Searching for the New World Order: A Panel Analysis of Conspiracy Engagement Using Google Trends Data

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Abstract

Which states tend to be more conspiratorial, why, and how have these rankings changed over time? Using a unique Google Search panel dataset for the term "New World Order," we create a conspiracy index and investigate the distribution of conspiracy engagement over time and the demographic, economic, and political correlates of New World Order conspiracy searches. In particular, this paper finds support for Uscinski's "losers" hypothesis of conspiracy belief: we find robust positive associations between unemployment, SNAP share, and poverty rates with the conspiracy index and strong negative associations between log earnings and the conspiracy index. Additionally, we find a remarkable decline in the conspiracy index and convergence between states both before and after COVID. Finally, we also find a positive relationship between conservatism and Republicanism with the conspiracy index, a relationship that has become stronger over time.

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1 Introduction

Modern conspiracy discourse has been dominated by the belief that we live in a golden age of conspiracy theories and by the stereotypical image of the isolated, angry, online conspiracy theorist. How accurate are these assumptions? Using a unique Google Search panel dataset approach for the term "New World Order," we compute a cross-time, cross-state per capita conspiracy index and investigate the distribution of conspiracy engagement over time and the demographic, economic, and political correlates of conspiracy search interest. We find evidence of a steady decline in New World Order conspiracy engagement with remarkable state convergence. Additionally, we find that partisan gaps in conspiracy engagement have similarly converged over time, although briefly growing in 2020. The demographic correlational evidence is broadly aligned with previous literature, finding that female share, white share, median age, and educational attainment are negatively correlated with the conspiracy index. We find strong evidence for the "losers" hypothesis with positive relationships between greater Black share, single-parent share, poverty rates, SNAP rates, uninsurance rates, Republicanism, and conservatism with the index. Additionally, using labor market variables, we find strong positive correlations between unemployment and the index and strong negative correlations between log earnings per capita and the index, robust with adjusting for multiple controls. We investigate potential modeling gains from non-linear functional form and find little to no predictive benefit across all our variables. We conclude with a brief discussion of the advantages and limitations of this panel data methodology.

2 Background

In this section, we provide background on the sociological frameworks used to understand why conspiracy belief spreads and for whom. We then summarize previous empirical literature and explain the unique role of big data in the space and conclude with a brief summary of the New World Order Conspiracy.

2.1 Theoretical Literature

A recap of the academic study of conspiracy theories would be incomplete without mention of Richard Hofstadter who traced the political roots of anti-Masonic, anti-Catholic, and anti-communist conspiracy movements arguing that these movements had a fundamental "paranoid style" that tended to see the world in exaggerated battles of good and evil and inherent suspiciousness (Hofstadter 1964). This characterization has been criticized for oversimplifying and pathologizing conspiracy movements, and more recent literature has focused on how conspiracy belief is related to institutional distrust, existential disenchantment, and "agency panic" (Aupers 2012; Melley 2000). In other words, as Joseph Uscinski puts it, "conspiracy theories are for losers," not in a pejorative sense but a structural one (Uscinski and Parent 2014). In particular, marginalized groups can use conspiracy theories to outsource and explain external personal and sociopolitical struggles, making conspiracy engagement deeply tied with broader historical and structural alienation.

2.2 Empirical Literature

Time Series. Although the dominant narrative is that we live in a golden age of conspiracy, Uscinski finds that the overall total number of conspiracy beliefs has not increased (Uscinski, A. Enders, et al. 2022).

Demographic Variables. Aligned with the theoretical frameworks about alienation, research has found positive associations between being black and conspiracy interest, particularly due to greater government distrust due to the racialized histories of medicine, civil rights, and natural disaster relief (Enders 2024; Crocker et al. 1999). The relationship between gender and conspiracy belief is more disputed with some finding positive relationships and others negative relationships, largely depending on the type of conspiracy belief in question (Enders 2024; Cassese, Farhart, and Miller 2020; Popoli and Longus 2021).

Economic Variables. Existing correlational evidence finds that income, occupational status, and education are negatively correlated with conspiracy belief (Prooijen 2017; Enders 2024). Additionally, greater inequality is positively correlated with conspiratorial belief and thinking in both cross-sectional and experimentally manipulated settings (McCluney et al. 2021). The literature is sparse on the relationship between labor market outcomes such as unemployment, labor force participation, and wage growth and conspiracy belief.

Political Variables. The relationship between conspiracy belief and partisan identity has been investigated heavily and deeply contested. Hofstadter's identification of the paranoid style to right-wing movements has led to the dominant assumption that conservative identification is positively associated with greater conspiracy interest. There is some evidence to support the claim that conservatism is positively correlated with COVID and vaccine related conspiracies (Uscinski, A. M. Enders, et al. 2020). However, much of the literature resists the left vs. right framing of partisan identity and conspiracy belief and finds that conspiracy belief is only partisan insofar as the underlying conspiracy is partisan in nature (Enders 2021; Miller, Saunders, and Farhart 2016; Mercier and colleagues 2025; Smallpage, A. M. Enders, and Uscinski 2017). For instance, Pizzagate, a conspiracy surrounding a Democrat child-eating cabal, implicates a particular party, and thus may fall more on partisan grounds. Studies that focus on general measures of conspiratorial thinking find an even distribution across political affiliation and more related to institutional distrust than partisanship per se.

Despite the richness of survey data, most current empirical studies are limited to cross-sectional splits of the United States, and unable to link individuals to specific states, preventing geographic analysis. Additionally, these survey measures require self-reported data which may fail to accurately capture true conspiracy engagement. Finally, having more continuous time-series data can illustrate more dynamic changes over time, less sensitive to recent events creating anchoring bias in survey responses. Overall, we hope turning toward digital panel data can provide greater robustness in testing the findings above.

3 Methods

In this section, we outline how the conspiracy index was constructed, the datasets used, and justify our choice to study the "New World Order" term.

We construct a state-by-year panel dataset for all fifty U.S. states from 2010 to 2025 excluding District of Columbia and Puerto Rico using Google Search intensity scores for the topic "New World Order." These raw intensity scores are not directly comparable across years or states because they do not reflect the true number of searches, but rather a relative share of the maximum interest within a time period relative to other states. However, because we are able to take multiple yearly cross sections of these relative shares combined with an aggregated United States time-series, we compute a comparable index through the following procedure:

Let NWO Searches_{st} denote the number of searches for "New World Order" in state s and year t, and let $\text{Total Searches}_{st}$ denote total searches in state s and year t. The share of national "New World Order" searches coming from state s is:

$$\text{\% of Total NWO Searches}_{st} = \frac{\text{NWO Searches}_{st}}{\sum_j \text{NWO Searches}_{jt}}$$

The state-level search intensity is:

$$c_{st} = \frac{\text{NWO Searches}_{st}}{\text{Total Searches}_{st}}$$

The Google Trends cross-sectional relative region score is normalized by the highest state value in year t:

$$C_{st} = 100 \times \frac{c_{st}}{\max_j(c_{jt})}$$

Next, the relative Google Trends score is multiplied by the state internet population:

$$C_{st} \times \text{Internet Population}_{st}$$

The internet population is constructed by multiplying the total population by the population share that has internet using Census data. Unfortunately, the Census only started collecting data on internet penetration in 2013, and is missing internet data in 2020 and 2025, so we use 2013 internet data for 2010, 2011, and 2012 and 2024 internet data for 2025. 2020 data is an average of 2019 and 2021 internet data.

$$\text{Internet Population}_{st} = \text{Total Population}_{st} \times \text{Internet Penetration \%}_{st}$$

The implied share of national "New World Order" search interest assigned to state s is:

$$\text{Implied NWO Share}_{st} = \frac{C_{st} \times \text{Internet Population}_{st}}{\sum_j C_{jt} \times \text{Internet Population}_{jt}}$$

If we assume that Internet Population$_{st} \propto$ Total Searches$_{st}$ at a constant rate k across states, across time, this implied share is equivalent to the unobservable actual raw % of Total NWO Searches$_{st}$.

$$\text{\% of Total NWO Searches}_{st} = \frac{C_{st} \times \text{Internet Population}_{st}}{\sum_j C_{jt} \times \text{Internet Population}_{jt}}$$

Finally, the conspiracy index is calculated by multiplying this state share by the annual value, Y_t, dividing by the internet population for a per capita weighting.

$$\boxed{\text{Conspiracy Index}_{st} = Y_t \left(\frac{\text{\% of Total NWO Searches}_{st}}{\text{Internet Population}_{st}} \right)}$$

The annual national Google Trends score is constructed as the average of the monthly values. Let M_{mt} denote the national monthly Google Trends score in month m of year t.

$$Y_t = \frac{1}{12} \sum_{m=1}^{12} M_{mt}$$

In summary, the relative Google Trends score C_{st} is first weighted by state internet population to allocate the national annual Google Trends score Y_t across states. The allocated state-level search interest is then divided by state internet population to obtain a per-capita state-year conspiracy search index.

