Beyond the Stats: Realities, Perception, and Social Media Discourse on Poverty

By Paul Bose, Lorenzo Lupo, Mahyar Habibi, Dirk Hovy, and Carlo Schwarz*

Poverty is a persistent issue that transcends economic indicators. Traditional approaches to understanding poverty have primarily concentrated on determining who falls below the poverty line. However, this narrow lens fails to capture the disparities between the realities of poverty, individuals' subjective perceptions, and social media narratives. We delve into the subtle distinctions between three dimensions: 1) who the poor are, 2) how people perceive their own economic situation, and 3) how poverty is portrayed on social media. To that end, we develop county-level measures for each of these dimensions and investigate the extent to which poverty realities explain perceived poverty and social media discussions. Furthermore, we want to understand which other county-level characteristics predict increased poverty perception and social media discourse above and beyond what would be expected based on a county's poverty level. Finally, we investigate whether the social media discussion of poverty accurately reflects the gender and ethnicity shares of poverty in the United States. By highlighting the county-level differences between the three poverty dimensions, our findings contribute valuable insights into the ever-growing economic research on poverty and its psychological impacts (e.g., Deaton, 2016; Saez and Zucman, 2020; Haushofer and Salicath, 2023).

I. Data and Methodology

We use three main data sources. First, we collect official poverty statistics from the US Census. Second, we create measures of poverty *perception* from the Gallup Daily Tracker. Third, we generate a measure of poverty-related social media discourse based on a representative sample of US Twitter users. Appendix Table A1 provides summary statistics for the three measures. Appendix Figure A1 visualizes the geographic distribution. We describe each of the measures in the following.

A. Poverty Statistics US Census

As our primary measure of poverty, we obtained the county-level share of the population living below the poverty line in 2018 from the US Census website. This data gives us a measure of poverty based on income. In our robustness checks, we look at alternative measures based on 1) the proportion of the population on food stamps (also from the US census) and 2) the social deprivation index (SDI) from the Robert Graham Center (2018). These alternative measures capture additional dimensions of poverty, such as food insecurity, employment situation, or living conditions.

B. Perceived Poverty from Gallup

Our measure of individuals' perception of their own economic condition is based on the Gallup Daily Tracker. The Gallup Daily Tracker is a large nationally representative poll of US respondents. Each day from 2007 to 2018, Gallup interviewed 1,000 respondents on various political, social, and economic issues. As such, the Daily Tracker contains several survey items that allow us to measure how individuals in a county perceive their own economic situation. For our analysis, we use the survey years from 2013 to 2018. We create a measure of perceived poverty based on 12 questions (see

* Bose, paul.bose@unibocconi.it; Lupo, lorenzo.lupo2@unibocconi.it; Habibi, mahyar.habibi@phd.unibocconi.it; Hovy, dirk.hovy@unibocconi.it; Schwarz, carlo.schwarz@unibocconi.it, Bocconi University. The project is supported by Cariplo Foundation grant agreement 2022-1480. We also thank Derya Durmush for her excellent research assistance.

Appendix Table A2). We recode the questions into indicator variables and calculate the average across all questions. As a result, the index measures how many of the selected questions a respondent affirmed. We aggregate our poverty perception index to the county level based on the locations the respondents provided in the survey. We also use indexes from Gallup for general and financial well-being as alternative measures.

C. Poverty-Related Social Media Discourse

Lastly, we construct a measure of the amount of poverty-related social media discourse based on a sample of 498k representative US Twitter users.[1] We collected the users' Tweets in the sample, which gives us 399 Million Tweets from 2006 to 2022. For our analysis, we focus on English Tweets from the subset of 163k users, which we can geolocate to the county level. This restriction leaves us with a final sample of 129 Million Tweets.

We build on the methodology developed by Bose et al. (2024) and Lupo et al. (2024) to identify the amount of poverty-related Twitter content. We first ask the language model GPT[2] to develop ten poverty-related concepts (e.g., debt and financial struggles, food insecurity). We then prompt GPT to generate five statements for each of the ten concepts. This procedure provides us with a set of fifty prototypical statements covering a broad array of poverty-related issues.[3]

We then encode the prototypical statements and Tweets via a sentence embedding model (Reimers and Gurevych, 2019).[4] Thus, each Tweet is represented as a 768-dimensional vector that captures its semantic content. We then use the cosine similarity of each Tweet with the poverty-related statements to filter poverty-related Tweets. We consider a Tweet to be poverty-related if the cosine similarity to the GPT-created prototypes is above 0.5.[5] In total, we identified 607k poverty-related Tweets. Our measure of poverty-related discourse on social media is the share of Tweets from a county related to poverty.[6]

II. Results

A. Relation between Poverty Measures

We begin by analyzing how poverty, perceived poverty, and poverty discussion on social media relate to each other at the county level. We plot the measures against each other in binned scatter plots (see Figure 1). To make the scales of the measures comparable, we transform all measures into ranks such that 1 is the county with the lowest poverty, perceived poverty, or poverty discussion, counting up to the county with the highest value. In panel (a), we plot the census measure of poverty and our measure of perceived poverty. We find a strong positive correlation between the measures. The estimated regression coefficient of 0.465 indicates that a county which is ten ranks higher in the poverty distribution is, on average, five ranks higher in the level of perceived poverty by its inhabitants. In panel (b) Figure 1, we show a similar plot for the comparison of the measure of poverty and our measure of poverty-related social media discourse. Perhaps surprisingly, the extent of poverty-related social media discourse is negatively correlated with a country's poverty level. Both the regression coefficient (-0.073) and R^2 (0.01) are far smaller than before.[7]

Taken together, these findings highlight that while people in counties more affected by poverty indeed perceive themselves as poorer, Twitter discussions on poverty do *not* occur in the US counties that are ac-

[1] The user sample was originally collected by Siegel et al. (2021), by queueing the Twitter API with random user ids and collecting accounts that the authors could geolocate in the US.

[2] We use `gpt-3.5-turbo` through OpenAI's API.

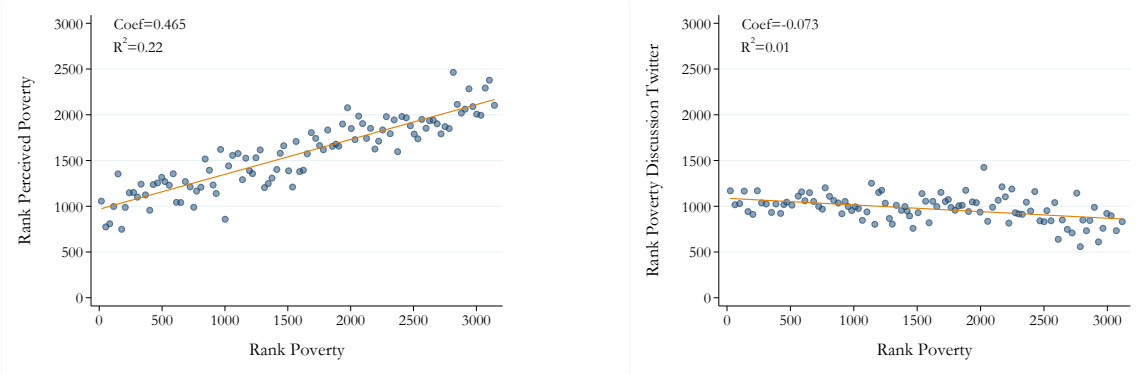
[3] The complete list of poverty-related concepts and statements can be found in Table A3.

