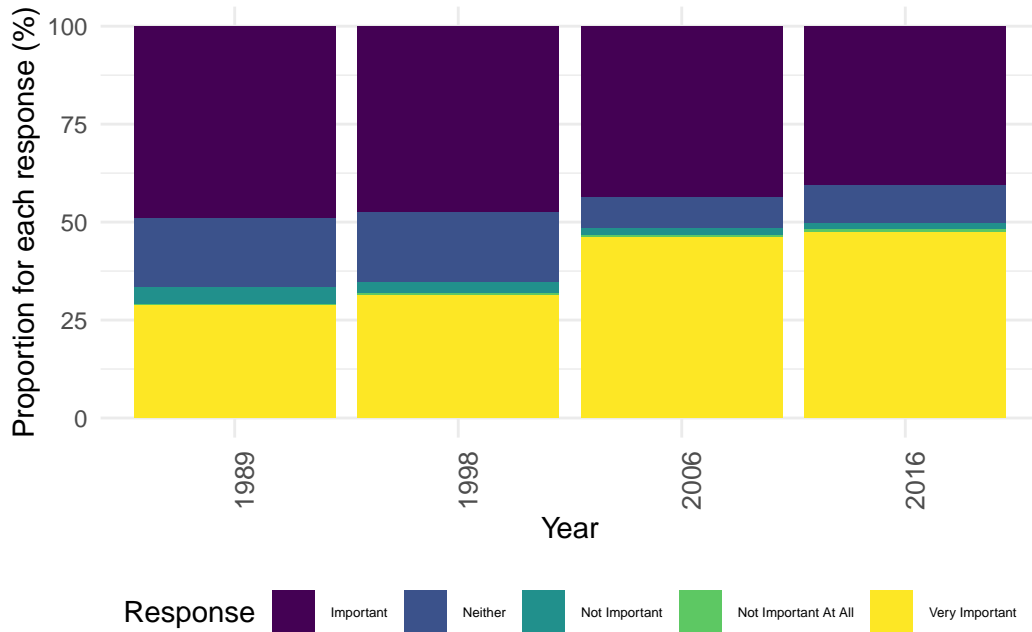


Figure 4: Proportion of Responses to Importance of Social Usefulness in Job

4.2 Gender

Women generally placed more importance on occupations that help others, are interesting, and are useful to society. The disparity between attitudes of women and men was largest for the importance of occupations that help others, and it is evident how this translates to women working in care work. In 2021, 77.6% of the 21.2 million U.S. care workers were women (Daily 2022). Care work includes occupations in which workers care for others like children, persons with disabilities, seniors, and include industries such as education, healthcare, personal services, and more (“Study: Women Working in Paid Care Occupations” 2022). Despite the essential work the care industry does, it has historically been underpaid work and home health care workers had an average salary of \$13.81 from 2018 to 2020 (Gould, Sawo, and Banerjee 2021). The issue worsens when intersectional impacts are considered, as care workers are disproportionately women of colour. The change in attitude disparity between 1989 and 2016 may be a sign of more supportive views for care work and lowered inequality; however, the continued low pay of care workers is evidence that changing attitudes have not largely improved the care economy.

The general trend of lower importance across all three factors for men may also be an indication of persisting stereotypes that men need to prioritize pay and supporting their own family. This may be a feedback loop, where men believe they must be making more money to support their family while women believe their value is in care work, and when men receive higher pay than

their female counterparts it is confirmed that they are responsible for monetarily supporting the family.

4.3 Age

4.4 Culture

Generally, the data shows an increasing support for occupations that help others, contribute to society, and are interesting. These factors can be categorized into intrinsic motivations which are aspects of an occupation which are desired because they are enjoyable in themselves, while extrinsic motivations refer to aspects sought for reasons outside of work (Bogue 2021). In individualistic cultures, intrinsic motivations have a stronger link to job satisfaction whereas in collectivist countries, extrinsic factors are intrinsically motivating (Monnot 2019), (Huang and Vliert 2003). (Santos, Varnum, and Grossmann 2017) has found that there are more individualistic relational practices in the United States and that the use of individualistic words has increased over time. The relation between individualistic culture and intrinsic motivations in combination with increasing individualism in the U.S. may explain the increase in importance of occupations with intrinsic value. The U.S. also scores below average on uncertainty avoidance according to the Culture Factor Group, perhaps contributing to an increased openness to taking a riskier job that may be more interesting or rewarding (“Country Comparison Tool: United States,” n.d.). An exploration to pursue in the future is comparing various intrinsically and extrinsically motivating factors with changes in individualism and uncertainty avoidance over time and across cultures.

