Exploring the Impact of County, State-Level Economic Factors on Sentiment Toward the Presidential Incumbent and Challenger: A Test of Economic Voting Theory

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1 Introduction

In 2020, the United States faced severe economic downturn due to the COVID-19 pandemic, with many states experiencing stagnant economic growth and higher poverty levels (Reality Check Team, 2020). Albeit unfortunate, these conditions foster an ideal environment to determine how economic slumps influence political behavior. Interestingly, economic voting theory suggests that voters electorally support the incumbent and oppose the challenger when the economy is strong but turn against the incumbent and favor the challenger when the economy is weak (Lewis-Beck and Nadeau, 2010). Whilst traditionally applied to ballot behavior, social media has introduced a new avenue for expressing public sentiment. This study extends economic voting theory to posts on Twitter. Regarding economic factors, this research focuses on unemployment, taxes, housing costs, wages, income inequality, poverty, personal consumption expenditure, and GDP, which are directly relevant to Americans' economic concerns (Gallup, 2019; Silver, 2025). Therefore,we want to examine whether economic conditions—such as unemployment, taxes, housing costs, poverty, personal consumption expenditures, income inequality, income per capita, and GDP—predict public sentiment toward political candidates. More specifically, I aimed to test whether worse/better economic conditions are associated with more negative/positive sentiment toward the president and more positive/negative sentiment toward the challenger, as suggested by economic voting theory.

In U.S. presidential elections, voters are generally sociotropic and retrospective (Leighley, 2010; Sartorius, 2015), meaning they evaluate county and state-level economic conditions and their respective year-end economic growth. In addition, they assess their county and state's current economy (Healy and Lenz, 2013; Hopkins, 2017; Kinder and Kiewiet, 1981; Sartorius, 2015). At the county and state level, voters typically assess factors, such as unemployment, taxes, housing costs, wages, personal income, personal consumption expenditures, income inequality, poverty rate, and GDP (Silver, 2025). Research consistently shows that economic conditions sway electoral outcomes (Lewis-Beck and Stegmaier, 2000; De BenedictisKessner and Warshaw, 2020), and that election-related tweets can serve as proxies for determining who people would vote for (Fujiwara et al., 2023). Crucially, I assume American tweeters yield the same preferences and behaviours as American voters. Therefore, in line with economic voting theory, worse/better economic conditions at the county and/or state level should result in more negative/positive tweets about the president and more positive/negative tweets about the challenger. Now, we move onto our methodology section.

2 Data

This study combines political tweet data from the 2020 U.S. election with county and state-level economic indicators to explore how economic conditions relate to digital political expression. The tweet data comes from the publicly available "US Election 2020 Tweets" dataset on Kaggle, which includes over 7 million tweets. Using geolocation and text classification, tweets were aggregated by county and state, and categorized by negative sentiment toward Trump or Biden using a sentiment analysis tool.

County-level economic variables were sourced from the U.S. Census Bureau and the Bureau of Economic Analysis (BEA). These indicators include GDP, poverty rate, housing costs, unemployment rate, income per capita, income inequality (Gini index), and population, along with growth rates calculated from 2019 to 2020. Each county represents one observation. State-level indicators include GDP, poverty, unemployment, taxes, housing prices, personal income, and personal consumption expenditure along with their growth rates. These variables were sourced from BEA, BLS, U.S. Census, the Tax Foundation, and the FHFA. To incorporate public infrastructure, this study adds library data scraped from archived versions of PublicLibraries.com using the Wayback Machine. Importantly, this data was only used for the machine learning regressions. The dataset captures the number of libraries per county in 2020, providing a measure of investment in public learning resources.

Overall, the final dataset contains county-level economic and tweet data (n = 1,500). This structure allows a nuanced analysis of how economic factors shape online political sentiment.

3 Summary Statistics and Visualization

3.1 Description of Explanatory Variables

To begin, our negative tweet frequencies for Trump and Biden are heavily skewed towards 0 with minimal variance as most counties have a small number of total tweets for Trump and Biden. This phenomenon stems from most counties not having that many Twitter users who actively post. To remediate this issue, I applied an arcsin transformation for my linear regression to account for this strong left-handed skewness. This skewness indicates selection bias permeating tweets counts for all counties, which may stem from low population and/or social media usage.