[4] We use `paraphrase-multilingual-mpnet-base-v2` though the Hugging Face hub.

[5] As we show in the Figure B3, our findings are robust to alternative thresholds.

[6] In Appendix Table A4, we show several examples of Tweets. In unreported results, we have also confirmed that the results are similar if we instead use the count of poverty-related Tweets.

[7] In Appendix Figure B1, Figure B2, and Figure B3, we show that this result holds independently of the measures we are considering.



(a) Poverty vs Poverty Perception

(b) Poverty vs Poverty Discourse

Figure 1. : Correlation between Measures

Note: Binscatter plots for the county-level rank of the share of people below the poverty line against a) the rank of the index of perceived poverty and b) the rank of the share of poverty-related Tweets.

tually affected by poverty. It is further worth noting that even though poverty and poverty perception are strongly positively correlated, actual poverty explains less than a quarter (R^2 =0.22) of a county's *perceived* poverty rank. As our next analysis step, we study which factors best predict the different poverty dimensions.

B. County-level Predictors

We investigate the county-level determinants of each of the three main measures using regressions of the following form:

$$(1) \quad Poverty\ Measure_i = \alpha + \boldsymbol{\beta}'\mathbf{X_i} + \epsilon_i$$

where $Poverty\ Measure_i$ is one of the three poverty measures, and X_i is a vector containing a broad set of county characteristics, including, among others, geographic features, demographic characteristics, and industry composition (see Appendix Table A1 for a full list). We again transform all variables into county-level ranks. The regression for poverty perception and social media discourse also controls for the county-level poverty rank. The regression results shed light on which county-level factors have the strongest predictive power for the different dimensions. We identify the optimal set of predictive variables for each regression using LASSO (Belloni, Chernozhukov and Hansen, 2014).

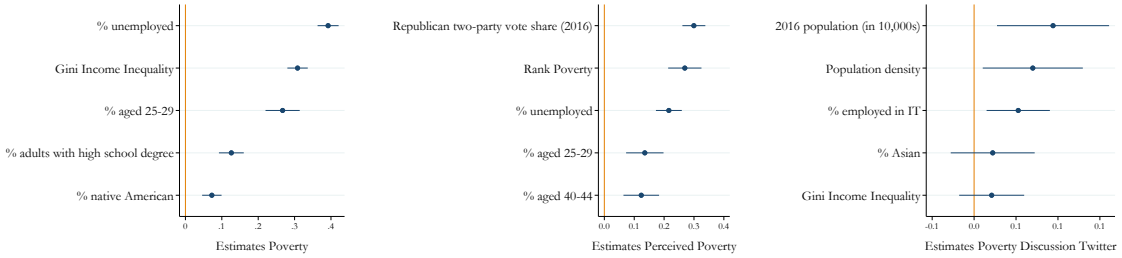
We visualize the five county characteristics with the largest estimated coefficients in Figure 2.[8] From this analysis, three findings stand out. First, economic conditions best explain poverty (e.g., unemployment, the China shock). Second, conditional on a county's poverty level, the level of perceived poverty is strongly correlated with a county's Republican vote share, highlighting the political alignment of citizens who perceive themselves as poor. Lastly, poverty discussion on social media occurs in more urban counties.

The results indicate that perceived poverty and poverty discussion on social media are predicted by a substantially different set of county characteristics than actual poverty. Therefore, poverty discourse on social media does not appear to be driven by first-hand experience of poverty. Next, we investigate if the social media discussions on poverty differ from poverty realities and if there are misperceptions about the groups affected by poverty.

C. Poverty Discourse vs Poverty Statistics

For this last analysis, we split the social media discussions on poverty by gender and ethnic groups. We use simple keyword matching for gender, and the large language

[8] All coefficients are shown in Appendix Figure B4.



(a) Poverty (b) Poverty Perception (c) Poverty Discourse

Figure 2. : Cross-sectional Predictors of Measures

Note: Coefficient plots of the five strongest predictors for each of the three poverty measures based on the regressions from Equation (1). All variables are transformed into ranks, and heteroskedasticity-robust standard errors are used.

model Flan-T5 (Chung et al., 2022) to annotate[9] Tweets that mention one of the following ethnic groups: African-American, Asian, Hispanic, White. We also allow the model to make multiple mentions. We then calculate the share of poverty-related Tweets that mention each of the groups. We confirmed that our approach can accurately (0.76 macro-F1) identify mentions of gender or ethnicity by checking a random subsample of 200 Tweets. For comparison, we use the share of each group among the people below the poverty line. Figure 3 plots the resulting shares for the six groups.

We find that Male poverty is underrepresented on social media compared to Female poverty. More strikingly, a disproportionate amount of attention is also paid to Black poverty, even though Black poverty is three times less prevalent than White poverty. There also is a marked disparity between the discussion of Black and Hispanic poverty on social media. Despite both groups making up a similar share of the poverty-affected population, the poverty of Hispanics is rarely discussed on social media compared to Black poverty.

The documented pattern suggests that poverty-related social media discourse neither takes place in counties heavily affected by poverty nor does it paint an accurate picture of the affected groups. Instead, the findings indicate that social media discourse, similar to traditional news media, contributes to the racialization of poverty (e.g., Gilens, 1996) and stereotypes (e.g, Ash et al., 2021).

[9]Leveraging `google/flan-t5-xxl` through the Hugging Face Hub and the annotation code by Lupo et al. (2023), available at github.com/lorelupo/pappa.

III. Discussion

The results from this paper shed light on the complex distinction between different poverty dimensions. We show that while poverty statistics are a strong predictor of perceived poverty, many additional non-economic factors contribute to the extent to which inhabitants of a county consider themselves poor. Further, we documented that the social media discussion on poverty occurs in different counties and paints a distorted picture of poverty statistics. The pervasive use of social media by journalists, politicians, and academics opens the door for substantial biases, especially in critical high-stakes decisions that might lead to the misallocation of attention and resources. Future research could investigate if biased social media narratives distort individuals' poverty perceptions.

REFERENCES

Ash, Elliott, Ruben Durante, Maria Grebenschikova, and Carlo Schwarz. 2021. "Visual representation and stereotypes in news media." *Working Paper.*

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen.

