Media Effects and Party Support Volatility in US: A Synthetic Data Approach

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Abstract

Research on media use and partisanship has expanded rapidly. The literature is populated with studies using partisanship as an independent variable driving differences in media usage or partisanship as the dependent variable, analyzing the exogenous effects of media usage or media coverage. While most studies treat partisanship as either an independent or dependent variable, we follow approaches that examine media effects conditional on partisan predispositions. This study examines media attention and party support dynamics in the United States using a novel synthetic data approach. In addition to employing traditional survey data, we generate synthetic voter microdata using Bayesian networks fitted to ANES observations, building on recent interest in computational approaches to survey research (Argyle et al. 2023) while addressing key limitations of LLM-based synthetic samples identified by Bisbee et al. (2024). By comparing the observed ANES data with Bayesian network-generated synthetic samples, we explore new methods for detecting voting intention and party support among potential voters, including the application of Pearl's do-calculus for causal inference about media effects. This 'silicon-augmented survey research' generates hypotheses through synthetic data exploration and validates findings against human survey data.

Introduction: Media Effects and Partisan Volatility[1]

Media consumption and partisan attitudes are now deeply intertwined in American politics. While traditional models of media effects focused on persuasion and agenda-setting, recent scholarship emphasizes the role of selective exposure

[1]This paper is in the first draft version. The author would like to thank the reviewer, conference organizers and participants for their valuable feedback and suggestions.

and media choice in reinforcing existing political predispositions (Iyengar and Hahn (2009)).

The American National Election Studies (ANES) has long served as the gold standard for measuring public opinion and voting behavior in the United States. However, traditional survey methods face mounting challenges in reaching volatile voter segments—particularly young voters, non-partisans, and those disengaged from conventional political processes.

The Challenge of Volatile Voters

American elections have witnessed increasing electoral volatility in recent cycles. The phenomenon of swing voters, ticket-splitters, and late-deciding voters presents both methodological challenges for pollsters and strategic puzzles for campaigns. Understanding how volatile voters consume media is central to explaining partisan dynamics.

Synthetic data approaches

Argyle et al. (2023) introduced the concept of "silicon samples"—synthetic survey respondents generated by large language models that can simulate human opinion distributions. While this approach opens promising avenues for survey research, subsequent work has identified important limitations regarding variance reduction, prompt sensitivity, and temporal instability (Bisbee et al. (2024)). This study builds on the innovative spirit of computational approaches to survey research while employing an alternative methodology—Bayesian network-based synthetic data generation—that addresses several of these limitations while enabling principled causal inference through Pearl's do-calculus framework (Pearl (2009)).

Literature Review

From Minimal Effects to Conditional Media Influence

The systematic study of media effects on voting behavior has evolved through several theoretical paradigms. The Columbia school's pioneering work established the "minimal effects" hypothesis: Lazarsfeld et al. (1944) and Berelson et al. (1954) found that mass media primarily reinforced existing predispositions rather than converting voters, with information flowing indirectly through opinion leaders. The Michigan school's concept of party identification as a "perceptual screen" (Campbell et al. 1960) similarly implied constrained media influence—partisan attachments, often inherited from parents, filtered political information in ways that limited direct persuasion.

The agenda-setting breakthrough of the 1970s revitalized media effects research by identifying subtler influence mechanisms. McCombs and Shaw (1972) demonstrated that media shapes which issues citizens consider important, while Iyengar and Kinder (1987) extended this framework to show how news coverage alters evaluative criteria (priming) and attributions of responsibility (framing). Zaller's (1992) Receive-Accept-Sample model synthesized these traditions, proposing that media effects are moderated by political awareness: highly aware citizens receive more information but resist counter-attitudinal messages, while less aware citizens receive fewer messages but are more susceptible when exposed.