3.2 Description of Outcome Variables

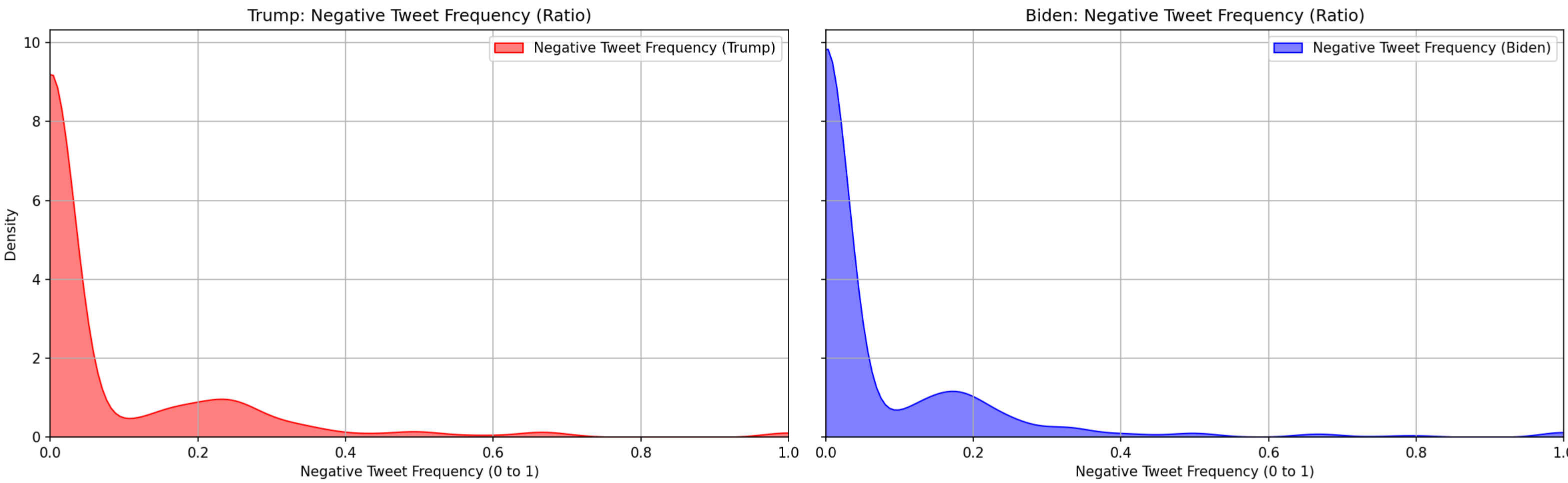

Figure 1: Distribution of Negative Tweet Frequencies for Trump and Biden

There is substantial variation in economic indicators across counties and states. State-level unemployment averages 7.3% (SD = 1.5%), while county-level unemployment is 5.23% with greater variance, suggesting regional economic disparities. Higher unemployment likely fuels dissatisfaction with the incumbent. State per capita income averages \$56,854 (SD = \$7,800), compared to \$28,990 at the county level, with lower-income areas potentially expressing more negative sentiment. State tax rates (mean = 5.4%, SD = 1.5) and housing price indices (mean = 427, SD = 117) also vary widely, with rising housing costs possibly contributing to tweeter frustration. State PCE (mean = \$410,565, SD = \$422,016) and county GDP (mean = \$114,978, SD = \$2.43 million) show stark disparities, likely tied to economic dissatisfaction. Income inequality is high across counties (Gini mean = 0.44, SD = 0.04), as is poverty (mean = 15%, SD = 6%), both of which may intensify negative sentiment. State-level poverty shows similar patterns with less variation.

From 2019 to 2020, state unemployment rose by 109%, signaling severe economic strain, while income rose modestly (5.8%) and GDP and PCE declined by 2–2.2%, likely increasing negativity toward the incumbent. County-level growth trends mirror these patterns. Library counts (mean = 6.4, SD = 7.6) vary widely by county, but their relationship with economic sentiment remains speculative.

3.3 Scatterplots

I removed outliers (outside of 2.5 std) for all my plots. The following indicators were excluded due to lack of significance: state tax rate growth, average local tax rate growth, combined rate growth, max local tax rate growth, GDP growth, 2020 poverty rate, poverty rate growth, tax rate, average local tax rate, combined rate, max local tax rate, personal income growth, and income inequality growth (Gini %). In addition, many of our scatter plots with significant relationships completely deviated from economic voting theory. For example, higher per capita income correlates with higher negative tweets toward Trump, contradicting economic voting theory—stronger personal financial conditions should not increase blame on the incumbent. In contrast, Biden receives more negativity in poorer states, who should retaliate against Trump, not Biden.

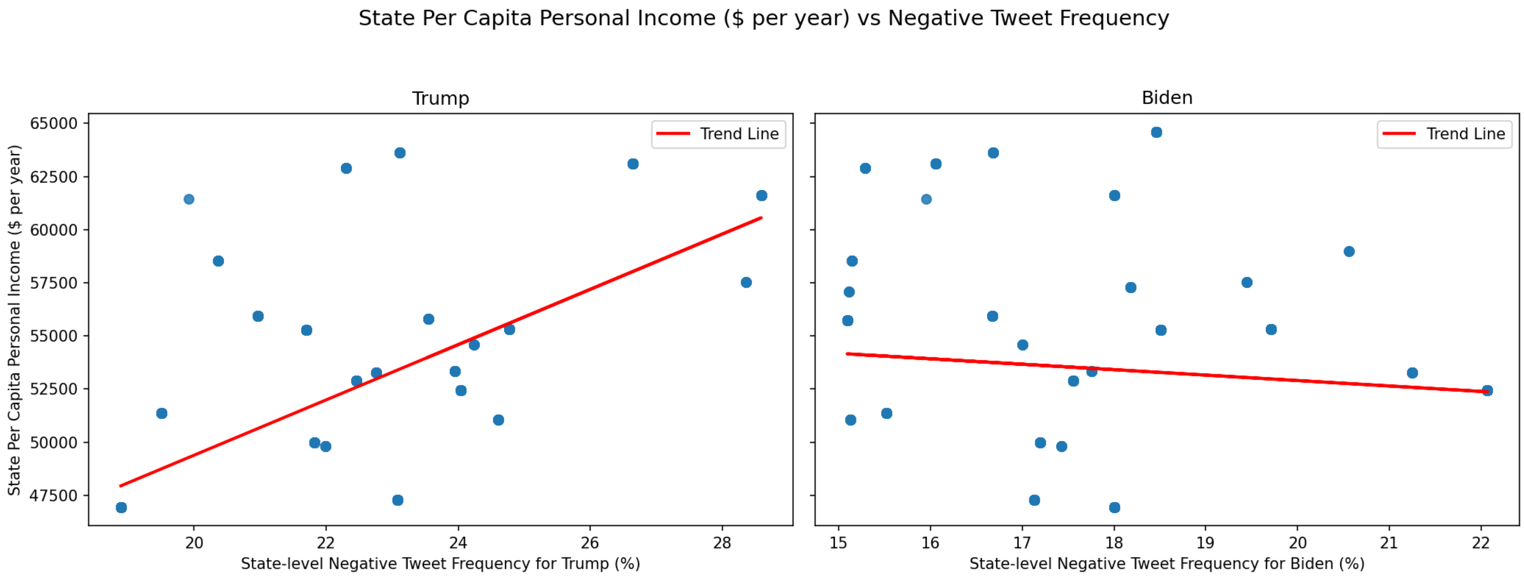

Figure 2: State Per Capita Personal Income ($ per year) versus Negative Tweet Frequency

Albeit rare, some line plots were consistent with economic voting theory. For example, even though state-level income growth has little association with negative tweets toward Trump, tweet negativity increases as income growth rises for Biden—strongly supporting economic voting theory.

