How does one's income and income metrics in their county influence attitudes towards government spending on social services?

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Abstract

This study investigates how individual income and county-level income metrics influence attitudes towards government spending on social services. Using data from the American National Election Studies and county-level economic indicators from Chetty et al. (2014), we employ a fixed effects model to control for unobserved heterogeneity across states and years. We find a clear negative relationship between one's income level and support for government social spending. Higher income individuals and those in upper social classes exhibit less support for spending on social programs. At the county level, higher income inequality is associated with greater support for social spending, though the effect is only marginally significant. Other county-level metrics like median household income, top 1% income share, and size of the middle class do not significantly predict attitudes. Our results suggest that individual economic circumstances are the dominant factor shaping views on social spending, while contextual inequality may also play a role. However, the model's explanatory power is limited, indicating other important factors beyond income also influence these attitudes.

1 Introduction

In democratic societies, public opinion and voter preferences play a key role in shaping government budgets and policy priorities. Understanding the relationship between income characteristics and attitudes towards government spending on social services is therefore imperative as income is one of the most fundamental socioeconomic factors that shapes individuals' life experiences and opportunities. With rising income inequality (Zia Qureshi, 2022), the systematic influence of income on people's views on social programs has major implications for politics and policymaking, as there could be a sharp divergence of policy preferences between the rich and the poor. This could exacerbate political polarization and make it harder to reach compromises on government spending.

Political discourse highlights opinions on social spending that reflect deeper philosophical divides about the appropriate role and size of government. Those with higher incomes may prefer lower taxes and limited redistribution, placing more emphasis on individual responsibility, while those with lower incomes may support a more expansive welfare state to provide opportunities and social protection. We will find through this study whether the data confirms this divide.

To investigate this question, we use the American National Election Studies dataset which is a comprehensive source for American voting behavior and public opinion, to understand the public attitude towards government spending on social services and also the provided income metrics, and from Chetty et al. (2014) which is a seminal study that analyzes analyzes intergenerational income mobility in the United States at a detailed geographic level, we derive county-level covariates and mobility statistics. We leverage variation in income characteristics across individuals and social classes to rigorously examine how economic position influences support for government spending on education, healthcare, and other social services.

2 Literature Review

Many theorists and researchers have speculated on the relationship between income characteristics and attitudes to government spending on social programs like education and healthcare. A study by Doherty et al. (2006) used lottery winners as a natural experiment to examine how exogenous changes in income affect political attitudes, particularly their views on redistribution and government spending. They found that higher lottery winnings were significantly associated with increased opposition to estate taxes and marginally associated with greater opposition to government redistribution of income. However, lottery winnings had little effect on broader views about economic inequality or the role of government in providing social services. This suggests that self-interest influences policy preferences most strongly when the personal financial implications are clear.

Wen and Witteveen (2021) found that individuals who perceive higher levels of social mobility are less supportive of government spending on education and more supportive of family contributions to college costs, an effect more pronounced in high socio-economic groups. An important consideration is returns to education which is strongly affected by perceptions of social mobility.

Elliott et al. (1997) studied the determinants of support for environmental spending in the United States and found that personal income was a significant predictor of attitudes, with support for environmental spending being higher among higher income individuals. The authors also noted that macroeconomic conditions such as economic downturns appeared to influence attitudes as well. This is an indication of economic factors beyond income affecting attitudes to government spending.

But the central role of income as a socioeconomic indicator that can potentially affect individuals' views on social services cannot be downplayed.Darin-Mattsson (2017) in their study of older adults found that income was the strongest and most robust predictor of health outcomes compared to other measures like education and occupational class. Healthcare is an important sector of government spending in social programs.

Delving further into the relationship between income and social services, Tan (2021) provided insights into how county-level income metrics, particularly income inequality, might influence attitudes towards social spending. They examined the association between county-level income inequality and COVID-19 cases and deaths in the United States. While their study doesn't directly address attitudes, it demonstrates that income inequality at the county level has tangible effects on health outcomes and how income and other socioeconomic factors create disparities that may influence public opinion on the need for social services and government intervention.

3 Data

3.1 American National Election Studies and Chetty Covariates

We used Time Series Cumulative Data file from the American National Election Studies (ANES) which contains 68,224 observations of 1030 variables. The dataset of county-level economic indicators from Chetty et al. contains 3138 observations of 613 variables.

3.2 Merged Dataset

The merged dataset *merged_county* which we created by combining relevant observations of the two datasets, contains 11,062 observations and 26 variables, spanning the years 1990-2000. We chose this timeframe as even though the ANES dataset spans several decades, the Chetty dataset is in this range.

To create this merged dataset, we extracted key variables including state, county, year, income group, social class, and attitudes towards government spending from the ANES dataset. The variable attitude towards government spending is described by the VCF0831 in the ANES dataset, and the question was "Some people think the government should provide fewer services, even in areas such as health and education, in order to reduce spending.