The transformation from broadcast-era scarcity to contemporary media abundance has fundamentally altered these dynamics. Prior (2007) demonstrates that expanded media choice enables citizens to opt out of news entirely or to selectively expose themselves to ideologically congenial sources. His "Conditional Political Learning" model shows that entertainment preferences now predict political knowledge gaps more strongly than demographic factors. Iyengar and Hahn (2009) provide empirical evidence of this ideological selectivity, documenting how Republicans and Democrats gravitate toward different news sources. Prior's framework highlights a methodological paradox central to our study: voters most susceptible to media influence—those with weak partisan attachments and low political engagement—are precisely those most difficult to reach using conventional survey methods. Research on survey nonresponse demonstrates systematic overrepresentation of politically engaged adults (Pew Research Center 2017), while Sciarini and Goldberg (2016) document that turnout bias has a "double cause" of overrepresentation and vote overreporting. Clinton et al. (2022) show that partisan nonresponse introduces selection bias that standard weighting cannot fully correct. These challenges motivate interest in computational approaches that can complement traditional survey research.

Synthetic Data Approaches in Political Research

Argyle et al. (2023) introduced "silicon samples"—synthetic survey responses generated by conditioning large language models on sociodemographic backstories. Their study demonstrated that GPT-3 could generate responses exhibiting "algorithmic fidelity" to human opinion distributions, with tetrachoric correlations exceeding 0.9 for partisan vote choice.

However, Bisbee et al. (2024) identified critical limitations through systematic evaluation of ChatGPT's ability to replicate ANES feeling thermometer responses. While aggregate means matched human surveys, they found: (1) significantly reduced variance, with 48% of regression coefficients statistically different from ANES-derived counterparts; (2) unpredictable prompt sensitivity; (3) temporal instability due to algorithm changes; and (4) demand effects where synthetic respondents infer and conform to researchers' hypotheses. These findings suggest LLMs capture central tendencies but are not yet reliable substitutes for human respondents—the reduced variance is particularly problematic for studying opinion heterogeneity across subgroups.

Our study builds on the innovative spirit of Argyle et al. while employing an alternative methodology—Bayesian network-based synthetic data generation—that addresses several of these limitations. Rather than relying on implicit patterns in language model parameters, we explicitly model the joint distribution of voter characteristics using directed acyclic graphs fitted to observed ANES data. This approach enables principled causal inference through Pearl's (2009) do-calculus while preserving variance structure and ensuring temporal stability and replicability.

Synthetic Data Generation Using Bayesian Networks

Our study employs Bayesian network-based synthetic data generation rather than LLM-based silicon samples. Bayesian networks encode joint probability distributions through directed acyclic graphs (DAGs) and conditional probability tables (Koller and Friedman (2009)). Pearl (1988), who coined the term in 1985, emphasized their capacity for distinguishing causal from evidential reasoning—a property central to our application.

The DAG structure offers two key advantages for social science research. First, the graph provides an economical representation of conditional independence assumptions: each node is conditionally independent of its non-descendants given its parents (Lauritzen (1996)). This property enables the joint distribution to be factorized as the product of conditional distributions, dramatically reducing the parameters required to specify complex multivariate relationships. Second, the graphical representation makes theoretical assumptions explicit and available for scholarly critique, addressing calls for greater transparency in computational social science (Grimmer et al. (2021)).

When interpreted causally, directed edges represent causal rather than merely associational relationships. This enables the crucial distinction between observational and interventional distributions. Under Pearl's (2009) semantics, if a node X is set to state x through intervention (notated do(X = x)), the probability distribution changes through "graph mutilation": removing all edges into X and setting X to the intervened value. This transformation, formalized through do-calculus, allows researchers to predict intervention effects from observational data—precisely the counterfactual reasoning required for estimating media effects on political behavior.