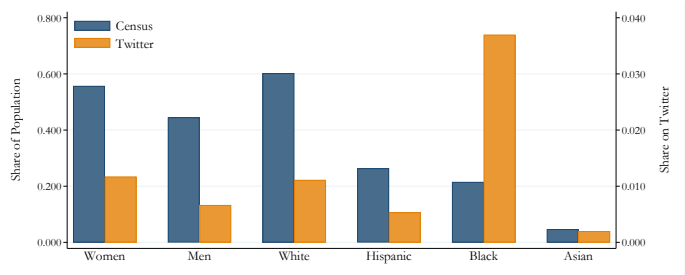


Figure 3. : Poverty Statistics vs Social Media Discourse

Note: Comparison between official poverty statistics and the social media discourse on poverty on Twitter. Blue bars (left axis) show each group's share among the total number of people in poverty in the US. Orange bars (right axis) show the share of Tweets mentioning the indicated group among the total number of Tweets about poverty. Appendix Figure B5 shows the shares when removing mentions of foreign countries. Appendix Figure B6 shows the shares of Twitter discussion separately by state.

2014. "High-dimensional methods and inference on structural and treatment effects." *Journal of Economic Perspectives*, 28(2): 29–50.

Bose, Paul, Lorenzo Lupo, Mahyar Habibi, Dirk Hovy, and Carlo Schwarz. 2024. "MENTALISM: Measuring, Tracking, and Analyzing Inequality using Social Media." *Working Paper*.

Chung, Hyung Won, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. "Scaling instruction-finetuned language models." *arXiv preprint arXiv:2210.11416*.

Deaton, Angus. 2016. "Measuring and understanding behavior, welfare, and poverty." *American Economic Review*, 106(6): 1221–1243.

Fujiwara, Thomas, Karsten Müller, and Carlo Schwarz. 2023. "The Effect of Social Media on Elections: Evidence from the United States." *Forthcoming Journal of the European Economic Association*.

Gilens, Martin. 1996. "Race and poverty in America: Public misperceptions and the American news media." *Public Opinion Quarterly*, 60(4): 515–541.

Haushofer, Johannes, and Daniel Salicath. 2023. "The psychology of poverty: Where do we stand?" *Social Philosophy and Policy*.

Lupo, Lorenzo, Oscar Magnusson, Dirk Hovy, Elin Naurin, and Lena Wängnerud. 2023. "How to Use Large Language Models for Text Coding: The Case of Fatherhood Roles in Public Policy Documents."

Lupo, Lorenzo, Paul Bose, Mahyar Habibi, Dirk Hovy, and Carlo Schwarz. 2024. "DADIT: A Dataset for Demographic Classification of Italian Twitter Users and a Comparison of Prediction Methods." *Working Paper*.

Reimers, Nils, and Iryna Gurevych. 2019. "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks." Association for Computational Linguistics.

Robert Graham Center. 2018. "Social deprivation index (SDI)."

Saez, Emmanuel, and Gabriel Zucman. 2020. "The rise of income and wealth inequality in America: Evidence from distributional macroeconomic accounts." *Journal of Economic Perspectives*, 34(4): 3–26.

Siegel, Alexandra A, et al. 2021. "Trumping Hate on Twitter? Online Hate in the 2016 US Election Campaign and its Aftermath." *Quarterly Journal of Political Science*, 16(1): 71–104.

Online Appendix: Beyond the Stats: Realities, Perception, and Social Media Discourse on Poverty

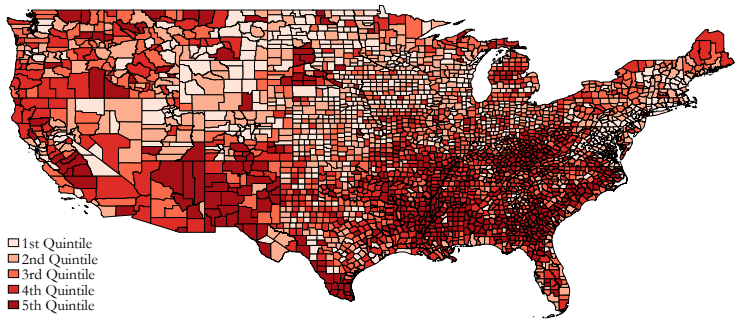
By: Paul Bose, Lorenzo Lupo, Mahyar Habibi Dirk Hovy, and Carlo Schwarz

Additional Details on the Data

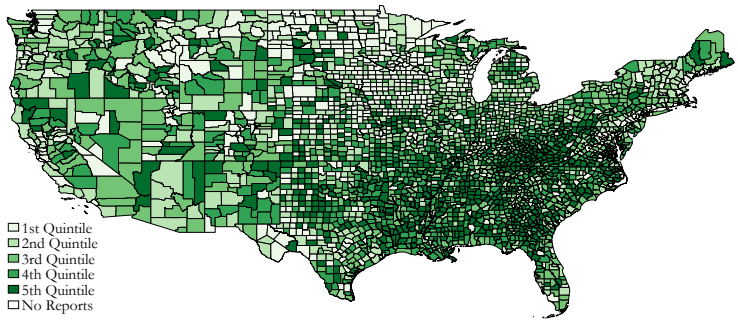
Table A1—: Summary Statistics

	Mean	SD	Min.	Median	Max.	Obs.
Poverty Measures						
% below Poverty Line	16.78	8.31	2.40	15.40	65.20	3,220
% receiving Food Stamps	14.40	8.04	0.00	13.20	59.60	3,220
Social Deprevation Index	-0.26	0.92	-2.14	-0.27	2.14	3,142
Poverty Perceptions						
Poverty Perception Index	0.50	0.06	0.00	0.50	1.00	3,138
Financial Well-being Index	60.80	6.23	28.17	60.97	94.09	3,133
Well-being Index	61.61	3.59	36.67	61.59	79.88	3,133
Twitter Poverty Discusson						
% Poverty Tweets (Baseline)	0.00	0.01	0.00	0.00	0.13	1,945
% Poverty Tweets (Threshold: 0.4)	0.03	0.02	0.00	0.02	0.50	1,945
% Poverty Tweets (Threshold: 0.6)	0.00	0.00	0.00	0.00	0.02	1,945
Other Control Variables						
2016 population (in 10,000s)	10.33	33.16	0.01	2.60	1013.79	3,108
Population density	261.27	1733.47	0.10	45.60	69468.40	3,108
Area in square miles - Total area	1004.00	1328.12	2.00	645.89	20104.83	3,108
% aged 20-24	6.33	2.37	0.88	5.80	27.38	3,108
% aged 25-29	5.97	1.28	2.52	5.86	15.17	3,108
% aged 30-34	5.85	0.96	2.68	5.73	12.35	3,108
% aged 35-39	5.82	0.79	2.65	5.80	10.51	3,108
% aged 40-44	5.62	0.75	1.75	5.64	10.19	3,108
% aged 45-49	6.11	0.78	2.45	6.14	9.24	3,108
% aged 50+	39.48	6.56	10.76	39.43	74.96	3,108
% White	76.93	19.74	2.81	84.21	97.98	3,108
% Black	9.02	14.37	0.00	2.21	85.15	3,108
% native American	1.72	6.37	0.00	0.42	90.14	3,108
% Asian	1.40	2.40	0.00	0.69	36.50	3,108
% Hispanic	9.33	13.73	0.50	4.09	96.25	3,108
Gini Income Inequality	0.45	0.04	0.33	0.44	0.62	3,220
% unemployed	5.50	1.94	1.80	5.30	24.10	3,108
% employed in IT	1.20	1.37	0.00	0.96	20.95	3,108
% employed in construction/real estate	7.02	5.14	0.00	6.03	100.00	3,108
% employed in manufacturing	14.30	12.50	0.00	11.36	72.28	3,108
% adults with high school degree	34.77	7.07	7.50	35.20	54.80	3,108
% adults with college degree	21.89	3.81	8.40	21.80	35.60	3,108
Exposure to Chinese import competition	2.81	2.75	-0.63	2.18	43.08	3,107
Republican two-party vote share (2016)	0.63	0.16	0.04	0.66	0.95	3,108
% Twitter Users	0.77	0.52	0.00	0.67	8.00	3,108