The following tables summarize the data manipulation for a given year.

		Unobservable				**Observable**	
Year	Subregion	NWO Searches$_{st}$	% of Total NWO Searches$_{st}$	Total Searches$_{st}$	c_{st}	C_{st}	Internet Population$_{st}$
2010	CA	32	$\frac{32}{83} \approx 38.55\%$	50	$\frac{32}{50} = 0.64$	100	$50k$
2010	TX	35	$\frac{35}{83} \approx 42.17\%$	80	$\frac{35}{80} = 0.4375$	68.36	$80k$
2010	FL	16	$\frac{16}{83} \approx 19.28\%$	40	$\frac{16}{40} = 0.40$	62.5	$40k$
$\sum$		83	100%				

		Observable					
Year	Subregion	C_{st} × Population$_{st}$	Implied NWO Share$_{st}$	Y_{st}	% Total × Y_{st}	Internet Population$_{st}$	Conspiracy Index$_{st}$
2010	CA	5,000k	$\frac{5{,}000k}{12{,}968.75k} \approx 38.55\%$	40	15.42	$50k$	$\frac{0.304}{k}$
2010	TX	5,468.75k	$\frac{5{,}468.75k}{12{,}968.75k} \approx 42.17\%$	40	16.87	$80k$	$\frac{0.211}{k}$
2010	FL	2,500k	$\frac{2{,}500k}{12{,}968.75k} \approx 19.28\%$	40	7.71	$40k$	$\frac{0.193}{k}$
$\sum$		12,968.75k	100%		40		

This conspiracy index panel is merged with panel datasets from the US Census, Cooperative Election Study, MIT Elections Lab, and the Federal Reserve Economic Data for demographic, economic, and political variables.

Because Census data for 2020 and 2025 are unavailable, the demographic correlational analysis drops these years from the sample. However, because 2020 was likely an outlier year, this data limitation is not overly concerning.

"New World Order" was chosen as the topic of interest for three main reasons. Originally used by twentieth-century political leaders to describe geopolitical shifts, the term has since come to describe a broad range of secretive totalitarian world governments. As such, the term has robust cross-sectional and time-series data availability. Terms such as "government cover up," "shadow government," and "secret government" fail to have valid state-level data in lower population regions such as the Midwest and the central United States. Other terms such as the "Great Reset" or "QAnon" fail to have valid pre-2020 data due to their recency. Secondly, because the term is not frequently used by laypeople, we believe it better captures true conspiracy engagement compared to other terms. For instance, while "QAnon" is certainly conspiracy-related, it is difficult to understand whether a "QAnon" search is from an individual seriously engaging with QAnon ideas or simply staying up to date with recent news since the term has entered the public lexicon. Finally, the "New World Order" term is often used to refer to a broad range of shadow government conspiracies including the Illuminati, Freemasons, Reptilians, globalist elites, anti-Semitic beliefs about Jewish plots, and COVID biopower. As such, we believe the results can be broadly representative of anti-government conspiracies.

Key advantages of our methodology include state and year level analysis which allows us to see how stable correlations are across time and across states. In particular, state and regional level differences are identifiable allowing for broader correlations with labor market variables unexplored previously.

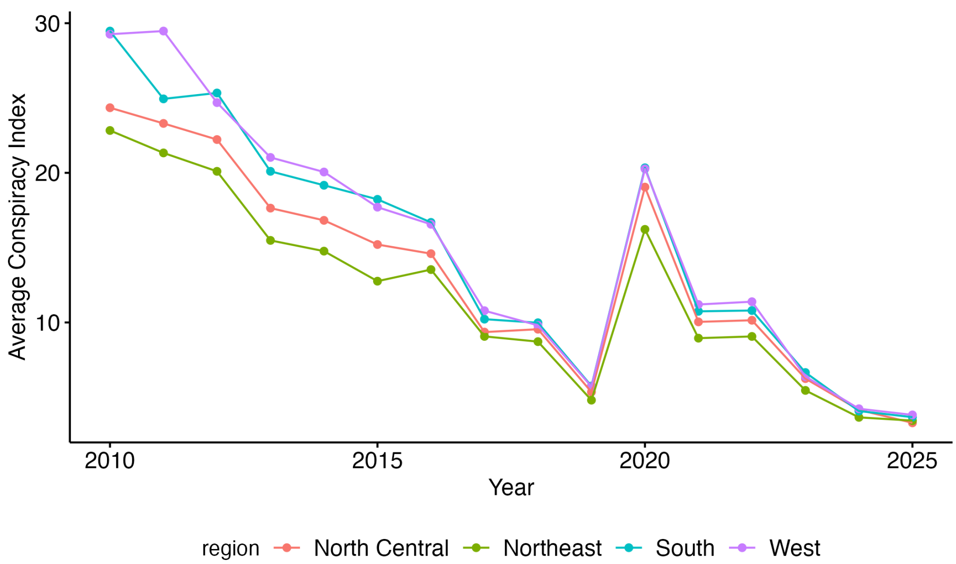
We split our analysis into two broad portions. First, we explore the changes in the distribution of conspiracy interest over time with a particular focus on interstate divergence and political divergence. Next, we conduct a correlational analysis of demographic, economic, and political variables with the conspiracy index, observing how sensitive the coefficients are to time and state fixed effects and non-linear functional form.

4 Results

4.1 Distributional Analysis

Contrary to popular belief, **Figure 1** shows a steady decrease in search intensity of the "New World Order" term with a large spike during 2020 followed by a sharp decline. In particular, while it took 10 years for the index to reach an all-time low of 4, it only took 5 years after COVID to reach this all-time low again, potentially illustrating how the COVID shock to "New World Order" conspiracy interest was relatively temporary. These yearly national declines are substantial and statistically significant as shown in **Figure 3**. However, given that the index comprises of a single term, an alternative interpretation may be that the term "New World Order" has fallen out of use in the past 15 years and is being substituted with other terms such as "deep state" while true conspiracy engagement remains constant. While such investigations are outside of the scope of this paper, further research is warranted to uncover this potential substitution effect. Regardless, this provides further empirical support for Uscinski's claim that we do not live in a golden age of conspiracy and in fact, search interest in the "New World Order" has fallen to record lows in the past 15 years.

Figure 1: Conspiracy Index Time Series by Region



In particular, in **Figure 2**, we find more suggestive evidence of a strong convergence of conspiracy index scores across states as the standard deviations steadily fall between 2010-2020, rise sharply in 2020, followed by falling rapidly after. This convergence is especially strong in recent years as **Figure 12** illustrates how between 2020 and 2025, the distributions have become much tighter and the centers have shifted to the left.

Interestingly, 2020 was not only a shock to the overall levels of NWO conspiracy engagement but also to the standard deviations, implying conspiracy engagement rose for some states more than others. This heterogeneous "2020 effect" is visually illustrated in **Figure 5** where there is a moderate positive linear relationship between average pre-2020 conspiracy index scores and the change from 2019 to 2020 in the conspiracy index score. This suggests that potentially exogenous shocks to conspiracy interest may affect states with a greater conspiracy history more than others. This may potentially speak to some kind of latent, dormant conspiracy interest that can be re-awoken like lighting a conspiracy keg but is also consistent with the counter-narrative of language substitution discussed previously. However, the relative historical conspiracy index rankings of states do not appear very predictive of current rankings. **Figure 6** illustrates a weak positive relationship between a state's 2010 conspiracy index percentile rank and 2025 index percentile rank with an R^2 of 0.1614. As such, there appear to be many other factors besides historical conspiracy engagement that determine present-day levels.

Who are these old and new high conspiracy index states? **Figure 7** illustrates a plot of the 2010-2015 average conspiracy index scores and the 2020-2025 average conspiracy index scores. All values lie below the 45 degree line, implying all states had lower average conspiracy indices in 2020-2025 compared to 2010-2015. Additionally, the vertical dispersion is much less than the horizontal dispersion, giving further evidence of the convergence effect in recent years. It appears historically and currently high conspiracy states include Missouri, Nevada, Wyoming, Arkansas, and Oklahoma.