The application of Bayesian networks to synthetic data generation builds on substantial methodological literature. Raghunathan et al. (2003) established foundational principles for generating synthetic microdata through sequential modeling of conditional distributions. Subsequent work demonstrated that Bayesian networks capture complex dependency structures while maintaining computational tractability (Gogoshin et al. (2021)). The U.S. Census Bureau has employed related approaches for privacy-preserving data release, including the Longitudinal Business Database (Kinney et al. (2011)) and the SIPP Synthetic Beta (Benedetto et al. (2018)).

Our application incorporates several innovations. We integrate latent class analysis (LCA) into the network structure to capture unobserved heterogeneity in voter types—a critical consideration given documented heterogeneity in media effects across population subgroups (Dilliplane (2014)). The latent type variable serves as a dimensionality reduction device, summarizing complex interactions among demographic variables while providing interpretable voter segments. Cross-year alignment of latent classes uses the Hungarian algorithm (Hornik (2005)) to enable meaningful comparison across election cycles.

We specify the DAG structure based on substantive theory rather than learning it algorithmically from data. Structure learning algorithms may identify associations that lack causal interpretation—a concern particularly acute when the goal is counterfactual inference rather than prediction (Heckerman et al. (1995)). Our theory-driven structure encodes established relationships from the media effects literature: demographic characteristics shape latent political predispositions, which influence media consumption patterns, which in turn affect turnout and vote choice. This causal ordering is consistent with Prior's (2007) conditional political learning model and Zaller's (1992) receive-accept-sample framework.

Advantages Over LLM-Based Approaches

This approach offers four advantages over LLM-based alternatives:

Transparency. The DAG makes causal assumptions explicit: demographics influence latent voter types, which shape media exposure, which affects turnout and vote choice. Critics can inspect and challenge these assumptions directly—unlike the opaque computations underlying LLM responses.

Distributional fidelity. Fitting conditional probability tables to observed data preserves variance structure. Our validation shows Total Variation Distance metrics of 0.001–0.003 for turnout and propensity score AUCs between 0.506 and 0.509—classifiers cannot distinguish synthetic from observed records.

Causal inference. Pearl's do-calculus enables counterfactual analysis through graph mutilation, simulating interventions like universal exposure to left-leaning media while removing confounding pathways.

Constraint enforcement. Non-voters cannot express candidate preferences by design, eliminating logically impossible combinations that LLM prompting may generate.

This framework also addresses the reproducibility concerns raised by Bisbee et al. (2024) regarding closed-source LLMs. We fit separate Bayesian networks for each election year (2016, 2020, 2024) rather than pooling across cycles.

This design choice recognizes that electoral contexts differ substantially: the media environment evolves, candidate-specific factors vary, and the relationship between media exposure and voting behavior shifts across elections. LLM-based approaches using a single pretrained model cannot easily accommodate such temporal heterogeneity.

Positioning Within "Silicon-Augmented Survey Research"

We conceptualize our approach not as an implementation of Argyle et al.'s silicon samples, but as a complementary method within what we term "silicon-augmented survey research." This methodology uses synthetic data generated from fitted probabilistic models to complement—not replace—traditional survey analysis. The synthetic data serves three functions in our research design:

Theoretical exploration. Synthetic samples allow us to explore patterns difficult to observe in finite human samples, generating hypotheses for subsequent empirical investigation.

Counterfactual simulation. The Bayesian network framework enables simulation of interventions (e.g., "what if all voters consumed only left-leaning media?") that cannot be directly observed but are theoretically meaningful.

Methodological validation. Comparison between synthetic and observed data checks whether our probabilistic model adequately captures the joint distribution of variables, with discrepancies pointing to model misspecification or unmodeled heterogeneity.

Where LLM-based approaches may excel at generating open-ended responses and capturing qualitative features of human reasoning, structured probabilistic models offer advantages for quantitative hypothesis testing and causal inference with categorical survey data.