4.5 Technology

References

- Bogue, Andrew. 2021. “Understanding the Difference Between Intrinsic and Extrinsic Motivations.” Talent Today. 2021. <https://www.talented.com/blog/understanding-the-difference-between-intrinsic-and-extrinsic-motivations/#:~:text=Extrinsic%20motivators%20include%20salary%2C%20job,and%20opportunities%20for%20personal%20growth>.
- “Country Comparison Tool: United States.” n.d. The Culture Factor Group. <https://www.hofstede-insights.com/country-comparison-tool?countries=united+states>.
- Daily, The Economics. 2022. “Over 16 Million Women Worked in Health Care and Social Assistance in 2021.” 2022. <https://www.bls.gov/opub/ted/2022/over-16-million-women-worked-in-health-care-and-social-assistance-in-2021.htm>.
- Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. <https://github.com/sfirke/janitor>.

- Gould, Elise, Marokey Sawo, and Asha Banerjee. 2021. “Care Workers Are Deeply Undervalued and Underpaid: Estimating Fair and Equitable Wages in the Care Sectors.” Working Economics Blog. 2021. <https://www.epi.org/blog/care-workers-are-deeply-undervalued-and-underpaid-estimating-fair-and-equitable-wages-in-the-care-sectors/>.
- Huang, Xu, and Evert Van De Vliert. 2003. “Where Intrinsic Job Satisfaction Fails to Work: National Moderators of Intrinsic Motivation.” *Journal of Organizational Behavior* 24 (2): 159–79. <https://doi.org/10.1002/job.186>.
- Monnot, Matthew J. 2019. “The Effect of Incentives on Intrinsic Motivation and Employee Attitudes: A Multilevel Study Across Nations and Cultural Clusters.” *Thunderbird International Business Review* 60 (4): 675–89. <https://doi.org/10.1002/tie.21949>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Santos, Henri C., Michael E W Varnum, and Igor Grossmann. 2017. “Global Increases in Individualism.” *Psychological Science* 28 (1, 9): 1228–39. <https://doi.org/10.1177/0956797617700622>.
- Spinu, Vitalie, Garrett Grolemond, and Hadley Wickham. 2023. *Lubridate: Make Dealing with Dates a Little Easier*. <https://lubridate.tidyverse.org>.
- “Study: Women Working in Paid Care Occupations.” 2022. Statistics Canada. 2022. <https://www150.statcan.gc.ca/n1/daily-quotidien/220125/dq220125a-eng.htm>.
- Su, Betty W. 2001. “The u.s. Economy to 2010.” <https://www.epi.org/blog/care-workers-are-deeply-undervalued-and-underpaid-estimating-fair-and-equitable-wages-in-the-care-sectors/>.
- “What Trends Distinguished the u.s. Economy over the Past Decade?” 2019. PBS. 2019. <https://www.pbs.org/newshour/show/what-trends-distinguished-the-u-s-economy-over-the-past-decade>.
- Wickham, Hadley. 2023. *Tidyverse: Easily Install and Load the Tidyverse*. <https://tidyverse.tidyverse.org>.
- Wickham, Hadley, Winston Chang, Lionel Henry, Thomas Lin Pedersen, Kohske Takahashi, Claus Wilke, Kara Woo, Hiroaki Yutani, and Dewey Dunnington. 2023. *Ggplot2: Create Elegant Data Visualisations Using the Grammar of Graphics*. <https://ggplot2.tidyverse.org>.
- Wikipedia. 2024. “Early 1990s Recession in the United States.” Wikipedia. 2024. https://en.wikipedia.org/wiki/Early_1990s_recession_in_the_United_States.
- Xie, Yihui. 2023. *Knitr: A General-Purpose Package for Dynamic Report Generation in r*. <https://yihui.org/knitr/>.