Finally, we find suggestive evidence of converging partisan differences in conspiracy index scores. In **Figure 8**, we use two methods of state political party classification using the CCES political party self-identification responses and federal presidential election data. For the former, we classify a state as Republican in a given year if the average CCES score exceeds 4 (Moderate) and Democrat if the average CCES score is below 4. We sensitize this classification in panel (b) by increasing the boundary to exceeding 4.25 for Republicans and below 3.75 for Democrats. For the latter, we classify a state as Republican depending on which political party won in the latest presidential election. Panel (c) uses the 2 years before and after a presidential election for political party classification while Panel (d) classifies a state's political party for the entire 4 years after the election. All four graphs indicate that on average, Republican states appear to have slightly higher conspiracy index scores, while any partisan gaps from 2010-2016 have largely shrunk over time. In particular, in **Figure 9**, across our four sorting approaches, we find statistically significant partisan gaps that steadily declined from 2010 to 2018, rose in 2018-2021 and declined since then.

4.2 Correlational Analysis

Figure 10 summarizes the relationships between the conspiracy index and a range of demographic, economic, and political variables. A pooled panel data analysis suggests that Asian share, college education share, median age, inequality, log earnings, and rent burden share are negatively correlated with the index while white share, labor force participation, poverty rates, SNAP share, unemployment, uninsurance rates, and conservatism are positively correlated with the index. A full table of correlational estimates is available in **Table 1**. We sensitize these correlations using year and state demeaned index values and find that many relationships are sensitive to inter vs. intra state and year comparisons. In fact, after adjusting for time and state fixed effects, only uninsurance rates has any relationship with the index.

The sensitivity of the estimates to state and year fixed effects is unsurprising since many of the chosen variables essentially represent the fixed effects. **Table 2** shows how nearly all variables except income, rent burden share, and unemployment have over 70% of their variation explained by state fixed effects, implying that most of the variation is found across states rather than within states making state fixed effects inappropriate for a correlational analysis. On the other hand, unemployment and log earnings have a majority of their variation explained by time fixed effects, implying variation is found across years and making time fixed effects inappropriate for a correlational analysis. Given that 86.5% of the variation in the conspiracy index is found in year fixed effects, almost all variation is mainly found within states compared to across states making time fixed effects difficult to use with the conspiracy index since it leaves little residual variation. Given the results in **Table 2**, we believe that, with exception to unemployment and log earnings, most other variables should be interpreted using time fixed effects to account for the steady nationwide decline in the conspiracy index. Unemployment and log earnings are exceptions since these values vary little across states but greatly with macroeconomic conditions (and thus by year). A visualization of the strongest linear relationships (unemployment, SNAP share, poverty rate, college share, log earnings per capita, and political affiliation) is shown in **Figure 11**.

The pooled correlations are broadly aligned with the prior literature. In particular, similar to Enders et al. 2024, we also find negative associations with education, income, and age. After adjusting for time fixed effects, the relationships between black share and white share are also consistent with Enders. We also find a negative correlation with Asian share, female share, and single-parent share. Given this is a state-level analysis, we should treat these correlations carefully, since it only suggests that states with more single-parents or less women and Asians tend to have higher conspiracy index values, not that these individuals tend to have higher conspiracy values. While the existence of individual-level demographic correlations makes state-level demographic correlations more likely, (if Black individuals are more likely to believe conspiratorial, we expect states with more black people to exhibit higher conspiratorial tendencies), state-level analysis is ripe with omitted variable bias. While this is a limitation of our methodology, the fact that the state-level demographic correlations match the individual demographic correlations in the broader literature is reassuring.

Analyzing economic and ”distress” variables, we find strong suggestive evidence in support of the ”losers” hypothesis. In particular, we find a strong robust negative correlation between log earnings and the conspiracy index and positive correlations between the poverty rate, SNAP rate, and unemployment with the conspiracy index. These coefficients remain stable even when adjusting for racial share, gender, age, inequality, political affiliation, and college share as shown in **Table 3, 4, 5, and 6**. Additionally, the negative relationship between earnings and the conspiracy index and the positive relationship between poverty and the conspiracy index are both statistically significantly non-zero and incredibly stable for every year from 2010 to 2025. Interestingly, in **table 3**, the coefficient on college share becomes statistically significantly positive after adjusting for log earnings in both regression (8) and (9), potentially giving suggestive evidence that the mechanism behind college share's negative relationship with the conspiracy index may not be through improved human capital or reasoning capabilities but rather through income.

At first glance, two correlations may appear to undercut the losers hypothesis, but they are ultimately spurious or explained by other variables: the robustly negative relationship between the Gini coefficient and the conspiracy index and rental burden share. While it is strange that states with greater inequality tend to have less conspiracy engagement, we find that adding time fixed effects causes the correlation to be statistically indistinguishable from zero. Additionally, as shown in **Table 7**, adjusting for the poverty rate, log earnings, and / or college share either causes the coefficient on rental burden to flip statistically significantly positive or statistically indistinguishable from zero (robust with year fixed effects).

Regarding political variables, while only conservatism was positively correlated in the pooled sample, when analyzing the relationship at the yearly level, **Figure 13** illustrates an extremely stable positive relationship between the index and conservatism, Republicanism, and the vote share (Republican - Democrat) in the 2012, 2016, 2020, and 2024 presidential elections. While the political partisanship visualization in **Figure 8** does not show a large gap between partisan identity and conspiracy interest, this is due to the graph using binary measures of partisan identity while the correlational analysis in **Figure 13** uses a continuous measure of partisan identity in analyzing the relationship. In particular, we see a growing upward trend in the correlation coefficient from 2010 to 2025, suggesting that partisan identity is becoming more predictive of the conspiracy index over time.

Finally, we explore the potential gains in explanatory power by modeling the relationship between demographic, economic, and political variables and the index nonlinearly. **Figure 14** plots the marginal increase in adjusted R^2 after adding a given variable in a linear and quadratic functional form. We find little benefit to modeling any of the relationships in a nonlinear fashion.

5 Conclusion

Overall, our panel dataset approach allows us to uniquely analyze geographic and temporal variation in conspiracy interest. In particular, we find evidence of a gradual decrease in the conspiracy index and a convergence of high conspiracy and low conspiracy states. While COVID did lead to a sharp rise in conspiracy interest, these increases were largely temporary and fell quickly to record-low amounts in 2025. Secondly, we also find suggestive correlational evidence that is consistent with the sociological literature surrounding conspiracy theories. In particular, we find strong evidence for the "losers" hypothesis as states with lower per capita incomes, higher poverty rates, larger SNAP-recipient shares, lower insurance take-up, and larger Black populations as well as years with lower incomes and higher unemployment are positively correlated with the index. These patterns are broadly aligned with the literature and consistent with the theoretical frameworks that frame conspiracy belief as a way of understanding and reacting to losses in societal standing or power. Finally, we find positive correlations with Republicanism and conservatism, correlations that have increased over time from 2010 to 2025. We hope these findings can add to the growing empirical literature surrounding conspiracy culture and illustrate how non-survey "big data" approaches can provide unique insights to the field.

We note that these results are purely descriptive and no causal claims can be made, given the possibility of omitted variable bias. Furthermore, the sensitivity of the correlations to state, year, and region fixed effects makes the interpretability of these relationships slightly unclear. Additionally, we assume that the Google Trends values are somewhat simple and unadjusted for outside of the scaling shown in the **Methods** page. A key, potentially untenable, assumption is that the scaling factor between Internet users and Google Searches, k, does not change by state or across time. It is possible that certain states search more per capita which is a threat to identification.

Finally, the index was only computed using one search term, so future research should be conducted to see how robust these results are to other more recently used phrases.