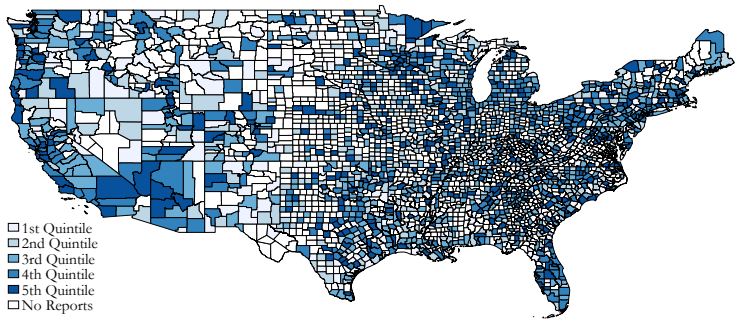
Note: This table provides county-level summary statistics for the measures of poverty, poverty perception, and poverty discourse that are used in the paper. The table further lists the full set of control variables used in Figure 2. The control variables are derived from the reproduction file of Fujiwara, Müller and Schwarz (2023) and the US census.



(a) Poverty



(b) Poverty Perception



(c) Poverty Discourse

Figure A1. : Maps

Note: This figure shows the geographic variation of the three poverty measures used in the paper: poverty perception, poverty discourse, and poverty discourse.

Table A2—: Selected Questions from Gallup Daily Tracker

Code	Question	Scale
M30	How do you evaluate your economic condition?	1-4
M91	Do you agree with the statement: I am watching my spending?	1-2
M92	Would you be able to make a major purchase (e.g., car)?	1-2
M93	Are you cutting back on how much money you spend?	1-2
M94	Are you feeling pretty good about the money you have to spent?	1-2
M95	Did you worry yesterday that you spent too much money?	1-2
M96	Do you agree with the statement: You have enough money?	1-2
M97	Do you have enough money to buy the things you need?	1-2
HWB5	Do you have enough money to do everything you want to do?	1-5
HWB6	Have you worried about money in the last 7 days?	1-5
WP30	How is your standard of living?	1-2
WP31	How is your standard of living changing?	1-3

Note: This table lists the questions that were selected from the Gallup Daily Tracker to generate the poverty perception index.

Table A3—: Poverty Concepts and Statements GPT

Concepts	Statements
Debt and financial struggles	I hate how debt keeps piling up and I can never seem to get ahead financially. Financial struggles are so frustrating, it feels like I'm constantly drowning in bills and expenses. Debt is such a burden, it's like a never-ending cycle of stress and anxiety. I can't stand how financial struggles limit my options and prevent me from enjoying life. Dealing with debt is overwhelming, it's like being trapped in a never-ending nightmare.
Food insecurity	Food insecurity is just an excuse for laziness and lack of motivation to work. Why should we care about food insecurity when there are more pressing issues like the economy and national security. People experiencing food insecurity should just learn to budget their money better and make smarter choices. Food insecurity is a result of poor personal choices and irresponsibility. It's not our responsibility to solve food insecurity; individuals should take care of themselves and their own needs.
Healthcare affordability	Healthcare affordability is a myth, as the costs of medical treatments and insurance premiums continue to skyrocket. The lack of healthcare affordability leaves many individuals unable to seek necessary medical care, leading to worsening health conditions. The current healthcare system fails to address the issue of affordability, leaving millions of people without access to basic healthcare services. The high deductibles and out-of-pocket expenses associated with healthcare plans make it nearly impossible for average individuals to afford necessary treatments. The pharmaceutical industry's exorbitant prices for life-saving medications contribute to the overall lack of healthcare affordability.
Housing instability	Housing instability leads to increased rates of homelessness and poverty. The lack of affordable housing options contributes to housing instability in our community. Housing instability disrupts children's education and hinders their overall development. The constant fear of eviction and unstable living conditions take a toll on individuals' mental health. Housing instability perpetuates a cycle of poverty and inequality, making it difficult for individuals to escape their circumstances.
Income inequality	Income inequality leads to a small percentage of the population hoarding a majority of the wealth, leaving the majority struggling to make ends meet. Income inequality perpetuates a cycle of poverty, as those born into lower-income households have limited opportunities for upward mobility. Income inequality creates social unrest and tensions, as it highlights the stark disparities between the rich and the poor. Income inequality hampers economic growth, as it limits the purchasing power of the majority and reduces overall consumer demand. Income inequality undermines the principles of fairness and equal opportunity, as it allows for advantages and privileges to be disproportionately distributed among the wealthy.

Concepts	Statements
Lack of access to basic needs	It's absolutely unacceptable that there are still people in this world who don't have access to clean drinking water. It's disheartening to see that some communities lack access to proper healthcare facilities, leaving them vulnerable and without necessary medical assistance. It's a shame that many children are deprived of education due to the lack of schools and educational resources in their areas. It's distressing to think that there are individuals who struggle to afford nutritious food, leading to malnutrition and health issues. It's appalling that some individuals don't have access to safe and secure housing, forcing them to live in dangerous and unsanitary conditions.
Limited educational opportunities	It's unfair that some students have access to top-notch schools and resources while others are stuck in underfunded schools with outdated textbooks. Limited educational opportunities perpetuate the cycle of poverty and hinder social mobility for disadvantaged communities. Without equal access to quality education, talented individuals from marginalized backgrounds are unable to reach their full potential. The lack of educational opportunities in rural areas deprives students of the chance to explore their interests and pursue their desired career paths. Limited educational opportunities create a knowledge gap between different socioeconomic groups, further deepening societal inequalities.
Limited upward mobility	Limited upward mobility means that no matter how much potential you have or how well you perform, you'll always be stuck in the same position. It's disheartening to see others around you getting promoted and moving up the ladder while you're left behind due to limited upward mobility. Limited upward mobility creates a sense of stagnation and can lead to a lack of motivation and enthusiasm in the workplace. It's demoralizing to know that no matter how much you improve your skills or acquire new knowledge, there's no chance for upward progression in your current job.
Social exclusion and marginalization	Social exclusion and marginalization perpetuate inequality and hinder social progress. It is disheartening to see how social exclusion and marginalization continue to divide communities. The concept of social exclusion and marginalization highlights the failure of our society to provide equal opportunities for all. Social exclusion and marginalization breed resentment and contribute to the breakdown of social cohesion. he devastating consequences of social exclusion and marginalization are evident in the lives of those who are left behind and forgotten.
Unemployment and underemployment	Unemployment and underemployment lead to financial instability and can push individuals into poverty. Lack of job opportunities and underemployment can result in wasted potential and talent. Unemployment and underemployment contribute to social inequality and can deepen existing disparities. The high rates of unemployment and underemployment indicate a struggling economy and lack of growth. Unemployment and underemployment can lead to feelings of frustration, hopelessness, and low self-esteem among individuals.