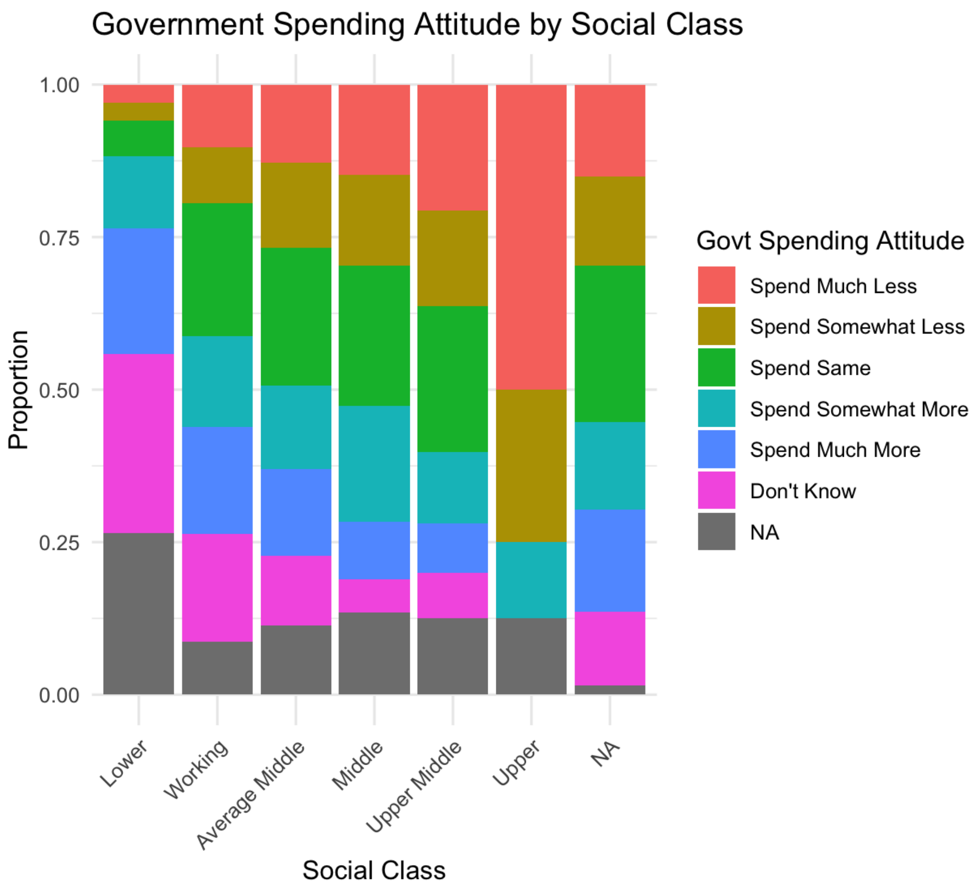

Figure 1: A stacked bar chart showing the proportion of each government spending attitude within each social class category

Suppose these people are at one end of a scale, at point 1. Other people feel that it is important for the government to provide many more services even if it means an increase in spending. Suppose these people are at the other end, at point 7. And of course, some other people have opinions somewhere in between, at points 2,3,4,5, or 6. Where would you place yourself on this scale, or haven't you thought much about this?". The Chetty dataset provided county-level economic metrics such as household income, Gini coefficient, income share of top 1%, and fraction of middle class.

The datasets were merged using county and state identifiers, resulting in a comprehensive dataset that links individual-level attitudes with county-level economic indicators. Some data transformations that were performed include recoding social class categories into a scale ranging from "Lower" to "Upper", recoding government spending attitudes into a 5-point scale from "Spend Much Less" to "Spend Much More", standardizing county-level economic variables to z-scores, creating income percentiles from the ANES income groups categorized as "0-16", "17-33", "34-67", "68-95", and "96-100". **Figure 1 shows a visual representation of how attitudes towards government spending vary across social classes.**

3.3 Empirical Strategy

To examine how individual income and county-level income metrics influence attitudes towards government spending on social services, we use a fixed effects model $felm$ from the lfe package in R to be able to control for unobserved heterogeneity across states and years. This model is designed to separate the effects of personal economic circumstances from the broader economic conditions in shaping the attitudes towards government spending on social services.

$$
\begin{aligned}
government\_spending\_scale = \beta_0 &+ \beta_1 income\_percentile + \beta_2 social\_class \\
&+ \beta_3 hhinc00\_z + \beta_4 gini\_z \\
&+ \beta_5 inc\_share\_1perc\_z + \beta_6 frac\_middleclass\_z \\
&+ \alpha s + \gamma t + \epsilon ist
\end{aligned} \tag{1}
$$

Here, $government\_spending\_scale$, which is the dependent variable, is the individuals' attitude to government spending and in the ANES dataset the values are on a scale from 0-8. The variables $income\_percentile$ and $social\_class$ are individual-level independent variables, also drawn from the ANES dataset, with the $income\_percentile$ being defined in the ANES Time Series Cumulative Data File. $hhinc00\_z$ which is the county-level household income, gini coefficient $gini\_z$ which measures income inequality, $inc\_share\_1perc\_z$ the income share of top 1% , the fraction of middle class in the county $frac\_middleclass\_z$ are also independent variables that have been standardized, taken from the Chetty covariates dataset. These variables were standardized to be able to compare their relative effects. After standardization, they represent how many standard deviations each county's household income, measure of income inequality, income share of the top 1%, and middle class fraction are from their respective means across all counties. We clustered standard errors at the state level to account for potential correlation of errors within states over time as we'll go on to explain. State fixed effects αs controls for time-invariant state-specific factors and year fixed effects γt controls for national trends over time.