6 Appendix

6.1 Distributional Analysis

Figure 2: Conspiracy Index Mean and SD Time Series

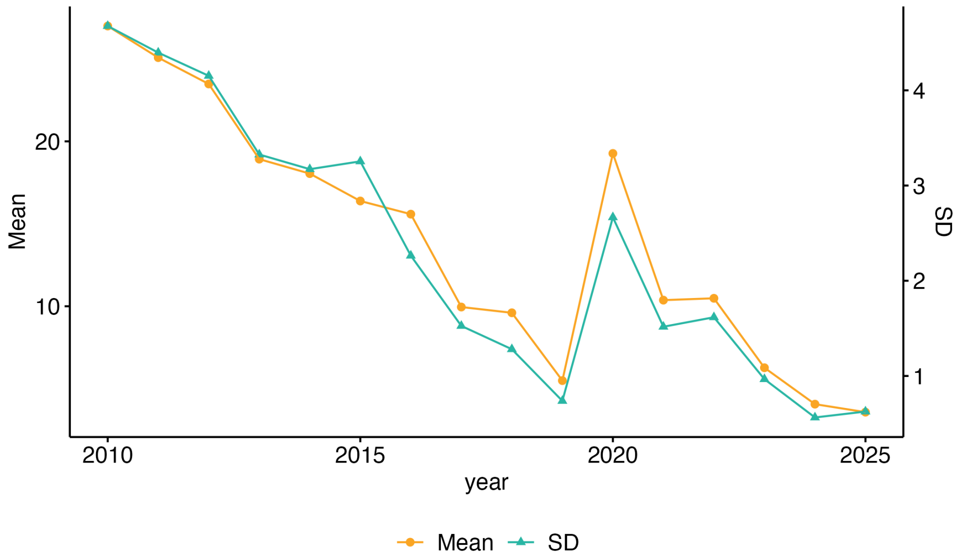


Figure 3: Conspiracy Index National Yearly Fixed Effects

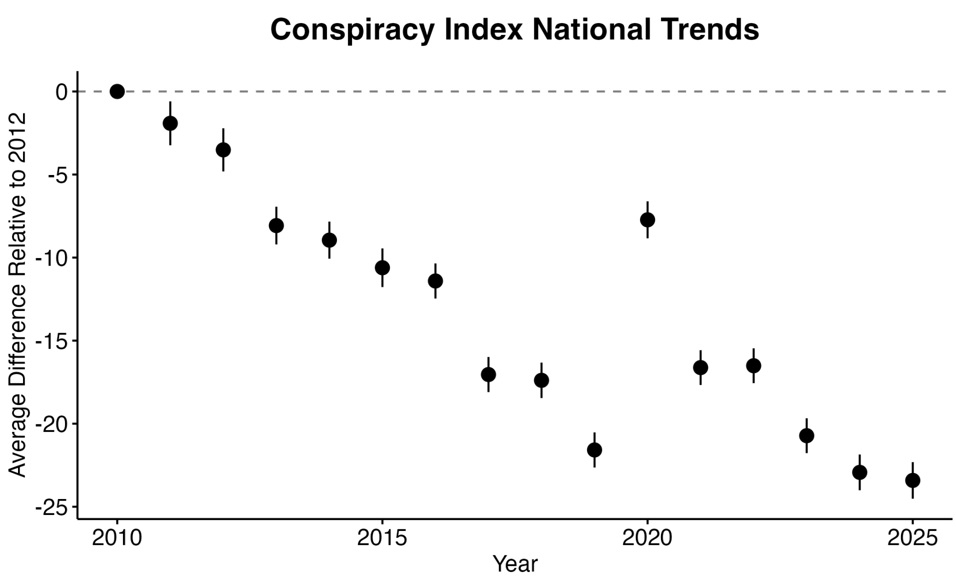


Figure 4: Conspiracy Index Yearly Distribution

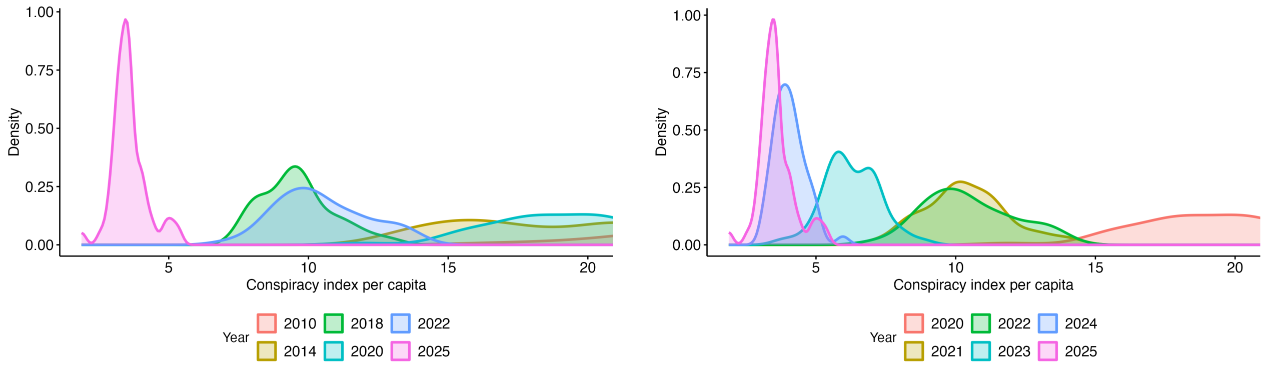


Figure 5: Relationship Between the 2020 Effect and Prior Index Levels (R^2 = 0.245, Slope =0.461*)**