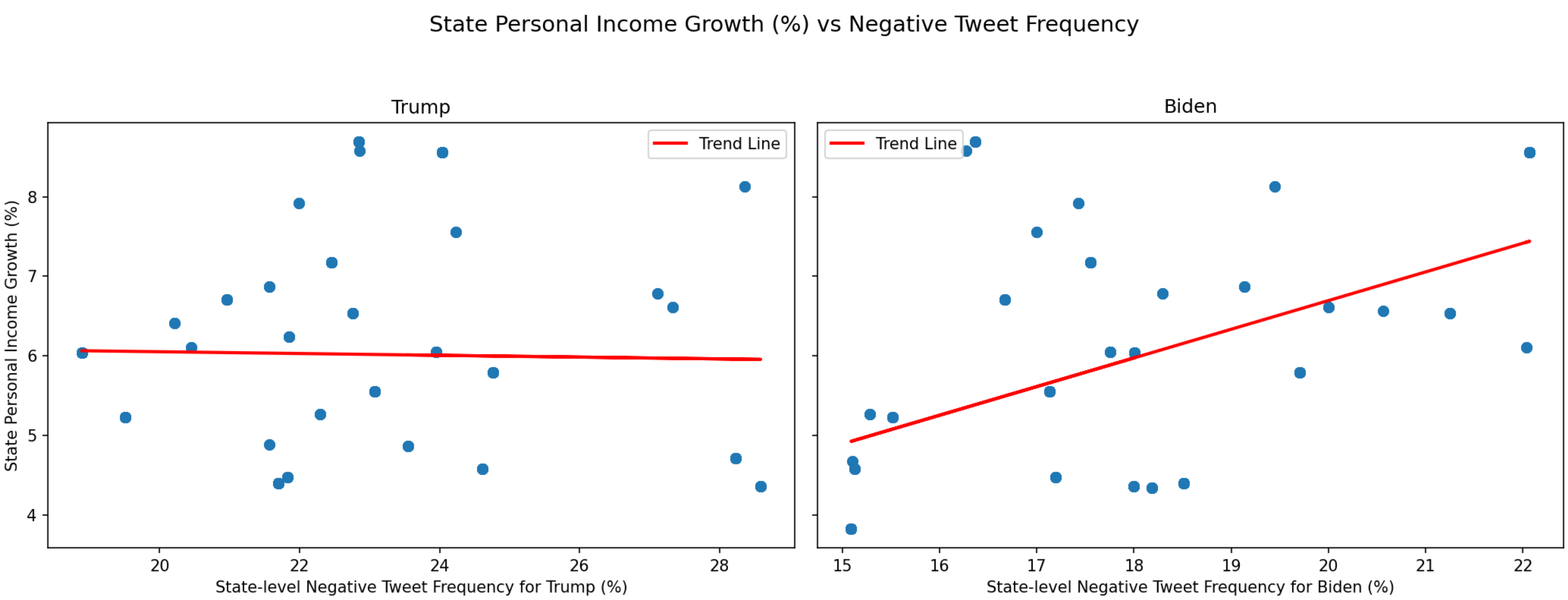

Figure 3: State Per Capita Personal Income ($ per year) versus Negative Tweet Frequency

Regarding my county-level scatter plots, I only included those with significant relationships. Interestingly, negative tweet frequency for Trump did not exhibit any significant relationships with county-level economic indicators; however, the same cannot be said for Biden.

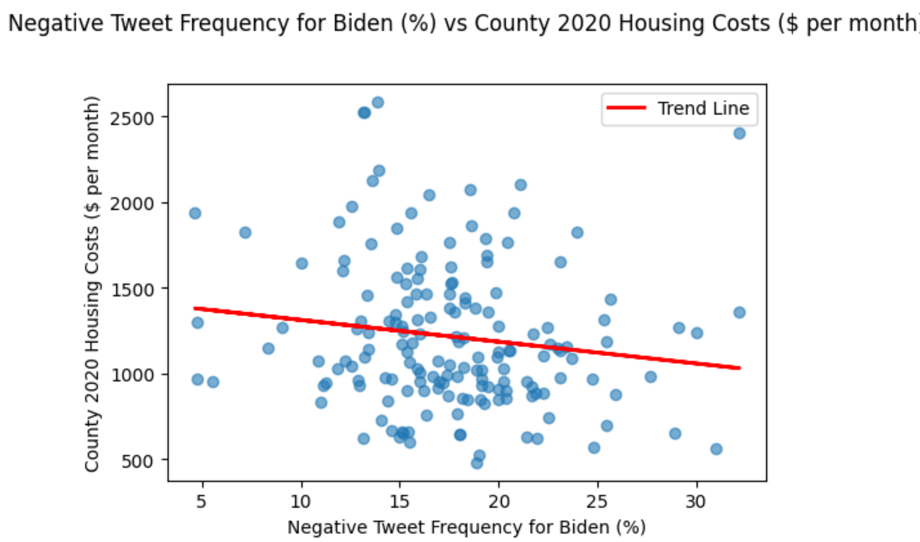

Figure 4: Negative Tweet Frequency for Biden (%) versus County 2020 Housing Costs ($ per month)

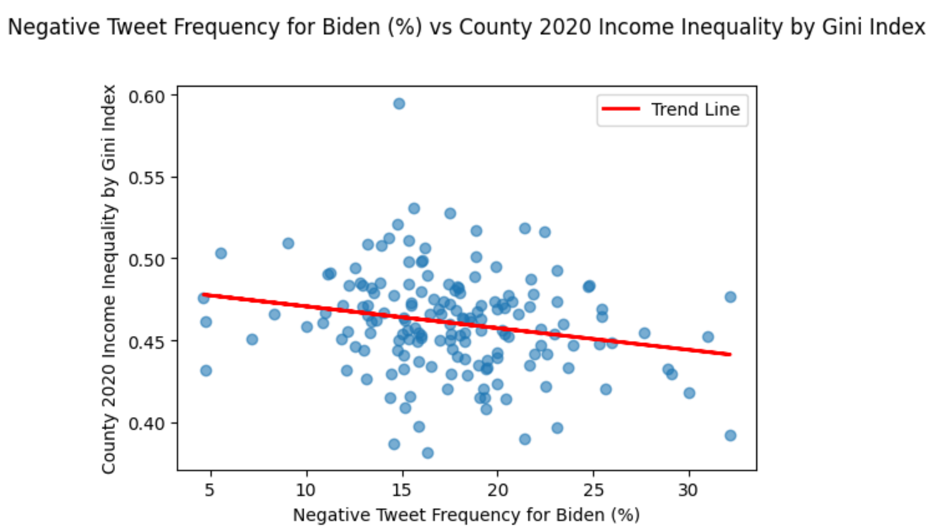

Figure 5: Negative Tweet Frequency for Biden (%) versus County 2020 Income Inequality by Gini Index

These Biden plots support economic voting theory, as economic conditions worsen (housing costs and income inequality), tweeters scrutinize the presidential challenger less.

Overall, my scatter plots indicate that American tweeters are more responsive to state-level economic conditions than to county-level economic conditions. Notably, the link between state and county-level economic factors and negative tweets about Biden seems weaker relative to Trump, suggesting that tweeters focus more on the presidential incumbent and their relation to the economy than the presidential challenger. Regarding our line plots, most tweeters do not seem to prefer growth rates (retrospective) over current economic conditions. Again, many of our relationships were incongruent with economic voting theory. Crucially, these scatter plots suggest that the most important state-level economic indicators are unemployment rate growth, unemployment rate, housing index, personal consumption expenditure, per capita personal income and its growth, and current-dollar GDP and its per capita equivalent by the strength of their line plot. Conversely, the most flagrant county-level economic indicators are housing costs per month and income inequality by Gini index.