The coefficients of individual-level variables like $income\_percentile$ and $social\_class$ represent the change in the government spending attitude scale associated with a one-unit change in the respective variable, holding other factors constant. In standardized county-level variables like $hhinc00\_z$, $gini\_z$, $inc\_share\_1perc\_z$, and $frac\_middleclass\_z$, the coefficients can represent change in the government spending attitude scale associated with a one standard deviation increase in the respective county-level metric, again holding other factors constant. This standardization allows for a direct comparison of the relative impact of these county-level factors on attitudes towards government spending.

From the literature review, we expect individuals with higher incomes to be less receptive to high spending, even though they would benefit from it. We also caution that our results should be interpreted as strong correlations rather than strict causations as though this model allows us to control for time-invariant state characteristics and national time trends, it cannot fully address all potential sources of endogeneity.

Finally, we include the fixed effect model described in 1 as written in R:

```
felm_model <- felm(govt_spending_scale ~ income_percentile
  + social_class + hhinc00_z + gini_z + inc_share_1perc_z
  + frac_middleclass_z | stateabbrv + year | 0 | stateabbrv,
  data = merged_county)
```
(2)

4 Results

From our regression results in Table 1, we can see that our expectation from the literature review has been realized as there is a clear negative relationship between one's income and government spending on social services.

All income percentiles show negative effects compared to the base category of 0-16 percentile. The largest effect is for the top income group of 96-100 percentile with a coefficient of -1.23882 and a highly significant p value less than 0.001. Higher income individuals are less supportive of government spending as when the income percentiles increase, the coefficients become very negative. We can also see this in figure 3 that as income percentile increases on the x-axis, the proportion of those wanting to "spend more" or "spend much more" on social services decreases while those wanting to "spend somewhat less" and "spend much less" increases, and the middle income percentile groups of 24-67 and 68-95 have the greater proportion of "spend same" attitude.

The same phenomenon is observed in social classes, with the effect becoming more negative as we move up the class ladder. "Upper" class shows the strongest negative effect with a coefficient of -3.03134 and highly significant p-value less than 0.01. "Working" class effect, however, is not significant. Figure 1 illustrates this clearly, with the proportion of those wanting the government to "spend more" or "spend much more" on social services decreasing as the hierarchy of social classes increases on the x-axis.

County-level household income $hhinc00\_z$ only shows a negative effect of income inequality -0.02656, which would have indicated that individual economic circumstances may be more important than county-level economic conditions in shaping attitudes towards government spending. Interestingly, however, this is not statistically significant as it has a p-value 0.72458. The density plot shown in figure 2 supports this as well, with the curves looking similar across the attitude groups, indicating that there is little to no relationship between the county household income and government spending attitude.

Notably, in counties with more inequality, people may be slightly more supportive of government spending on social services, as observed through the positive coefficient of the Gini coefficient $gini\_z$ 0.18968, and it's also marginally significant with a p-value of 0.05776. In figure 6, we can see that as income inequality increases (moving from Q1 to Q4), the average support for government spending consistently increases as well. The counties in the highest inequality quartile Q4 have a substantially higher average score, around 7.2, compared to around 5.1 for the lowest inequality counties Q1.

The income share of top 1% in the county $inc\_share\_1perc\_z$ had a small negative (-0.05128) effect as seen in figure 5 but it was statistically insignificant (0.64810). The fraction of middle class in the county $frac\_middleclass\_z$ had a small positive (0.04011) but statistically insignificant (0.46541) effect. From figure 4, we can see that there is no a clear linear relationship between the standardized fraction of middle class and attitudes towards government spending. Some bins show tendency towards "somewhat more" or "much more" spending but the significant proportion of NA shows that there are underlying factors that have not been taken into consideration.

The F-statistic of both the full and projected models are less than $2e^{-16}$ which means the models are highly statistically significant as a whole. The distribution of errors is relatively symmetric as the residuals have a range of -6.4206 to 5.8151 with a median -0.2732˜0. The R^2 value of 0.1105 means that the model explains 11.05% of the variance in the dependent variable *government_spending_scale*. The projected R^2 and $R^2_{adjusted}$ values are even lower at 0.0606 and 0.05226 respectively and therefore they're not good at explaining variance and there might be other important factors not accounted for in this model even though it's statistically significant overall.