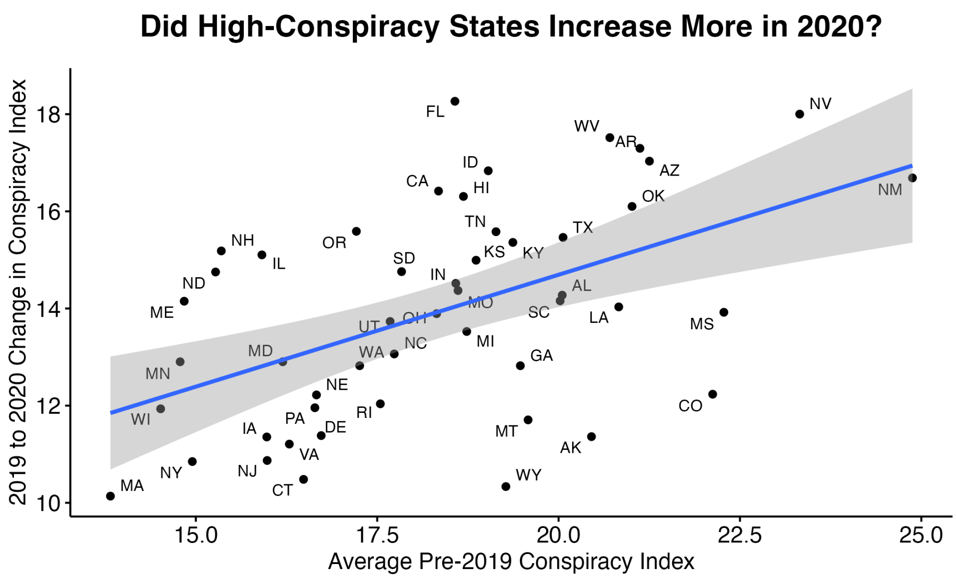


Figure 6: Historical Conspiracy Stickiness (Slope = 0.3975*, Adj. R^2 = 0.1384**

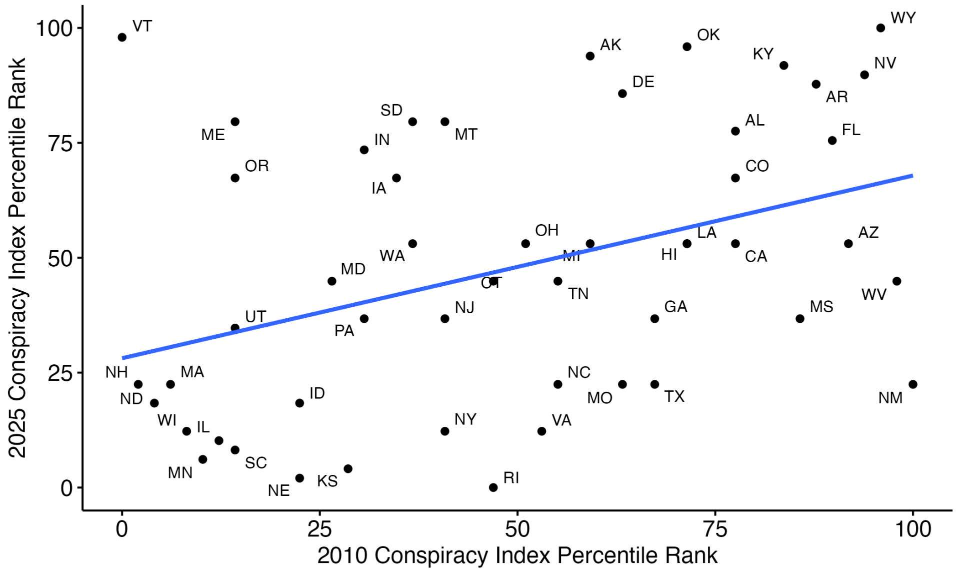


Figure 7: Changes in 2010-2015 vs. 2020-2025 Average Conspiracy Index

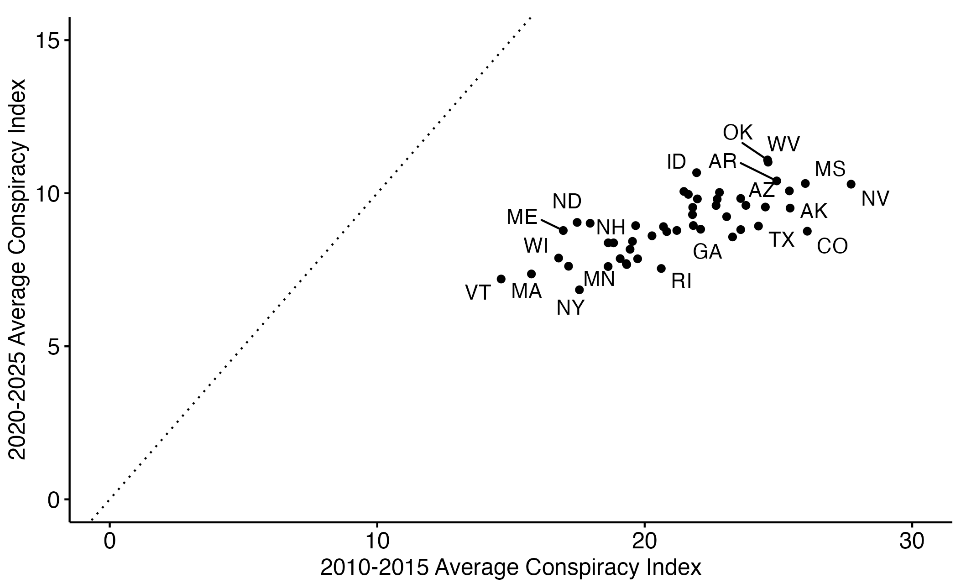
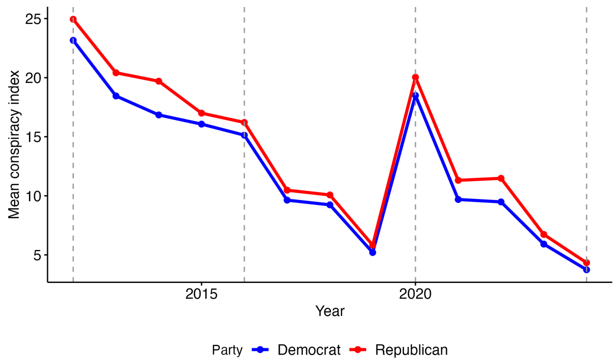
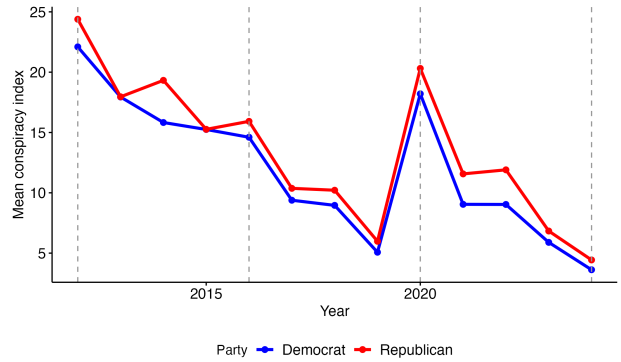


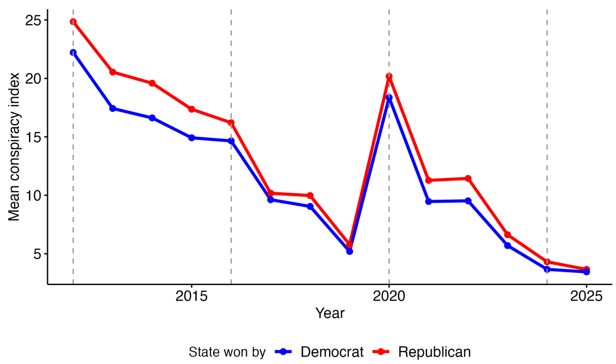
Figure 8: Political Partisanship Over Time



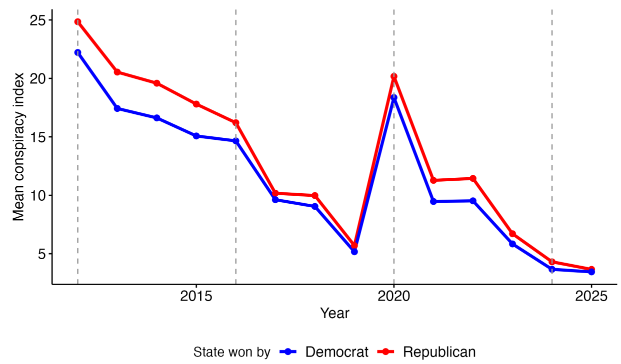
(a) CCES A



(b) CCES B

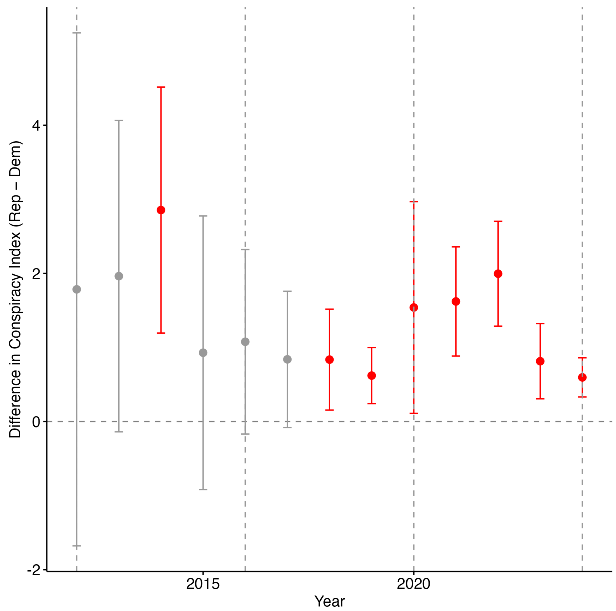


(c) Election A

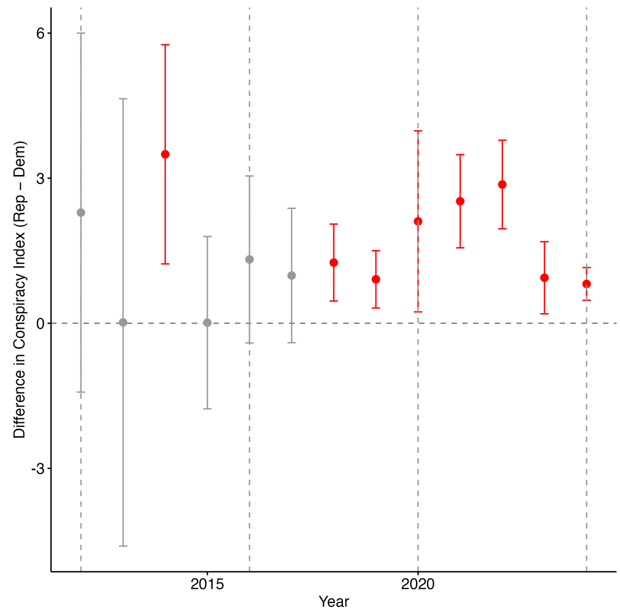


(d) Election B

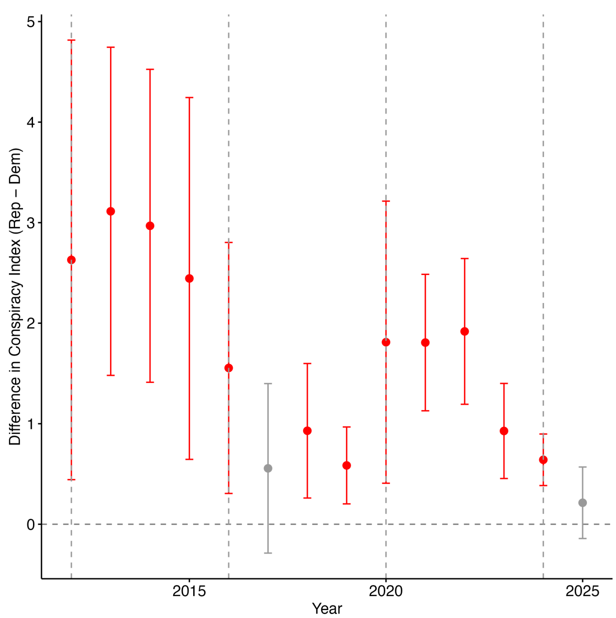
Figure 9: Political Partisanship Over Time