3.4 Geographical Maps

I created geomaps to visualize the geographical relationship between negative tweet frequency and key county and state-level economic indicators identified in our scatterplot analysis. Also, I omitted Alaska and Hawaii due to missing data points. Additionally, I identified housing costs and income inequality (measured by the Gini index) as the most important county-level indicators from previous scatterplots. Mapping key state and county-level data helps assess whether people place more weight on key state-level economic indicators compared to key county-level factors when tweeting.

To gain a more comprehensive understanding of key state-level economic conditions, I developed an aggregate economic index that equally weighs key state-level variables: unemployment rate, unemployment growth rate, housing index, state-level personal consumption expenditure, per capita personal income, and state-level current-dollar GDP. This index enables us to pinpoint regions that are either prosperous or economically disadvantaged. By comparing this index map with negative tweet frequency data, I can further explore how various economic factors at the state level align with political sentiment.

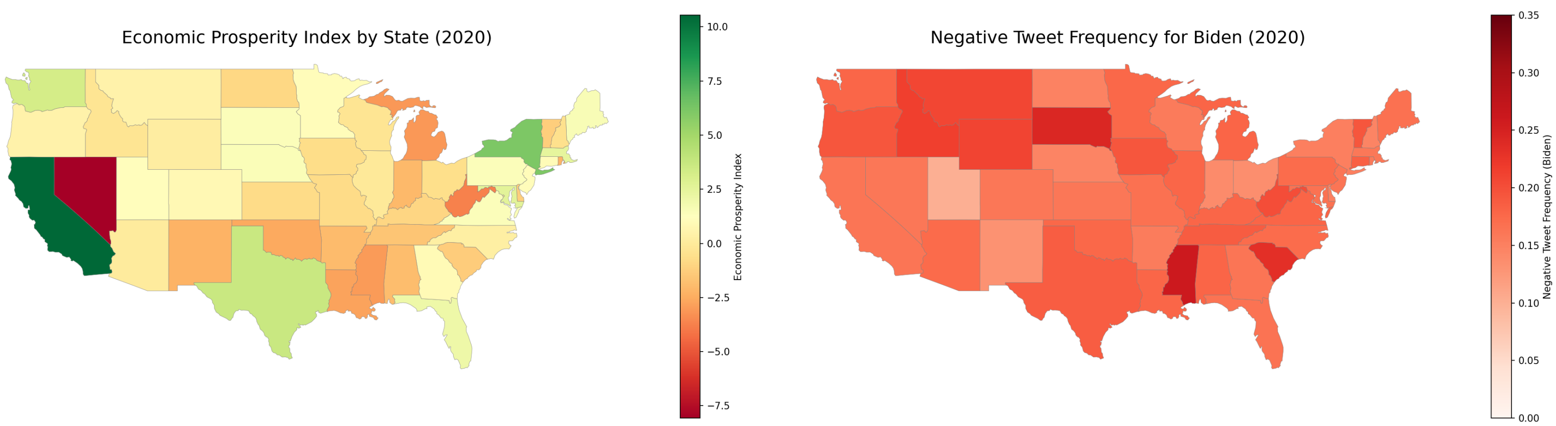

Figure 6: Aggregate Economic Prosperity Index and Negative Tweet for Biden

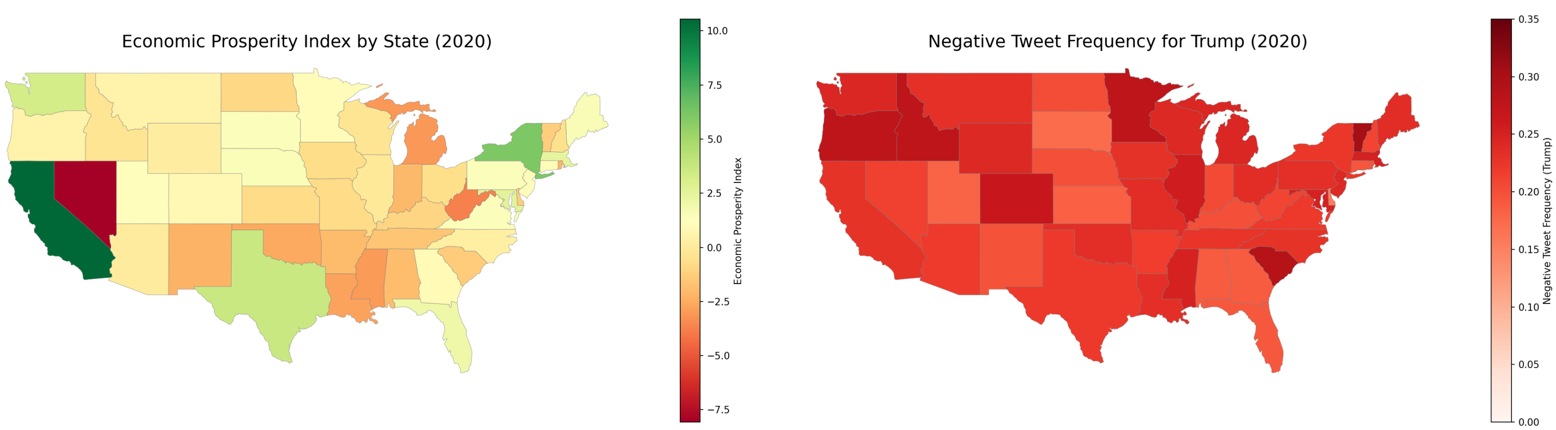

Figure 7: Aggregate Economic Prosperity Index and Negative Tweet for Trump

The state-level economic index map also revealed considerable variation in economic indicators across states. Interestingly, the states with the worst economies, such as Nevada, heavily relied on tourism, which was hit hard by COVID-19 shutdowns. One notable observation is that negative tweet frequencies targeting Trump and Biden do not show a strong correlation with the aggregate prosperity index. This notion contradicts economic voting theory as I would expect states with the worst economic indices to have higher/lower negative tweet frequencies for Trump/Biden. This complexity underscores that negative sentiment on Twitter is driven by extraneous stressors not related to politics, such as political propaganda. Our dataset contains some outliers. For example, Texas—an economically prosperous state—showed elevated negative tweet frequencies for Trump, while Florida, a more economically disadvantaged state, displayed less negative sentiment for Trump than expected. This contradicts traditional economic voting theory.