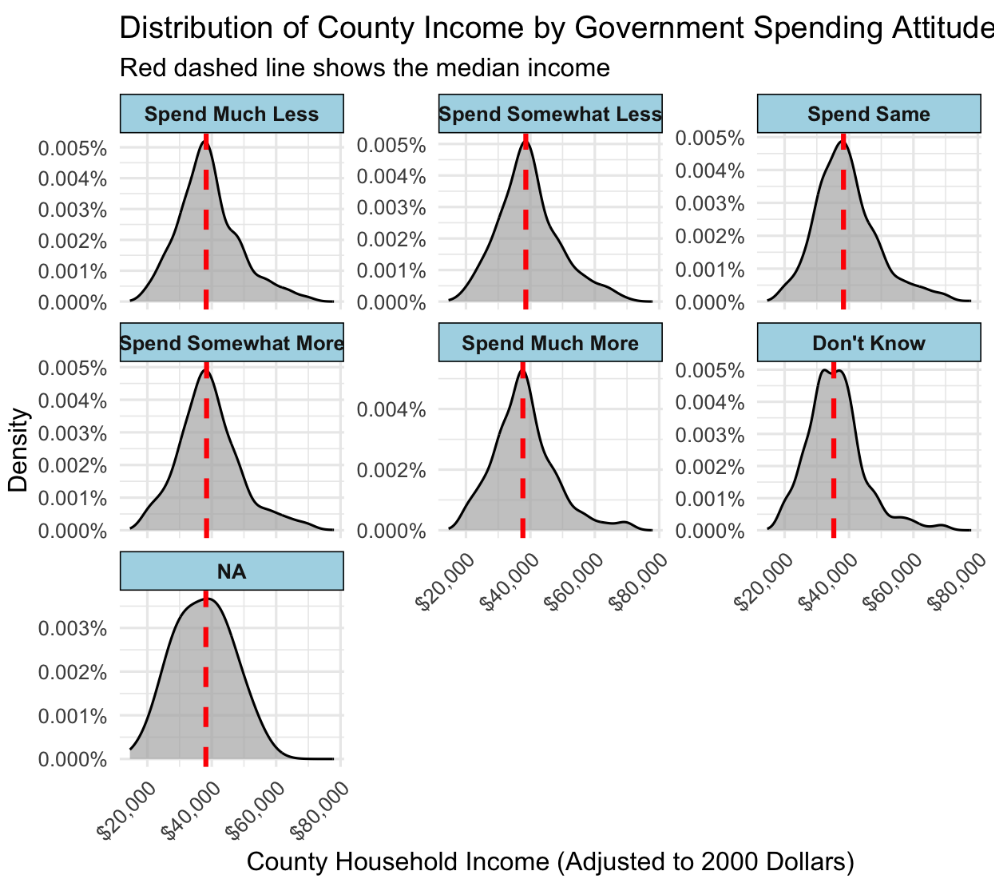

Figure 2: A density plot showing the distribution of county household income by government spending attitude.

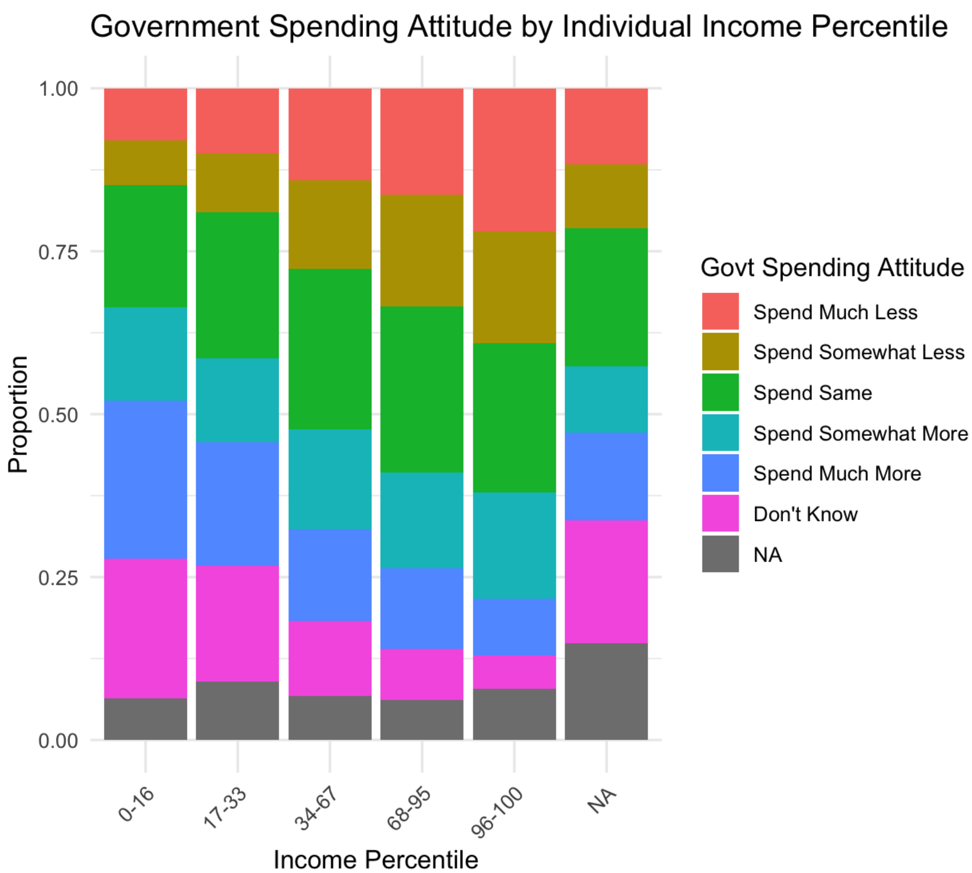

Figure 3: A stacked bar graph showing the proportion of government spending attitude within each individual income percentile.