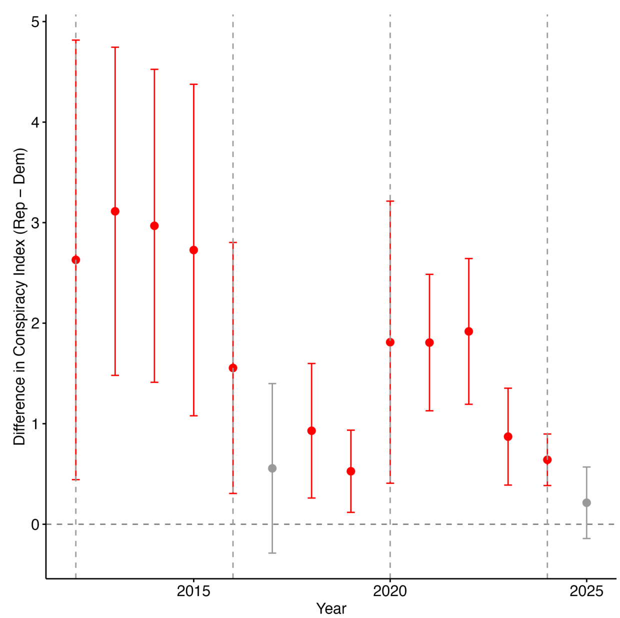
(a) CCES A



(b) CCES B



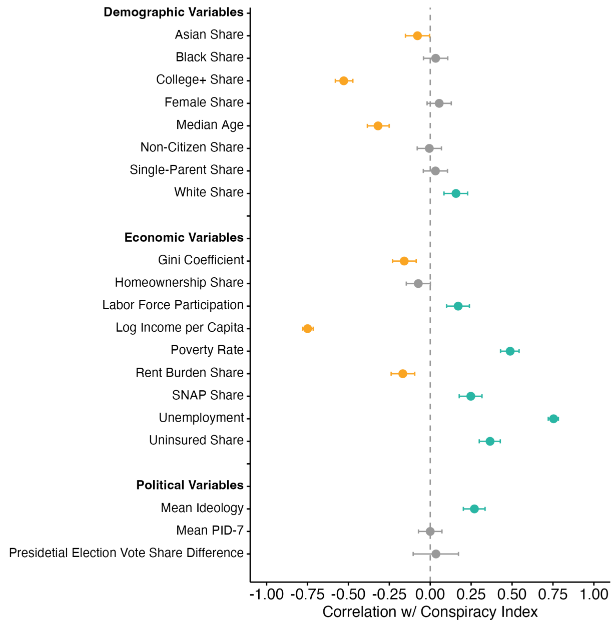
(c) Election A



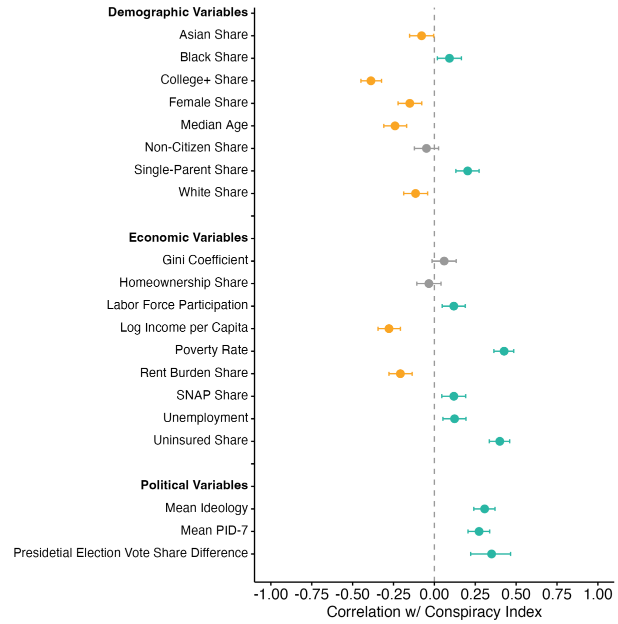
(d) Election B

6.2 Correlational Analysis

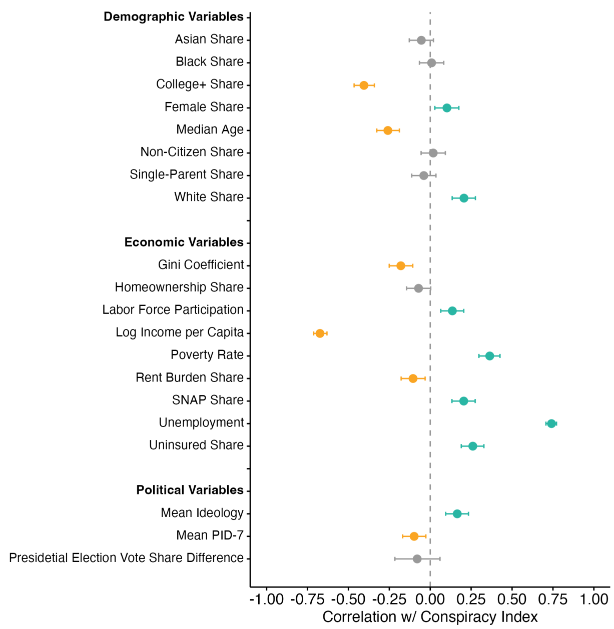
Figure 10: Correlational Analysis



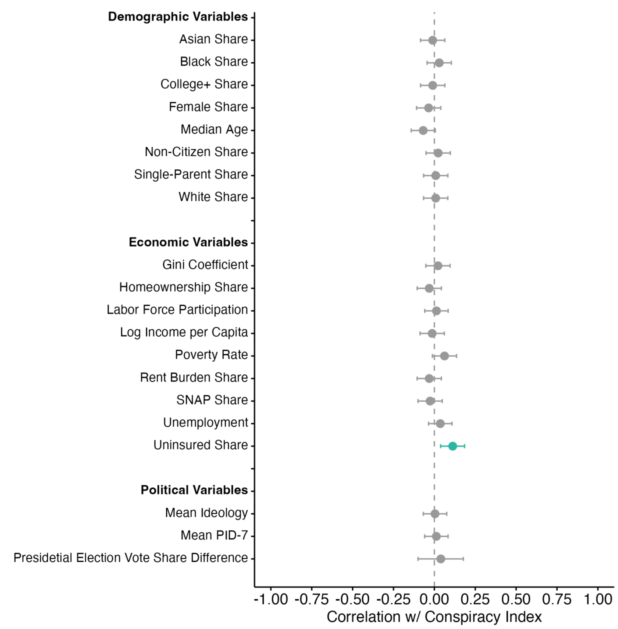
(a) Pooled Correlation



(b) Year Demeaned Correlation



(c) State Demeaned Correlation



(d) State Year Demeaned Correlation

Table 1: Correlations with Conspiracy Index

	Correlations			
	(1)	(2)	(3)	(4)
Panel A: Demographic Variables				
Share Asian	-0.078*	-0.078*	-0.054	-0.010
Share Black	0.033	0.092*	0.008	0.030
College+ Share	-0.529***	-0.388***	-0.405***	-0.010
Female Share	0.055	-0.150***	0.102**	-0.035
Median Age	-0.319***	-0.241***	-0.259***	-0.068†
Non-Citizen Share	-0.005	-0.049	0.018	0.023
Single-Parent Share	0.032	0.204***	-0.039	0.008
White Share	0.157***	-0.115**	0.206***	0.008
Panel B: Economic Variables				
Gini	-0.159***	0.060	-0.180***	0.022
Homeownership Share	-0.073†	-0.034	-0.071†	-0.031
Labor Force Part.	0.171***	0.119**	0.135***	0.013
Log Income per Capita	-0.749***	-0.278***	-0.674***	-0.014
Poverty Rate	0.488***	0.427***	0.364***	0.062
Rent Burden Share	-0.168***	-0.208***	-0.105**	-0.031
SNAP Share	0.248***	0.119**	0.205***	-0.026
Unemployment	0.754***	0.123***	0.741***	0.036
Uninsured Share	0.366***	0.400***	0.260***	0.112**
Panel C: Political Variables				
Mean Ideology	0.270***	0.307***	0.165***	0.004
Mean PID-7	0.000	0.273***	-0.098**	0.012
Year Fixed Effects	No	Yes	No	Yes
State Fixed Effects	No	No	Yes	Yes

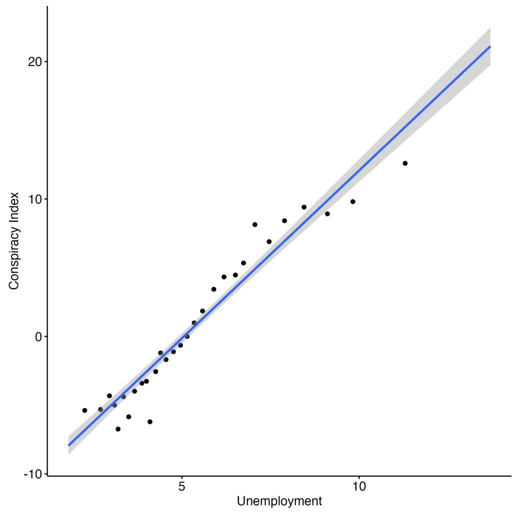
† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: R^2 from Fixed Effects Regressions