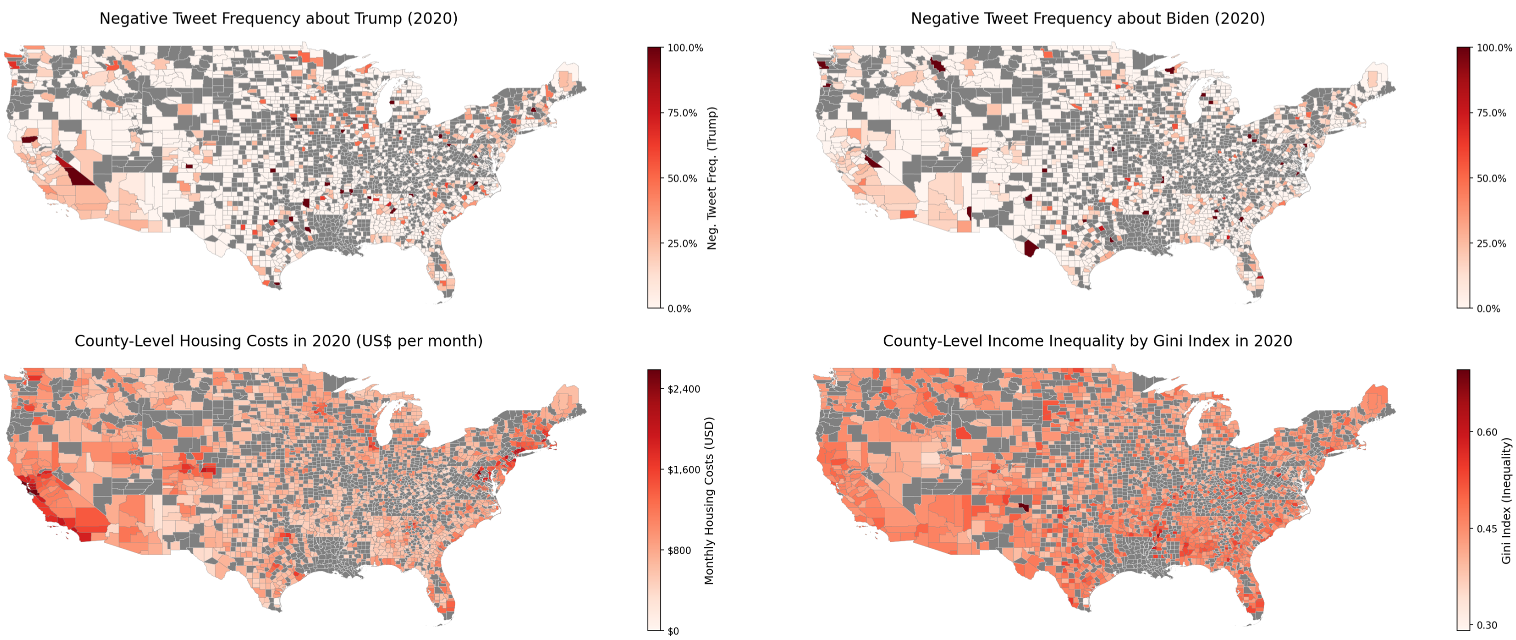

Figure 8: County-level Housing Costs in 2020, Income Inequality, and negative tweet frequency for Trump and Biden

At the county level, the analysis revealed a weaker correlation between negative tweet frequency and important county-level economic indicators. Again, this suggests that people tend to weigh state-level economic conditions more heavily than county-level economic indicators when forming their opinions. Additionally, many counties were grey on the map, indicating missing values. This highlights potential selection bias in our dataset, substantiating the need for more robust statistical methods, such as a Heckman selection model, to address these issues and improve the accuracy of our findings.

4 Regressions

4.1 Motivation

The aforementioned scatterplots suggest a linear relationship between economic variables and negative tweet frequencies for Trump and Biden. Knowing that political behaviour tend to follow retrospective and sociotropic inputs, I included current and growth economic variables at the state and county levels. In a similar vein, I combined growth and current economic variables to examine how past economic trends and present conditions collectively influence tweeting behavior. Additionally, state fixed effects were included to control for state-level extraneous variables, such as political climate, that could impact the frequency of negative tweets for specific regions. Finally, the arcsine transformation was applied to adjust the skewed distribution of the dependent variable. All models account for state-fixed effects.

4.2 Regression Assumptions

All multiple linear regression assumptions were met. Assumptions 1 and 2—zero mean of residuals and independent, identically distributed observations—were satisfied via the mean of residuals and Durbin-Watson tests. Assumption 3 (no large outliers) was addressed by excluding values beyond ±4 standard deviations. Assumption 4 (no perfect multicollinearity) also held.

However, imperfect multicollinearity was present among some regressors. Notably, state tax rate growth and state max local tax rate growth were nearly collinear, while state average local tax rate growth and combined rate growth showed moderate correlation. To resolve this, I excluded the four tax-related variables. Additionally, due to strong correlation between state personal consumption expenditure and state GDP, the latter was removed. For the full model, further correlation analysis led to the exclusion of three more variables: county income per capita, state poverty rate, and state PCE growth, to mitigate multicollinearity in the final regression.

4.3 Regression Models

Model 1: $Y_{\text{Trump/Biden},i} = \beta_0 + \sum_{i=1}^{6} \beta_i X_{\text{County Growth},i} + \sum_{j=1}^{7} \beta_j X_{\text{State Growth},j} + \sum_{k=1}^{m} \gamma_k D_{\text{State},k} + \epsilon$

Model 2: $Y_{\text{Trump/Biden},i} = \beta_0 + \sum_{i=1}^{7} \beta_i X_{\text{County Current},i} + \sum_{j=1}^{7} \beta_j X_{\text{State Current},j} + \sum_{k=1}^{m} \gamma_k D_{\text{State},k} + \epsilon$

Model 3: $Y_{\text{Trump/Biden},i} = \beta_0 + \sum_{i=1}^{24} \beta_i X_{\text{Full Model},i} + \epsilon$

Model 4: $Y_{\text{Trump/Biden},i} = \beta_0 + \sum_{k=1}^{6} \beta_k X_{\text{County Growth},k} + \sum_{l=1}^{7} \beta_l X_{\text{State Growth},l} + \lambda \cdot \text{IMR}_i + \epsilon_i$

However, our fourth model addresses potential sample selection bias using a two-stage approach: a probit selection equation followed by an outcome equation with the Inverse