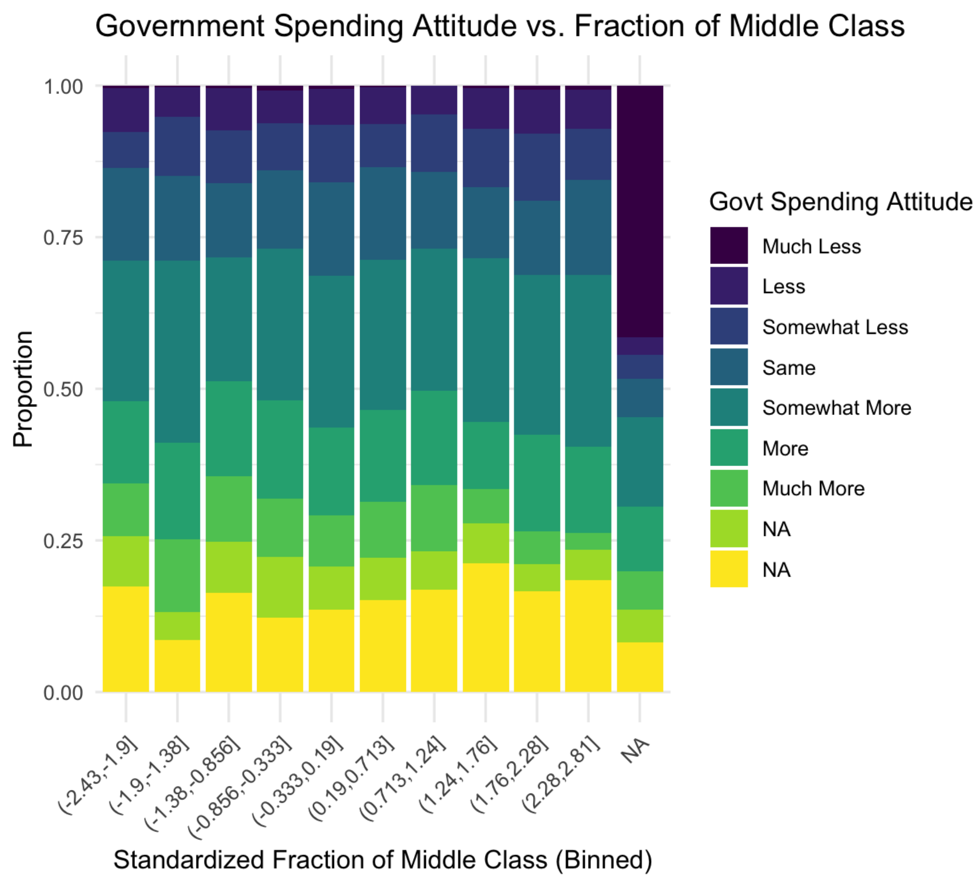

Figure 4: A stacked bar graph of the relationship of government spending attitude and the fraction of middle class in the county. The values of standardized fraction of middle class on the x-axis close to 0 indicate counties with an average fraction of middle class, positive values (e.g. 1, 2 etc.) indicate counties with above-average middle class fractions, and negative values (e.g. -1, -2, etc.) indicate counties with below-average middle class fractions.