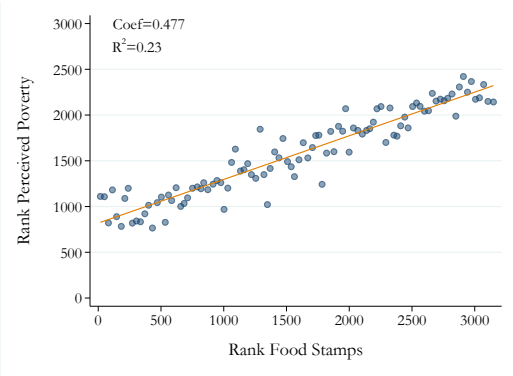
Note: This table lists the poverty concepts and poverty-related statements that were created by GPT which are used to identify poverty-related Tweets.

Table A4—: Example Poverty Tweets

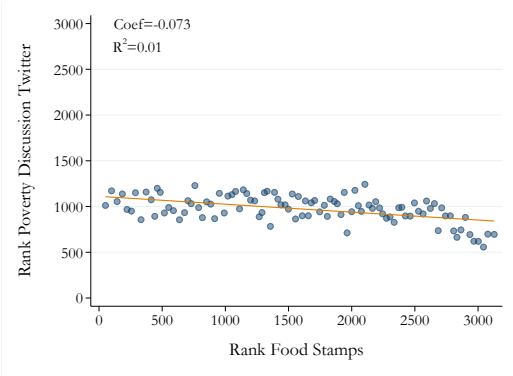
Tweet Text	**Similarity**
the amount of stress i have right now is ridiculous	0.643
over 2 million americans lack access to running water thanks to poorly-installed or poorly-maintained infrastructure. in the wealthiest nation in the world, this isn't acceptable. https://t.co/l4lwi7fukv https://t.co/imoedjleev	0.799
being so poor you're afraid a time will come when you can't feed yourself can throw an eating disorder into very sharp relief.	0.742
homelessness is trending in america	0.781
one of the many factors that lead to poverty is the lack of and the how of education.	0.812
rt blackafinstem: black students &; professionals are not offered or are able to take on the same opportunities given to their non-black pe...	0.765
girls from low-income families receive the least schooling https://t.co/ek5eekwbae	0.738
"rural poor are negatively impacted by not expanding medicaid. ""uncompensated care"" is a problem."	0.764
my life is just full of stressful things and not being able to afford life	0.758
talent is everywhere opportunity is not	0.743
feeling underemployed.	0.770
i'm tired of being broke, mentally and financially	0.714
income inequality.	0.827
ugh i hate how i get frustrated so easily. damn you finance!	0.718
rt @cleanh2oaction: no one in america should lack access to clean, safe, and affordable water - and yet during a pandemic when hand washing...	0.784
affordable healthcare for me is not affordable	0.825
why talented black and hispanic students can go undiscovered https://t.co/kpea1rb24o	0.723
the bills i have to pay greatly exceed the amount of money i make and the urge to cry is more of a constant thing now :-)	0.742
also 20% of the population controls 80% of the wealth. meaning that the government only needs to take care of that 20% to keep the economy running. the reason why major changes seem to impossible. income inequality.	0.730
rt skinny_que: you ever wonder what black people could achieve if they were given equal access to education and opportunities	0.732

Note: This table lists examples of the poverty-related Tweets that were identified based on the similarity to the statements created by GPT. The first column lists the text of the Tweet. The second column lists the maximum similarity of the Tweets to each of the poverty-related statements.