Mills Ratio (IMR). The probit selection equation, being the probability of observing a tweet, is modeled by a latent variable:

$$\text{TweetPresence}_i^* = Z_i^\top \gamma + \nu_i \tag{1}$$

with observation rule:

$$\text{TweetPresence}_i = \begin{cases} 1 & \text{if TweetPresence}_i^* > 0 \\ 0 & \text{otherwise} \end{cases}$$

where Z_i is a vector of selection variables ('County Population 2020', 'County 2020 Internet Access Percentage'), γ the associated coefficients, and $\nu_i \sim \mathcal{N}(0, 1)$. In addition, the IMR is calculated as:

$$\text{IMR}_i = \frac{\phi(Z_i^\top \gamma)}{\Phi(Z_i^\top \gamma)} \tag{2}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal PDF and CDF, respectively. **For all models**:

County Growth = {County Housing Cost Growth (%), County GDP Growth (%), County Income Growth (%), County Income Equality Growth (%), County Poverty Rate Growth (%), County Unemployment Rate Growth (%)}

State Growth = {State Unemployment Growth Rate, State Personal Consumption Expenditure Growth (%), State Personal Income Growth (%), State Housing Index Growth Rate, State GDP Growth Rate, State Poverty Rate Growth (%), State Income Inequality Growth (%)}

County Current = {County 2020 Housing Costs, County 2020 Income, County 2020 Gini

Index, County 2020 Poverty Rate, County 2020 Unemployment Rate, County 2020 GDP (Current Dollars), County 2020 GDP per capita$\}$

State Current = $\{$State 2020 Poverty Rate, State 2020 Income Inequality, State Unemployment Rate, State Personal Consumption Expenditure, State Per Capita Personal Income, State Tax Rate, State Housing Index$\}$

X_{full_model} = $\{$County Growth $\cup$ County Current $\cup$ State Growth $\cup$ State Current$\}$ / $\{$County 2020 Income per Capita ($ per year), State 2020 Poverty Rate (%), State Personal Consumption Expenditure Growth (%)$\}$

Table 1: Regression Results for Trump Sentiment

	(1)	(2)	(3)	(4)
County Housing Cost Growth (%)	0.002		0.002	0.002
	(0.002)		(0.002)	(0.002)
County GDP Growth (%)	-0.000		0.000	0.000
	(0.001)		(0.001)	(0.001)
County Income Growth (%)	0.001		0.002	0.000
	(0.002)		(0.002)	(0.002)
County Income Equality Growth (%)	-0.003		-0.001	-0.004*
	(0.002)		(0.002)	(0.002)
County Poverty Rate Growth (%)	0.000		0.000	0.001
	(0.001)		(0.001)	(0.001)
County Unemployment Rate Growth (%)	0.001***		0.001***	0.001***
	(0.000)		(0.000)	(0.000)
County 2020 Housing Costs ($)		0.000	0.000*	
		(0.000)	(0.000)	
County 2020 Income per Capita ($)		-0.000	-0.000	
		(0.000)	(0.000)	
County 2020 Income Inequality (Gini)		-0.549*	-0.418	
		(0.295)	(0.326)	
County 2020 Poverty Rate (%)		0.001	-0.000	
		(0.002)	(0.003)	
County 2020 Unemployment Rate (%)		0.000	-0.001	
		(0.004)	(0.004)	
County 2020 GDP		-0.000**	-0.000*	
		(0.000)	(0.000)	
County 2020 GDP per capita		0.000	0.000	
		(0.000)	(0.000)	
State Unemployment Growth Rate (%)	0.001**		0.002	0.001**
	(0.000)		(0.001)	(0.000)
State PCE Growth (%)	0.009		0.007	0.013*
	(0.016)		(0.024)	(0.007)
State Income Growth (%)	-0.003		0.003	0.004
	(0.009)		(0.013)	(0.005)
State Housing Index Growth (%)	-0.021*		-0.017	-0.002
	(0.011)		(0.015)	(0.007)
State GDP Growth (%)	0.022**		0.028*	0.007
	(0.011)		(0.015)	(0.006)
State Poverty Rate Growth (%)	0.008		0.008	0.008
	(0.013)		(0.018)	(0.008)
State Inequality Growth (%)	-0.065		-0.075	-0.015
	(0.043)		(0.062)	(0.025)
State 2020 Poverty Rate (%)		0.003	0.007	
		(0.013)	(0.026)	
State 2020 Inequality (Gini)		-0.332	1.096	
		(1.590)	(2.601)	
State Unemployment Rate (%)		-0.005	-0.023	
		(0.011)	(0.023)	
State PCE (B $)		-0.000	-0.000	
		(0.000)	(0.000)	
State Per Capita Income ($)		0.000	0.000	
		(0.000)	(0.000)	
State Tax Rate (%)		0.010	0.009	
		(0.010)	(0.012)	
State Housing Index		-0.000	-0.000	
		(0.000)	(0.000)	
IMR				0.139**
				(0.055)
Observations	1508	1508	1507	1508
R^2	0.115	0.100	0.125	0.216
Adjusted R^2	0.081	0.065	0.083	0.209
Residual Std. Error	0.277 (df=1451)	0.280 (df=1450)	0.277 (df=1436)	0.287 (df=1494)
F Statistic	3.373***	2.833***	2.941***	29.409***
	(df=56; 1451)	(df=57; 1450)	(df=70; 1436)	(df=14; 1494)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 2: Regression Results for Biden Sentiment