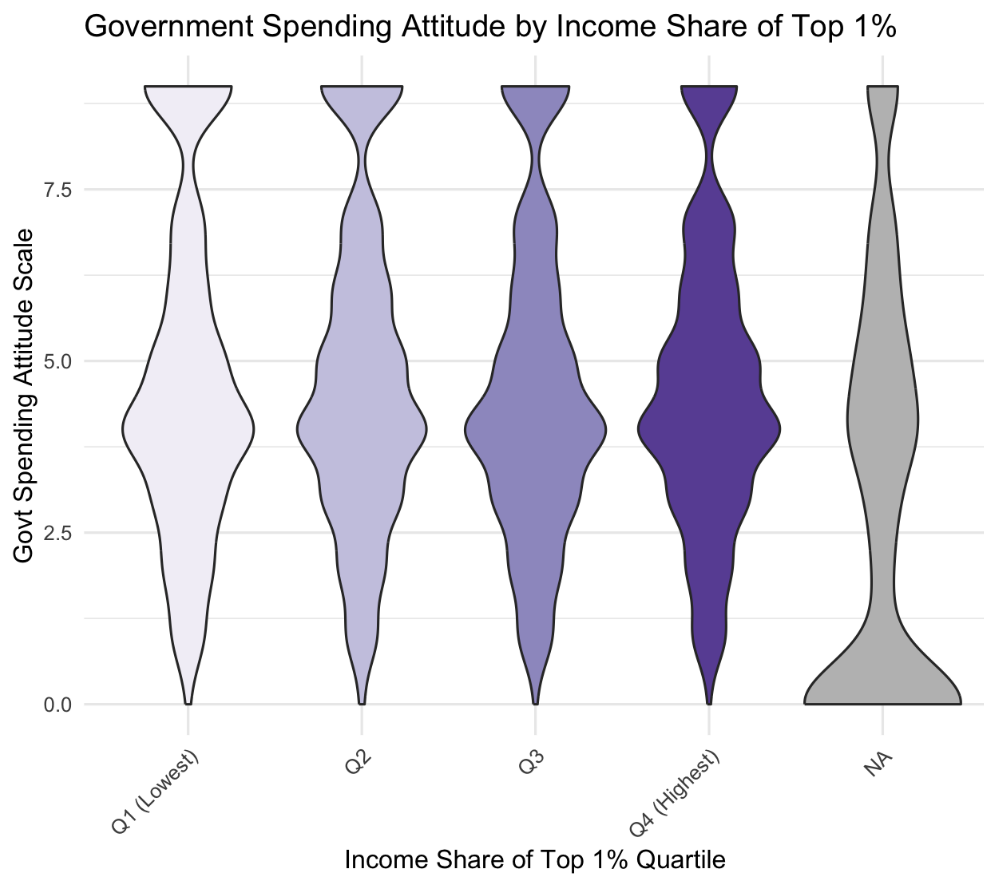

Figure 5: A violin plot showing the relationship between government spending attitude and the income share of the top 1%. On the x-axis, Q1 represents counties with the lowest income share of the top 1%, Q2 the counties with a low-to-moderate income share of the top 1%, Q3, the counties with a moderate-to-high income share of the top 1%, and Q4 the counties with the highest income share of the top 1%. NA is the counties with missing data for the income share of the top 1%.

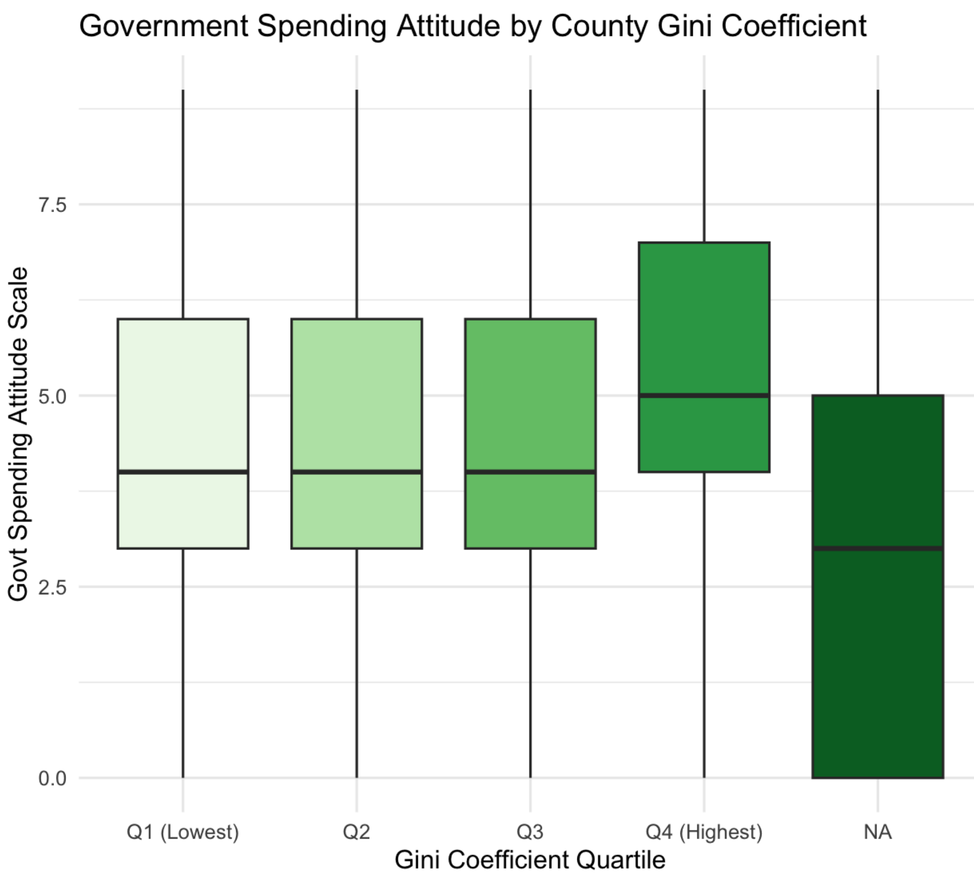

Figure 6: A box plot showing the relationship between government spending attitude and the measure of income inequality Gini coefficient for counties. On the x-axis, Q1 represents counties with the lowest income inequality i.e. lowest Gini coefficient, Q2 the counties with a low-to-moderate income inequality, Q3, the counties with a moderate-to-high income inequality, and Q4 the counties with the highest income inequality. NA is the counties with missing data for the Gini coefficient.

Table 1: Government Spending Attitude Regression Results

	Dependent variable: Government Spending Attitude Scale			
	Estimate	Cluster s.e.	t value	Pr(>|t|)
Income Percentile 17-33	−0.35413	0.11867	−2.984	0.00523**
Income Percentile 34-67	−0.91377	0.11011	−8.299	$1.10e-09$***
Income Percentile 68-95	−1.14380	0.12243	−9.343	$6.46e-11$***
Income Percentile 96-100	−1.23882	0.17209	−7.199	$2.50e-08$***
Social Class: Working	−0.89609	0.54469	−1.645	0.10916
Social Class: Average Middle	−1.26899	0.49994	−2.538	0.01589*
Social Class: Middle	−1.72518	0.58497	−2.949	0.00573**
Social Class: Upper Middle	−1.57881	0.53991	−2.924	0.00611**
Social Class: Upper	−3.03134	0.94186	−3.218	0.00283**
County Household Income (z-score)	−0.02656	0.07475	−0.355	0.72458
Gini Coefficient (z-score)	0.18968	0.09658	1.964	0.05776·
Income Share of Top 1% (z-score)	−0.05128	0.11137	−0.460	0.64810
Fraction of Middle Class (z-score)	0.04011	0.05433	0.738	0.46541
Observations	5542			
R^2 (full model)	0.1105			
$R^2_{adjusted}$ (full model)	0.1025			
R^2 (proj model)	0.06064			
$R^2_{adjusted}$ (proj model)	0.05226			
Residual Std. Error	2.199 (df = 5493)			
F Statistic (full model, *iid*)	13.92 on 49 and 5493 DF, p-value: < 2.2e-16			
F Statistic (proj model)	39.66 on 13 and 34 DF, p-value: < 2.2e-16			
Residuals:				
Min: -6.4206, 1Q: -1.4593, Median: -0.2732, 3Q: 1.2764, Max: 5.8151				