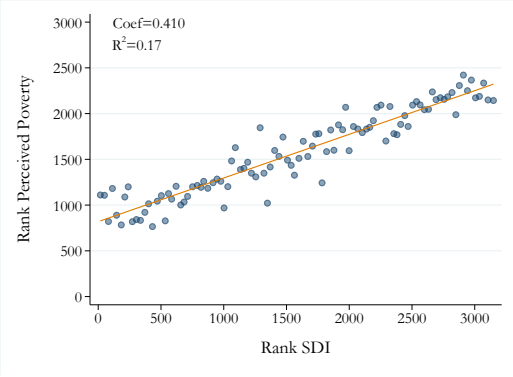
Additional Results



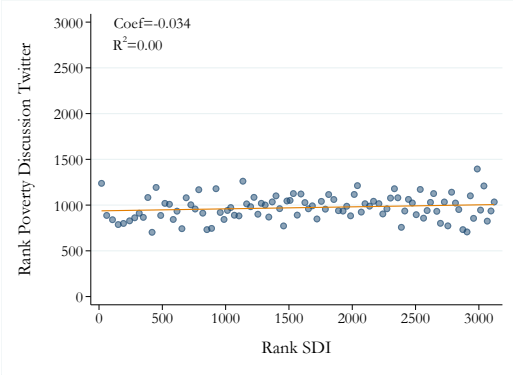
(a) Food Stamps vs Poverty Perception



(b) Food Stamps vs Poverty Discourse



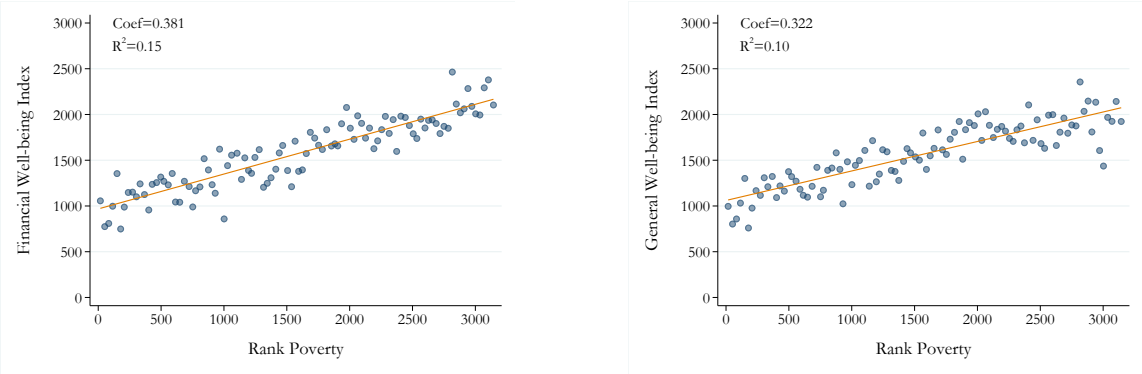
(c) SDI vs Poverty Perception



(d) SDI vs Poverty Discourse

Figure B1. : Alternative Poverty Measures

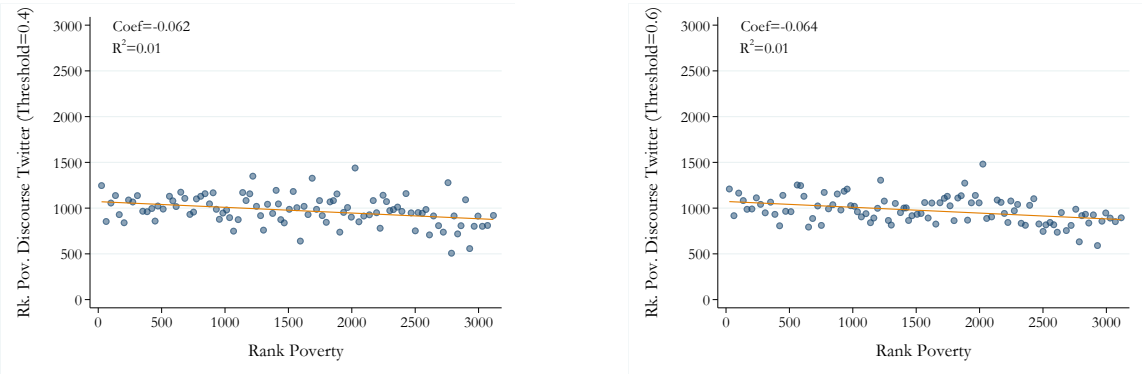
Note: These figures provide alternative versions of Figure 1 for alternative measures of poverty. The first row uses the share of people in a county receiving food stamps. The second row uses the social deprivation index. All variables are again transformed into ranks.



(a) Poverty vs Poverty Perception (b) Poverty vs Poverty Discourse

Figure B2. : Alternative Poverty Perception Measures

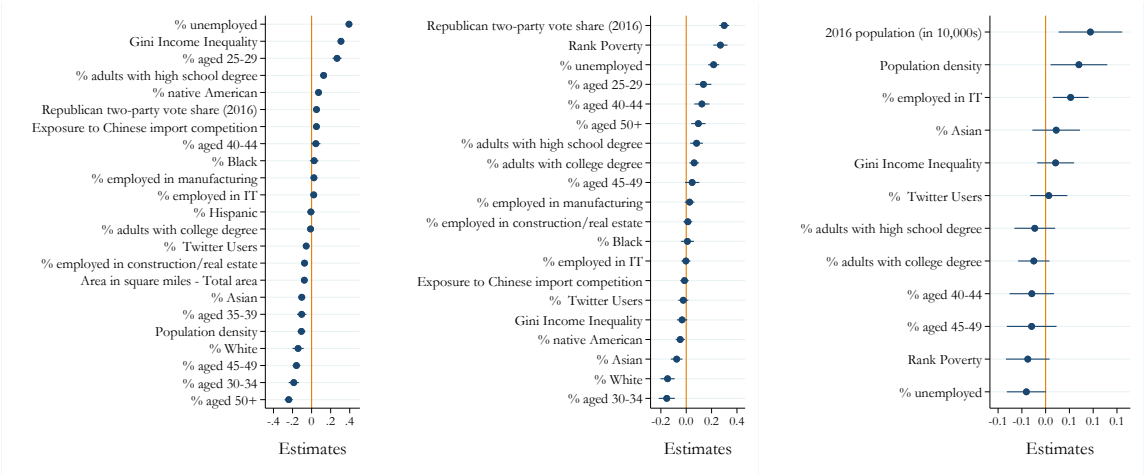
Note: These figures provide alternative versions of Figure 1 for alternative measures of poverty perception. The first row uses the financial well-being index from the Gallup Daily Tracker. The second row uses the general well-being index from the Gallup Daily Tracker. All variables are again transformed into ranks.



(a) Poverty vs Poverty Perception (b) Poverty vs Poverty Discourse

Figure B3. : Alternative Poverty Discourse Measures

Note: These figures provide alternative versions of Figure 1 for alternative measures of poverty discourse. The first row uses a similarity threshold of 0.4 to identify poverty-related Tweets. The second row uses a similarity threshold of 0.6 to identify poverty-related Tweets. All variables are again transformed into ranks.



(a) Poverty (b) Poverty Perception (c) Poverty Discourse

Figure B4. : Cross-sectional Predictors of Measures (All Variables)

Note: Coefficient plots of the predictors for each of the three poverty measures based on the regressions from Equation (1). All variables are transformed into ranks, and heteroskedasticity-robust standard errors are used in all regressions.