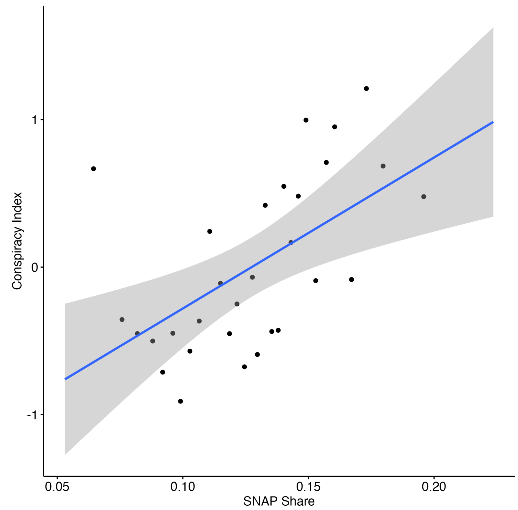
	R^2				
Variable	State FE	Region FE	Year FE	State + Year FE	Region + Year FE
Conspiracy Index	0.049	0.024	0.885	0.936	0.910
Panel A: Demographic Variables					
Asian Share	0.994	0.115	0.003	0.997	0.118
Black Share	0.998	0.550	0.000	0.998	0.551
College+ Share	0.771	0.249	0.218	0.990	0.467
Female Share	0.942	0.518	0.029	0.971	0.546
Median Age	0.900	0.304	0.077	0.977	0.381
Non-Citizen Share	0.984	0.121	0.003	0.987	0.124
Single-Parent Share	0.716	0.210	0.016	0.733	0.227
White Share	0.871	0.154	0.092	0.963	0.246
Panel B: Economic Variables					
Unemployment	0.224	0.026	0.650	0.874	0.675
Gini	0.870	0.243	0.056	0.927	0.300
Labor Force Part.	0.921	0.026	0.042	0.964	0.068
Log Income per Capita	0.378	0.130	0.610	0.988	0.740
Poverty Rate	0.796	0.261	0.149	0.945	0.410
Rent Burden Share	0.516	0.169	0.043	0.559	0.212
Homeownership Share	0.927	0.110	0.042	0.968	0.151
Uninsured Share	0.770	0.232	0.110	0.880	0.342
SNAP Share	0.773	0.126	0.085	0.858	0.210
Panel C: Political Variables					
Mean PID-7	0.776	0.191	0.031	0.807	0.223
Mean Ideology	0.766	0.305	0.049	0.815	0.355

Figure 11: Binned Scatterplot Between Variable and Conspiracy Index

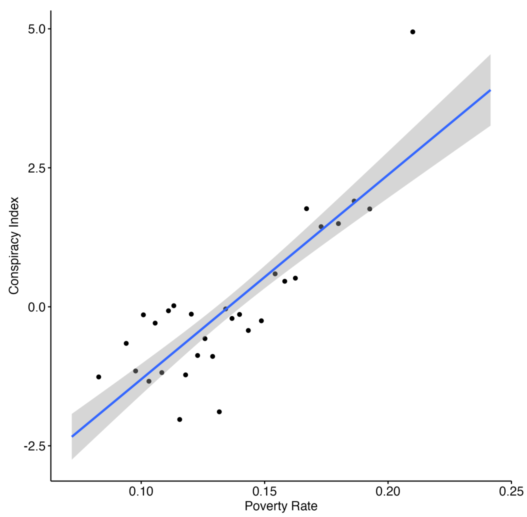
(a) Unemployment Rate (State FE)



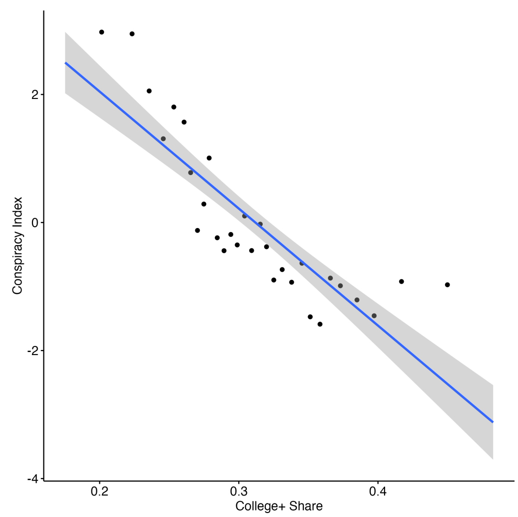
(b) SNAP Share (Year FE)



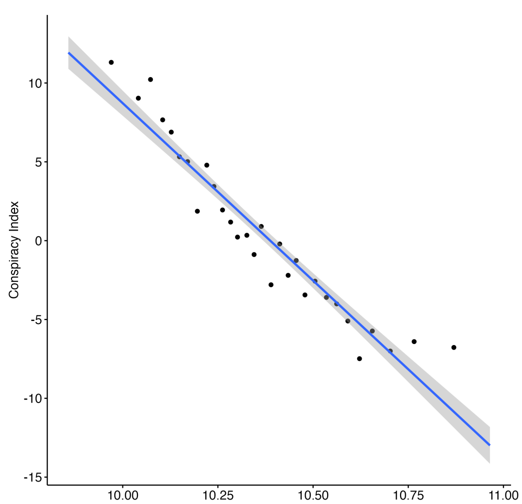
(c) Poverty Rate (Year FE)



(d) College+ Share (Year FE)



(e) Log Earnings per Capita (State FE)



(f) Political Affiliation (Time FE)

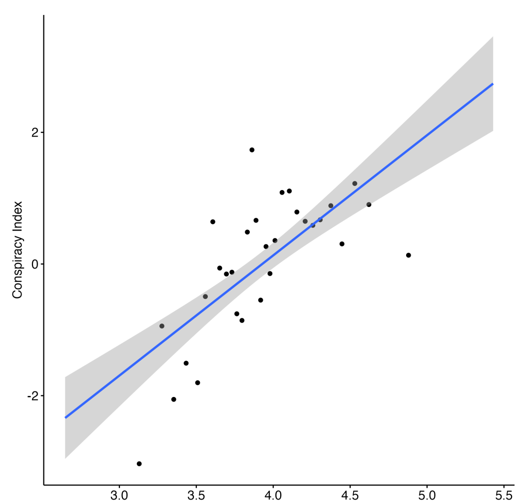


Table 3: Regression Results: Log Earnings Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	281.650***	285.092***	290.697***	315.115***	282.438***	290.249***	311.503***	386.775***	524.667***
	(7.953)	(8.216)	(9.043)	(18.274)	(7.980)	(9.062)	(8.327)	(14.555)	(33.136)
Log Earnings	-25.773***	-26.053***	-26.395***	-26.105***	-24.828***	-25.495***	-27.256***	-37.508***	-38.249***
	(0.761)	(0.781)	(0.822)	(0.799)	(0.822)	(0.779)	(0.739)	(1.573)	(2.142)
Share Black	–	-5.217*	–	–	–	–	–	–	1.964
		(2.183)							(3.501)
Share White	–	–	-3.493*	–	–	–	–	–	-2.625
			(1.393)						(1.952)
Female Share	–	–	–	-59.444*	–	–	–	–	-209.787***
				(27.553)					(50.054)
Age	–	–	–	–	-0.275**	–	–	–	-0.051
					(0.091)				(0.123)
Gini	–	–	–	–	–	-24.785*	–	–	-2.545
						(11.311)			(13.522)
Mean PID-7	–	–	–	–	–	–	-3.690***	–	-4.122***
							(0.457)		(0.646)
College+ Share	–	–	–	–	–	–	–	53.134***	42.981***
								(6.565)	(7.975)
Adj. R^2	0.561	0.564	0.564	0.564	0.567	0.564	0.597	0.605	0.650
N	699	699	699	699	699	699	699	699	699

Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Regression Results: Poverty Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-1.712	-2.634*	-9.235***	59.257**	30.490***	72.602***	4.063	22.849***	73.274**
	(1.082)	(1.117)	(2.101)	(18.669)	(4.341)	(6.062)	(2.455)	(3.738)	(24.578)
Poverty Rate	118.577***	137.710***	120.266***	129.476***	108.942***	161.073***	121.095***	50.638***	112.344***
	(8.018)	(9.259)	(7.971)	(8.660)	(8.134)	(7.963)	(8.043)	(13.258)	(17.777)
Share Black	–	-16.038***	–	–	–	–	–	–	-9.746*
		(3.221)							(3.912)
Share White	–	–	9.804***	–	–	–	–	–	6.973**
			(2.169)						(2.169)
Female Share	–	–	–	-123.619**	–	–	–	–	127.615*
				(37.765)					(52.610)
Age	–	–	–	–	-0.802***	–	–	–	-1.036***
					(0.100)				(0.113)
Gini	–	–	–	–	–	-172.863***	–	–	-139.577***
						(13.803)			(18.197)
Mean PID-7	–	–	–	–	–	–	-1.559*	–	-7.354***
							(0.606)		(0.668)
College+ Share	–	–	–	–	–	–	–	-49.242***	-30.121***
								(6.704)	(8.227)
Adj. R^2	0.238	0.269	0.268	0.251	0.296	0.391	0.243	0.296	0.528
N	699	699	699	699	699	699	699	699	699

Heteroskedastic standard errors in parentheses.