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.1 Conclusion

This study provides evidence that individual income is a key determinant of attitudes towards government spending on social services. Consistent with the literature, we find that higher income individuals are less supportive of social spending, likely because they expect to benefit less directly from such programs. This self-interested attitude is apparent across the income distribution and social class hierarchy.

At the county level, higher income inequality predicts somewhat greater support for social spending, perhaps reflecting a desire to mitigate disparities, but other contextual economic factors appear less influential. The limited explanatory power of our model underscores that other political, social, and demographic variables not captured here also shape views on the social safety net. Further research could examine a wider range of contextual factors and individual characteristics to develop a more complete model of the complex dynamics influencing these attitudes. Expanding the temporal and geographic scope of analysis would also help establish the generalizability of the relationships identified here.

References

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5 Appendix

Attached below is the code used to generate this analysis:

```
library(tidyverse)
library(ggplot2)
library(dplyr)
file_path = "/Users/likhitha/Documents/Data and Policy/uchicago-data-and-policy-scholar/
setwd(file_path)
anes_data <- read_csv("Data/ANES/anes_timeseries_cdf_csv_20220916.csv")
chetty_county <- read_csv("Data/Chetty/chetty_county.csv")



# filters for the range 1990-2000 and selects relevant variables
anes_data <- anes_data %>%
  filter(
    VCF0004 >= 1990 & VCF0004 <= 2000
  ) %>%
  select(VCF0901b, VCF0170d, VCF0004, VCF0114, VCF0148, VCF0148a, VCF0839)

names(anes_data)[names(anes_data) == "VCF0901b"] <- "stateabbrv"
names(anes_data)[names(anes_data) == "VCF0170d"] <- "cty2000"
names(anes_data)[names(anes_data) == "VCF0004"] <- "year"
names(anes_data)[names(anes_data) == "VCF0114"] <- "income_group"
names(anes_data)[names(anes_data) == "VCF0148"] <- "social_class_middle"
names(anes_data)[names(anes_data) == "VCF0148a"] <- "social_class_upper"
names(anes_data)[names(anes_data) == "VCF0839"] <- "govt_spending_scale"

chetty_county <- chetty_county %>%
  select(stateabbrv, cty2000, hhinc00, gini, inc_share_1perc, frac_middleclass,
         cs00_seg_inc, cs00_seg_inc_pov25, cs00_seg_inc_aff75, taxrate,
         subcty_total_taxes_pc, subcty_total_expenditure_pc, unemp_rate)

# merge by county
merged_county <- left_join(anes_data, chetty_county, by = c("cty2000", "stateabbrv"))
```

```
merged_county <- merged_county %>%
  mutate(
    social_class = case_when(
      social_class_middle == 0 ~ "Lower",
      social_class_middle %in% c(1, 2, 3) | social_class_upper %in% c(1, 2, 3) ~ "Workin
      social_class_middle == 4 | social_class_upper == 4 ~ "Average Middle",
      social_class_middle == 5 | social_class_upper == 5 ~ "Middle",
      social_class_middle == 6 | social_class_upper == 6 ~ "Upper Middle",
      social_class_middle == 7 ~ "Upper",
      TRUE ~ NA_character_
    ),
    is_upper_class = ifelse(social_class %in% c("Upper Middle", "Upper"), 1, 0),
    income_percentile = case_when(
      income_group == 1 ~ "0-16",
      income_group == 2 ~ "17-33",
      income_group == 3 ~ "34-67",
      income_group == 4 ~ "68-95",
      income_group == 5 ~ "96-100",
      TRUE ~ NA_character_
    ),
    govt_spending_attitude = case_when(
      govt_spending_scale %in% c(1, 2) ~ "Spend Much Less",
      govt_spending_scale == 3 ~ "Spend Somewhat Less",
      govt_spending_scale == 4 ~ "Spend Same",
      govt_spending_scale == 5 ~ "Spend Somewhat More",
      govt_spending_scale %in% c(6, 7) ~ "Spend Much More",
      govt_spending_scale == 9 ~ "Don't Know",
      TRUE ~ NA_character_
    )
  )


merged_county <- merged_county %>%
  mutate(across(c(hhinc00, gini, inc_share_1perc, frac_middleclass),
                ~scale(.) %>% as.vector(),
                .names = "{.col}_z"))
```

```r
install.packages("lme4")
library(lme4)


merged_county$income_percentile <- factor(merged_county$income_percentile,
                                          levels = c("0-16", "17-33", "34-67", "68-95",

merged_county$social_class <- factor(merged_county$social_class,
                                     levels = c("Lower", "Working", "Average Middle", "M




merged_county$govt_spending_attitude <- factor(merged_county$govt_spending_attitude,
                                               levels = c("Spend Much Less", "Spend Some
                                                          "Spend Somewhat More", "Spend


install.packages("lfe")
library(lfe)

felm_model <- felm(govt_spending_scale ~ income_percentile + social_class +
                     hhinc00_z + gini_z + inc_share_1perc_z + frac_middleclass_z |
                     stateabbrv + year | 0 | stateabbrv,
                   data = merged_county)

summary(felm_model)




library(dplyr)

ggplot(merged_county, aes(x = social_class, fill = govt_spending_attitude)) +
```

```
  geom_bar(position = "fill") +
  labs(title = "Government Spending Attitude by Social Class",
       x = "Social Class", y = "Proportion",
       fill = "Govt Spending Attitude") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

merged_county_clean <- merged_county %>%
  filter(!is.na(hhinc00) & !is.na(govt_spending_scale) &
           is.finite(hhinc00) & is.finite(govt_spending_scale))

# relationship between county income and government spending attitude

median_incomes <- merged_county_clean %>%
  group_by(govt_spending_attitude) %>%
  summarise(median_income = median(hhinc00, na.rm = TRUE))

ggplot(merged_county_clean, aes(x = hhinc00)) +
  geom_density(adjust = 1.5, fill = "gray70", alpha = 0.7) +
  geom_vline(data = median_incomes, aes(xintercept = median_income),
             linetype = "dashed", color = "red", size = 1) +
  facet_wrap(~ govt_spending_attitude, scales = "free_y") +
  labs(title = "Distribution of County Income by Government Spending Attitude (1990-2000
       subtitle = "Red dashed line shows the median income",
       x = "County Household Income (Adjusted to 2000 Dollars)",
       y = "Density") +
  theme_minimal() +
  scale_x_continuous(labels = scales::dollar_format(),
                     breaks = seq(20000, 80000, by = 20000)) +
  scale_y_continuous(labels = scales::percent_format(scale = 100)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1),
        strip.background = element_rect(fill = "lightblue", color = "black"),
        strip.text = element_text(face = "bold"))
```

```r
ggplot(merged_county, aes(x = income_percentile, fill = govt_spending_attitude)) +
  geom_bar(position = "fill") +
  labs(title = "Government Spending Attitude by Individual Income Percentile",
       x = "Income Percentile", y = "Proportion",
       fill = "Govt Spending Attitude") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```r
ggplot(merged_county, aes(x = cut(frac_middleclass_z, breaks = 10),
                          fill = factor(govt_spending_scale))) +
  geom_bar(position = "fill") +
  scale_fill_viridis_d(name = "Govt Spending Attitude",
                       labels = c("Much Less", "Less", "Somewhat Less", "Same",
                                  "Somewhat More", "More", "Much More", "NA")) +
  labs(title = "Government Spending Attitude vs. Fraction of Middle Class",
       x = "Standardized Fraction of Middle Class (Binned)",
       y = "Proportion") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```