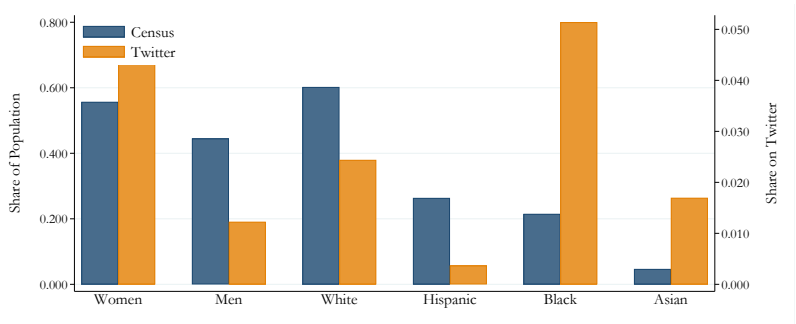
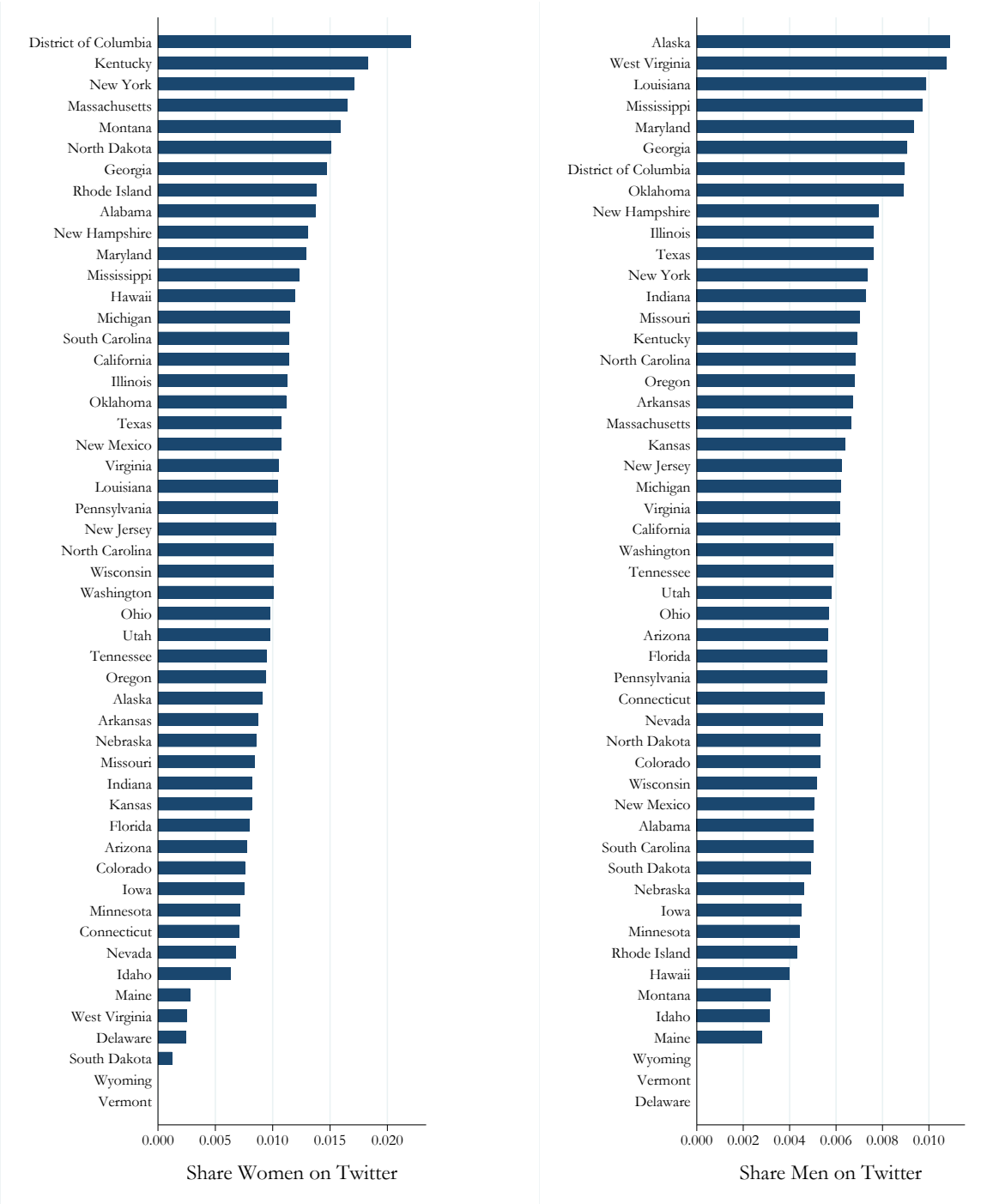


Figure B5. : Poverty Statistics vs Social Media Discourse (Excluding Foreign Countries)

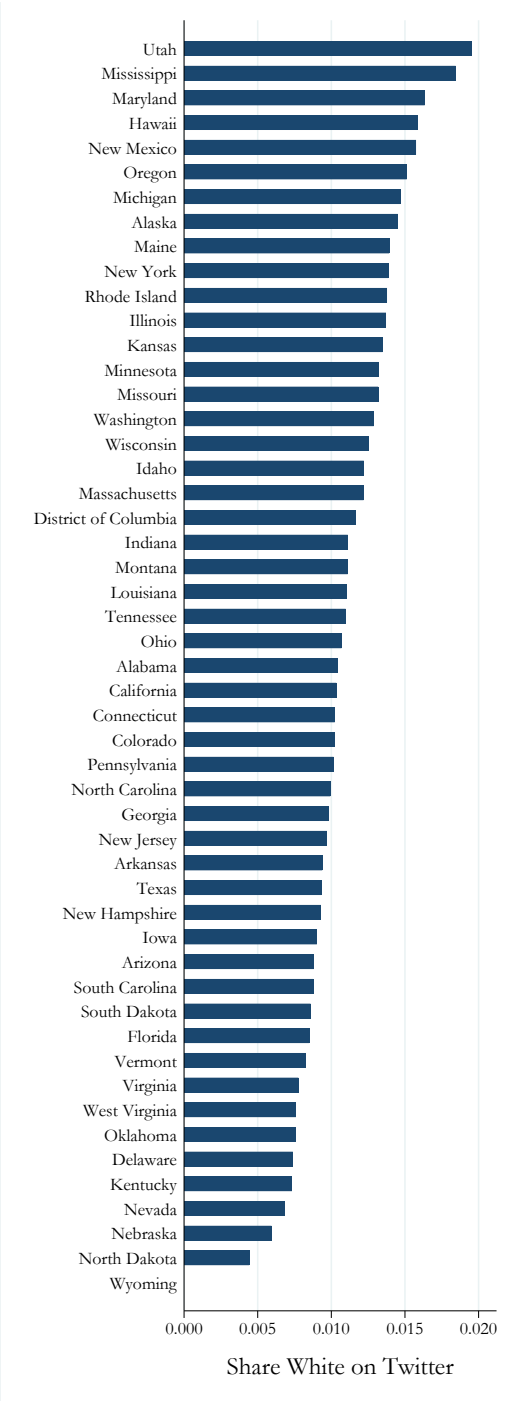
Note: This figure provides a comparison between official poverty statistics and the social media discourse on poverty on Twitter. The blue bars (left axis) show the share of the indicated groups among the total number of people in poverty in the United States. The orange bars (right axis) show the share of Tweets mentioning the indicated group among the total number of Tweets about poverty. In this figure, we excluded all Tweets that mention any foreign country.