	(1)	(2)	(3)	(4)
County Housing Cost Growth (%)	0.000		0.000	0.001
	(0.002)		(0.002)	(0.002)
County GDP Growth (%)	0.001		0.001	0.001
	(0.001)		(0.001)	(0.001)
County Income Growth (%)	-0.000		0.000	-0.001
	(0.002)		(0.002)	(0.002)
County Income Equality Growth (%)	0.000		0.001	-0.001
	(0.002)		(0.002)	(0.002)
County Poverty Rate Growth (%)	-0.000		-0.000	-0.000
	(0.001)		(0.001)	(0.001)
County Unemployment Rate Growth (%)	-0.000		-0.000	-0.000
	(0.000)		(0.000)	(0.000)
County 2020 Housing Costs ($)		0.000*	0.000*	
		(0.000)	(0.000)	
County 2020 Income per Capita ($)		-0.000	-0.000	
		(0.000)	(0.000)	
County 2020 Income Inequality		-0.215	-0.281	
		(0.279)	(0.312)	
County 2020 Poverty Rate (%)		0.000	0.000	
		(0.002)	(0.003)	
County 2020 Unemployment Rate (%)		0.001	0.000	
		(0.004)	(0.004)	
County 2020 GDP		-0.000	-0.000	
		(0.000)	(0.000)	
County 2020 GDP per capita		0.000	0.000	
		(0.000)	(0.000)	
State Unemployment Growth Rate (%)	-0.000		-0.002	-0.000
	(0.000)		(0.001)	(0.000)
State PCE Growth (%)	-0.016		0.004	-0.002
	(0.015)		(0.023)	(0.007)
State Income Growth (%)	0.000		0.010	0.003
	(0.008)		(0.012)	(0.004)
State Housing Index Growth (%)	0.006		-0.009	0.008
	(0.011)		(0.015)	(0.006)
State GDP Growth (%)	0.000		-0.012	-0.003
	(0.010)		(0.015)	(0.006)
State Poverty Rate Growth (%)	-0.008		0.021	0.001
	(0.012)		(0.018)	(0.007)
State Inequality Growth (%)	0.018		-0.048	0.017
	(0.041)		(0.060)	(0.024)
State 2020 Poverty Rate (%)		-0.004	-0.048*	
		(0.012)	(0.025)	
State 2020 Inequality		0.864	3.681	
		(1.503)	(2.487)	
State Unemployment Rate (%)		-0.010	0.006	
		(0.010)	(0.022)	
State PCE (B $)		-0.000	-0.000	
		(0.000)	(0.000)	
State Per Capita Income ($)		-0.000	-0.000**	
		(0.000)	(0.000)	
State Tax Rate (%)		0.000	0.007	
		(0.010)	(0.012)	
State Housing Index		0.000	0.001**	
		(0.000)	(0.000)	
IMR				0.088*
				(0.052)
Observations	1508	1508	1507	1508
R^2	0.068	0.073	0.078	0.183
Adjusted R^2	0.032	0.036	0.033	0.175
Residual Std. Error	0.265 (df = 1451)	0.265 (df = 1450)	0.265 (df = 1436)	0.270 (df = 1494)
F Statistic	1.897***	1.997***	1.743***	23.857***
	(df = 56; 1451)	(df = 57; 1450)	(df = 70; 1436)	(df = 14; 1494)

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

4.3.1 Analysis of Model 1

County-level economic growth had a minimal impact on negative tweets toward Trump, though county unemployment growth was significant (coefficient = 0.001). This suggests local economic changes have limited influence on Twitter sentiment. At the state level, unemployment growth (coefficient = 0.001) and personal income growth (coefficient = 0.022) significantly predicted negative Trump tweets. While the unemployment effect was modest, income growth showed a stronger relationship: a 1% increase led to a 2.2% rise in anti-Trump sentiment—contradicting economic voting theory, which would expect reduced negativity with rising income. For Biden, no growth variables were significant. These asymmetries imply that the public may hold Trump more accountable for economic conditions. Overall, state-level trends appear to influence sentiment more than county-level changes, especially in Trump's case.

4.3.2 Analysis of Model 2

In the Trump regression, 2020 county GDP was statistically but not economically significant (coefficient = -0.000), due to scaling issues. Still, the negative relationship aligns with economic voting theory, where stronger economies reduce incumbent criticism. Income inequality (Gini index, coefficient = -0.549) was economically but not statistically significant due to high standard error. No Trump state-level regressors were significant, possibly reflecting quicker public response to local shifts. For Biden, no regressors were significant, reinforcing the idea that economic sentiment was directed more at Trump. The lack of praise for Biden when Trump's performance falters contradicts traditional economic voting expectations.

4.3.3 Analysis of Model 3

In full regressions, county unemployment growth was again significant for Trump (coefficient = 0.001), consistent with economic voting theory, though economically minor. For Biden, state per capita income (coefficient = -0.000) and housing index (coefficient = 0.001) were significant. However, the positive link between housing costs and negative sentiment contradicts theoretical expectations, which predict reduced negativity during rising housing markets.

4.3.4 Analysis of Model 4

A Heckman selection model addressed potential bias from underrepresented counties on Twitter, using county-level population and internet access for selection. This model had the highest adjusted R^2. In the Trump model, the Inverse Mills Ratio (coefficient = 0.139) and both county and state unemployment rates (coefficient = 0.001) were significant, supporting economic voting theory and the presence of selection bias. State fixed effects (e.g., Georgia, New Hampshire, Tennessee) indicate local political or cultural factors also shape sentiment. In contrast, no variables—including the IMR—were significant in the Biden model, suggesting weaker links between economic indicators and sentiment toward Biden, possibly due to differing perceptions of economic responsibility.

My preferred specification is Model 4, as it accounts for selection bias, has the highest adjusted R^2 value, and aligns best with theoretical expectations — indicating that tweet patterns are shaped by retrospective and sociotropic evaluations. Moreover, it suggests that poorer economic conditions lead to more negative tweets about Trump and less negative tweets about Biden, in line with economic voting theory. Of importance, the county-level unemployment growth rate has been a statistically significant regressor for Trump across all regressions.

4.4 Machine Learning Regressions

Before proceeding with the analysis, I would like to note that I chose not to standardize my outcome variable by the 2020 county population. This decision was intentional to preserve the full set of predictors and maximize the model's predictive power: in predictive modeling, it's generally discouraged to discard or transform predictors in ways that may reduce their informational content. Additionally, maintaining consistency in how the outcome is defined across models facilitates a more meaningful comparison between my OLS regression and machine learning approaches.

To model non-linear interactions and capture more nuanced relationships, I included random forests. It takes many training sets from the population, builds a separate prediction model using each training set, and average the resulting predictions, reducing variance. It typically performs well when patterns are stable across entities.