```r
top1_data <- merged_county %>%
  mutate(top1_quartile = case_when(
    is.na(inc_share_1perc_z) ~ "NA",
    TRUE ~ as.character(cut(inc_share_1perc_z,
                            breaks = quantile(inc_share_1perc_z, probs = 0:4/4, na.rm =
                            labels = c("Q1 (Lowest)", "Q2", "Q3", "Q4 (Highest)"),
                            include.lowest = TRUE))
  )) %>%
```

```
  mutate(top1_quartile = factor(top1_quartile, levels = c("Q1 (Lowest)", "Q2", "Q3", "Q4


ggplot(top1_data, aes(x = top1_quartile, y = govt_spending_scale)) +
  geom_violin(aes(fill = top1_quartile)) +
  scale_fill_manual(values = c(RColorBrewer::brewer.pal(4, "Purples"), "grey")) +
  labs(title = "Government Spending Attitude by Income Share of Top 1%",
       x = "Income Share of Top 1% Quartile", y = "Govt Spending Attitude Scale",
       fill = "Top 1% Share Quartile") +
  theme_minimal() +
  theme(legend.position = "none",
        axis.text.x = element_text(angle = 45, hjust = 1))
```

```
gini_data <- merged_county %>%
  mutate(gini_quartile = case_when(
    is.na(gini_z) ~ "NA",
    TRUE ~ as.character(cut(gini_z,
                            breaks = quantile(gini_z, probs = 0:4/4, na.rm = TRUE),
                            labels = c("Q1 (Lowest)", "Q2", "Q3", "Q4 (Highest)"),
                            include.lowest = TRUE))
  )) %>%
  mutate(gini_quartile = factor(gini_quartile, levels = c("Q1 (Lowest)", "Q2", "Q3", "Q4

ggplot(gini_data, aes(x = gini_quartile, y = govt_spending_scale)) +
  geom_boxplot(aes(fill = gini_quartile)) +
  scale_fill_brewer(palette = "Greens") +
  labs(title = "Government Spending Attitude by County Gini Coefficient",
       x = "Gini Coefficient Quartile", y = "Govt Spending Attitude Scale",
       fill = "Gini Quartile") +
  theme_minimal() +
```

```
theme(legend.position = "none")
```