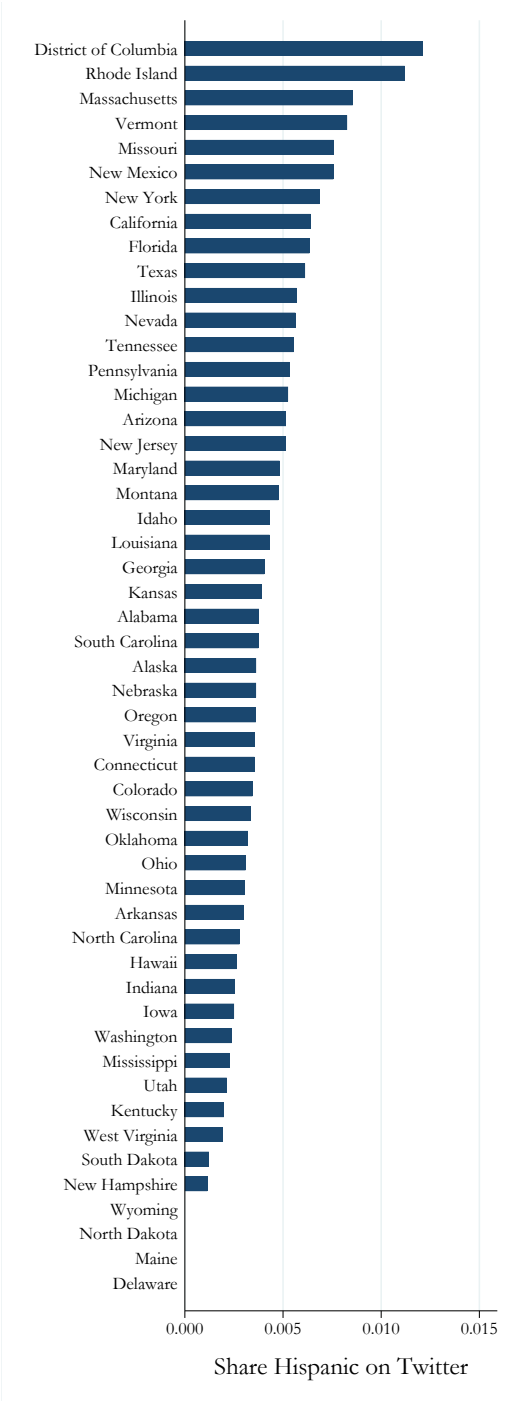
(a) Women (b) Men

Figure B6. : Social Media Discourse on Poverty by State

Note: This figure plots the shares of poverty-related social media discussions that mention specific genders or ethnic groups by state.



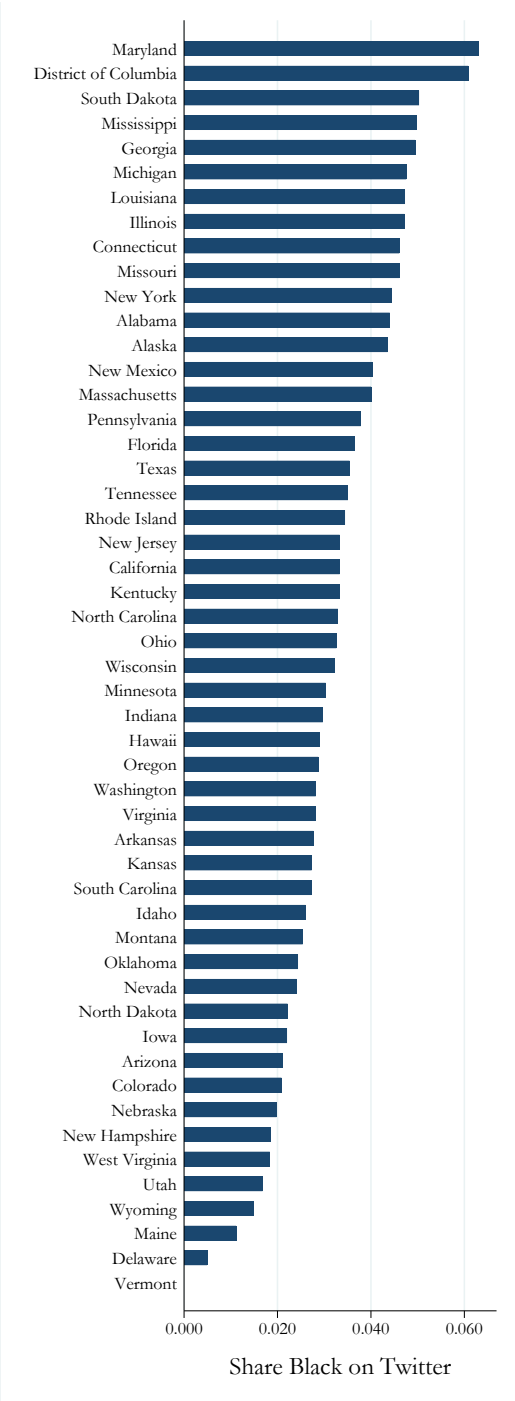
(c) White



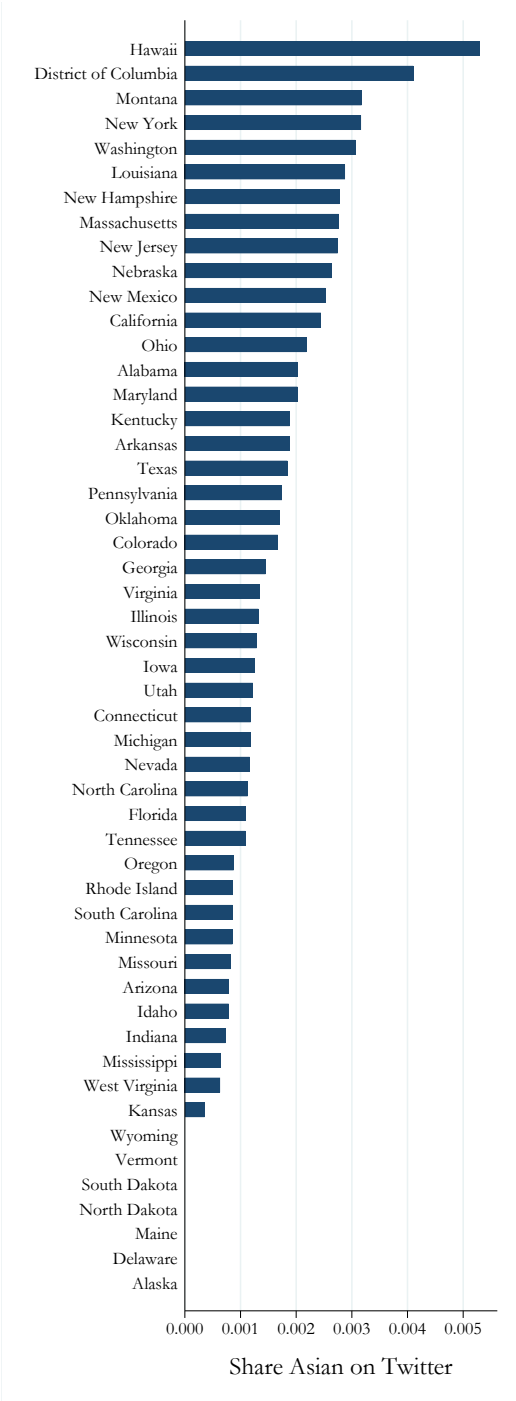
(d) Hispanic

Figure B6. : Social Media Discourse on Poverty by State

Note: This figure plots the shares of poverty-related social media discussions that mention specific genders or ethnic groups by state.



(e) Black



(f) Asian

Figure B6. : Social Media Discourse on Poverty by State

Note: This figure plots the shares of poverty-related social media discussions that mention specific genders or ethnic groups by state.