4.5 Random Forests Results

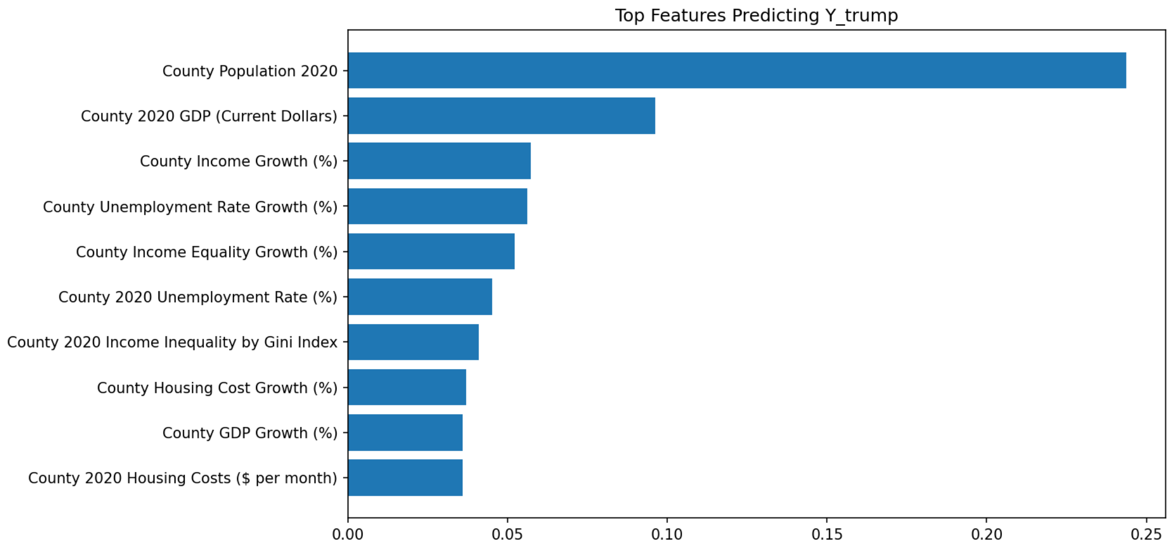

Figure 9: Importance Matrix Trump

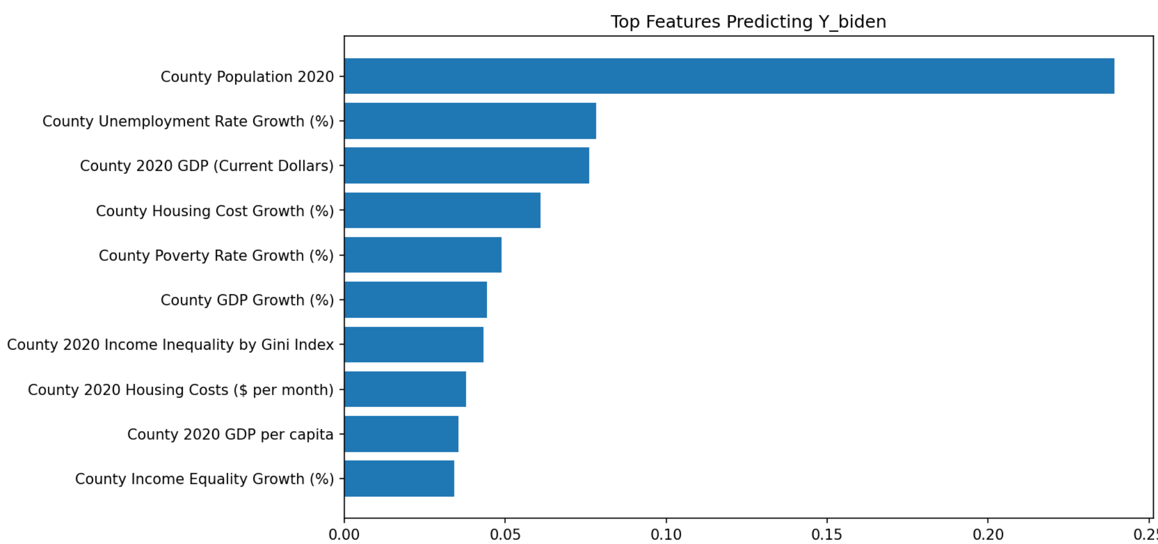

Figure 10: Importance Matrix Biden

For Trump, county-level predictors like population size, county GDP, income growth, and unemployment rate growth dominate, while for Biden, variables,such as population size, county 2020 GDP, and county unemployment rate growth seem to be the most important. Again, the omnipresence of population size as a predictor signals selection bias across counties. Overall, tweeters seem to be economically retrospective when making negative tweets. In addition, tweeters seem to be more concerned about smaller county-level economic changes relative to larger state-level ones, counter to our linear regressions. Crucially, I cannot assert that this model supports economic voting theory as it does not make any claims regarding directionality.

5 Comparison of all Regressions

The random forest model produced the lowest mean squared error (MSE$_{Trump}$ = 0.0331, MSE$_{Biden}$ = 0.0338) among all models, supporting its use for interpretation. However, unlike the linear regression models, the machine learning model includes population rates as predictors. Across all models, unemployment rate growth consistently emerged as one of the most important predictors of negative sentiment toward Trump. Interestingly, according to random forests, Twitter users appear to respond more strongly to county-level economic conditions than to state-level trends, which runs counter to initial expectations from our scatterplots and geographical mappings. In addition, Tweeters seem to care more about growth factors than current conditions, reflecting their retrospectiveness. However, our random forests cannot posit any claims regarding directionality and economic attribution, warranting an interpolation from our other methods. From our linear regressions and scatter-plots, we notice that economic voting theory is supported when it comes to the presidential incumbent for the most part; however, this relationship does not hold for the presidential challenger. In addition, the negative tweet frequencies are more strongly tied to the presidential incumbent than the presidential challenger when it comes to economic conditions.

6 Conclusion and Future Steps

This study tested economic voting theory in the context of social media by examining how county- and state-level economic conditions influenced negative tweet frequencies toward Trump and Biden during the 2020 U.S. presidential election. Consistent with theoretical expectations, worse economic conditions—particularly rising unemployment—were associated with increased negativity toward Trump, the incumbent. State-level economic indicators carried more weight in the scatterplots, while machine learning models suggested greater sensitivity to county-level variation. Across all models, unemployment rate growth was the most consistent predictor of anti-Trump sentiment. The Random Forest model achieved the lowest MSE, reinforcing its utility for prediction. Ultimately, these results indicate that tweeters respond to county-level shifts and that they tend to attribute economic conditions to the presidential incumbent more, leading to a stronger relationship between economic factors and respective negative tweet frequency relative to the challenger. Therefore, if the presidential challenger wants to improve how Tweeters view him, he should focus on improving county-level GDP, income growth, unemployment rate growth, and income inequality growth.

While this study reveals meaningful patterns between economic conditions and Twitter sentiment and clearly distinguishes from other economic voting theory papers that only use ballots instead of social media sentiment, several extensions could enhance future work. First, incorporating longitudinal tweet data across multiple election cycles would allow for a more dynamic time-series analysis of how economic trends shape political sentiment over time. Second, improving sentiment classification by using deep learning-based natural language processing (NLP) models could enhance the accuracy of tweet labeling. Finally, integrating user-level metadata (e.g., occupation, location precision, or political affiliation when available) could refine our understanding of how different demographic groups respond to economic signals.

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County Income: https://data.census.gov/table/ACSST1Y2023.S1901?q=income

County Income Inequality: https://data.census.gov/table/ACSDT1Y2023.B19083?q=Income+Inequality

County Population: https://data.census.gov/table/DECENNIALCD1182020.P1?q=population+total

County Poverty Rate: https://data.census.gov/table/ACSST1Y2023.S1701?q=poverty+rate

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