† p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5: Regression Results: Unemployment Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	1.010*	-6.864***	0.841†	58.843***	25.592***	41.925***	-13.986***	13.131***	14.848
	(0.434)	(1.357)	(0.446)	(14.085)	(3.151)	(4.383)	(1.796)	(1.311)	(20.053)
Unemployment	2.560***	2.721***	2.773***	2.806***	2.594***	2.776***	2.720***	2.336***	2.185***
	(0.080)	(0.078)	(0.081)	(0.082)	(0.078)	(0.078)	(0.078)	(0.082)	(0.097)
Share Black	–	-8.527***	–	–	–	–	–	–	-7.111*
		(1.914)							(3.399)
Share White	–	–	9.531***	–	–	–	–	–	4.599*
			(1.708)						(2.012)
Female Share	–	–	–	-116.918***	–	–	–	–	114.873**
				(28.024)					(44.432)
Age	–	–	–	–	-0.641***	–	–	–	-0.675***
					(0.078)				(0.091)
Gini	–	–	–	–	–	-90.645***	–	–	-66.123***
						(9.404)			(11.619)
Mean PID-7	–	–	–	–	–	–	3.600***	–	-1.478*
							(0.433)		(0.611)
College+ Share	–	–	–	–	–	–	–	-34.966***	-32.518***
								(3.249)	(4.106)
Adj. R^2	0.568	0.616	0.597	0.601	0.624	0.637	0.603	0.645	0.711
N	749	699	699	699	699	699	749	699	699

Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Regression Results: SNAP Share Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	6.708***	-2.920	6.696***	36.407†	53.288***	65.382***	1.712	33.051***	52.268*
	(1.122)	(2.198)	(1.128)	(20.063)	(4.146)	(6.440)	(3.392)	(1.934)	(24.286)
SNAP Share	59.978***	68.652***	62.840***	66.573***	81.188***	97.078***	64.300***	16.832*	21.716*
	(8.656)	(8.676)	(9.207)	(10.096)	(8.454)	(9.362)	(9.454)	(7.814)	(9.632)
Share Black	–	-3.386	–	–	–	–	–	–	-9.072*
		(3.171)							(4.101)
Share White	–	–	11.456***	–	–	–	–	–	7.919***
			(2.210)						(2.251)
Female Share	–	–	–	-60.455	–	–	–	–	177.437***
				(40.870)					(52.817)
Age	–	–	–	–	-1.279***	–	–	–	-1.297***
					(0.106)				(0.118)
Gini	–	–	–	–	–	-136.875***	–	–	-73.663***
						(14.733)			(15.606)
Mean PID-7	–	–	–	–	–	–	1.133	–	-7.405***
							(0.689)		(0.754)
College+ Share	–	–	–	–	–	–	–	-66.835***	-70.954***
								(4.112)	(5.554)
Adj. R^2	0.060	0.100	0.060	0.062	0.207	0.151	0.062	0.281	0.492
N	699	699	699	699	699	699	699	699	699

Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Regression Results: Rent Burden Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	27.491***	33.052***	-6.308	21.341***	291.584***	114.429***	28.278***	33.084***	383.986***	32.135†
	(2.999)	(1.441)	(4.023)	(1.862)	(8.277)	(6.898)	(2.623)	(1.326)	(16.164)	(17.823)
Rent Burden Share	-157.346***	-72.503***	46.684	-6.854	146.395***	-3.991	130.097***	5.493	77.823*	13.283
	(35.619)	(15.825)	(39.229)	(16.975)	(30.007)	(17.733)	(36.169)	(17.430)	(32.411)	(17.702)
Poverty Rate	–	–	123.722***	42.386***	–	–	–	–	-7.482	27.646***
			(9.134)	(4.015)					(11.329)	(6.083)
Log Income per Capita	–	–	–	–	-27.910***	-8.587***	–	–	-37.506***	-0.708
					(0.886)	(0.741)			(1.606)	(1.849)
College+ Share	–	–	–	–	–	–	-79.492***	-23.823***	44.431***	-11.399*
							(4.526)	(2.114)	(7.685)	(5.504)
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.027	0.877	0.238	0.899	0.581	0.897	0.291	0.896	0.609	0.902
N	699	699	699	699	699	699	699	699	699	699

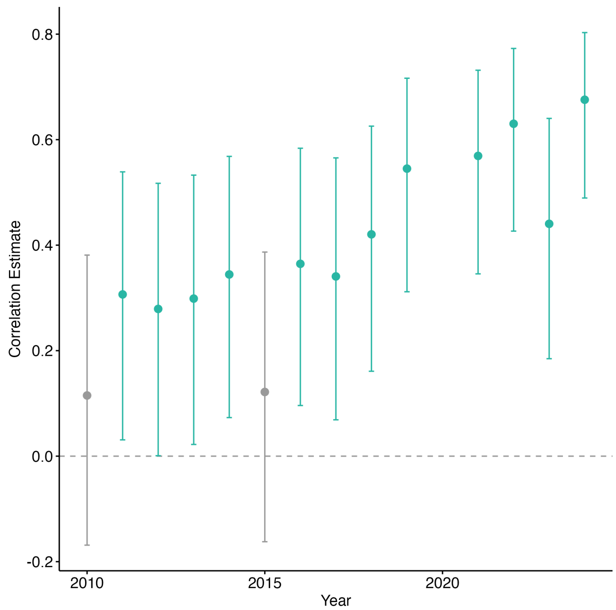
Heteroskedastic standard errors in parentheses.

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

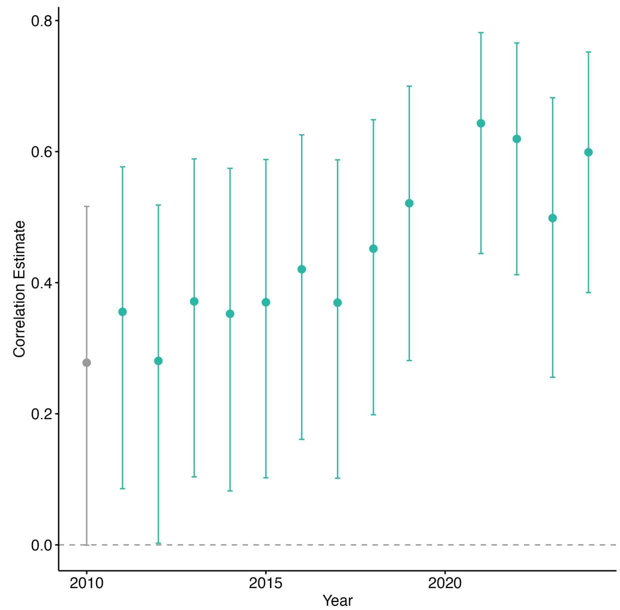
Figure 12: Relationship Between Economic Variables and Conspiracy Index Over Time

Figure 13: Relationship Between Political Variables and Conspiracy Index Over Time

(a) Political Affiliation
(1 = Very Democrat, 7 = Very Republican)



(b) Ideological Affiliation
(1 = Progressive, 5 = Conservative)



(c) Presidential Election Vote Share Difference
(Rep - Dem)

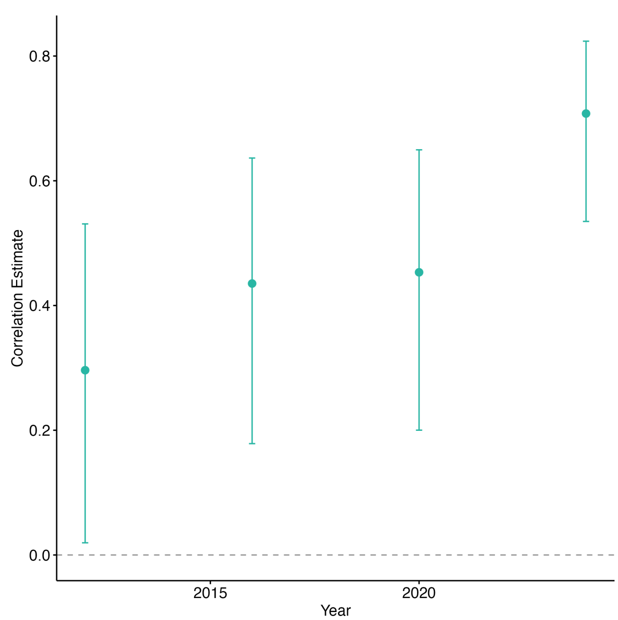


Figure 14: Marginal R^2 Additions (Linear vs. Quadratic Functional Form)