Theoretical Framework

Three theoretical considerations motivate our approach. First, following Prior (2007), we examine whether high-choice media environments differentially affect partisan stability across engagement levels. Second, following Zaller (1992), we consider how media exposure shapes the accessibility of partisan considerations. Third, we explore whether synthetic samples can illuminate patterns difficult to observe in finite human samples—while heeding Bisbee et al.'s (2024) cautions about interpretation.

The combination of conventional survey data and synthetic samples represents a novel mixed-methods approach. This methodology generates hypotheses through synthetic data exploration while validating substantive findings against human survey data.

Data and Methods

Conventional Survey Data: ANES

We employ data from the American National Election Studies (ANES), which provides comprehensive measures of:

- Media consumption patterns across traditional and digital platforms
- Partisan identification and strength of attachment
- Vote choice and electoral participation
- Demographic and socioeconomic characteristics

Data is from the 2016, 2020, and 2024 American National Election Studies (ANES) Time Series surveys.

Table 1: ANES Survey Data

Study	Pre-Election N	Post-Election N
ANES 2016	4,271	3,649
ANES 2020	8,280	7,449
ANES 2024	5,521	4,964
Total	**18,072**	**16,062**

Variable Selection and Harmonization

Strategy Overview

Harmonizing data across the 2016, 2020, and 2024 ANES waves required careful coding consistency. The harmonization process identified equivalent variables, and created consistent, common coding schema. Limiting categories was important because in later analysis the modeling would have failed from data sparsity.

Another design choice was maintaining the distinction between structural zeros, which are logically impossible combinations, such as non-voters having a vote choice, and missing data such as non-response or item skips. This distinction also proved essential for synthetic data generation. Bayesian Network models and similar require proper constraint handling to avoid generating implausible synthetic data.

Outcome Variables

Turnout (vote_any_harm)

The primary turnout measure is a harmonized binary variable indicating whether the respondent voted in the presidential election. All three ANES waves used consistent question wording for self-reported turnout. Responses were coded as "Voted" (1) or "Did not vote" (0). Item non-response for this item was minimal (typically <2%), and missing cases were excluded from the analysis.

Party (VoteChoice, pres_vote_cat to VoteChoice2)

Presidential vote choice was harmonized into four mutually exclusive categories to accommodate third-party candidates and non-voters across waves:

Democrat - Voted for the Democratic candidate (Clinton 2016, Biden 2020, Harris 2024)

Republican - Voted for the Republican candidate (Trump in all three waves)

Other - Voted for any third-party or write-in candidate

NoVote - Did not vote in the presidential election

Respondents coded as non-voters on the turnout variable (vote_any_harm = 0) were assigned to "NoVote," regardless of any stated preference or intent. The "Other" category aggregates all non-major-party votes, including Libertarian, Green, other minor-party candidates, and write-ins.

Media Exposure Variables

Media Exposure (MediaExposure) The media landscape evolved dramatically between 2016 and 2024, complicating harmonization. We classified respondents' media consumption into four categories based on the ideological leaning of their news sources::

Left - Consumed left-leaning sources with little to no right-leaning exposure

Right - Consumed right-leaning sources with little to no left-leaning exposure

Both - Consumed news from both left and right sources

None - Consumed neutral/local sources or none at all

Demographic Variables

Age (age_harm) ANES provided respondent age in years as a continuous measure, and the harmonization collapsed it into four categories:

18-29 - Young adults, emerging electorate

30-44 - Early to middle career adults

45-59 - Late career, pre-retirement adults

60+ - Retirement age and elderly voters

These categories align with generational cohort boundaries while ensuring adequate numbers in each combination.

Sex (sex_harm)

Sex was measured as a binary variable (Male/Female) across the datasets. Sex composition showed minor variation across waves, being typically 52-54% female.

Education (edu_harm) Educational attainment presented moderate harmonization challenges. The data was harmonized into the following categories:

High school or less - No high school diploma through high school graduate

Some college - Some college, associate's degree, vocational/technical training

4-year+ degree - Bachelor's degree or higher including graduate and professional degrees

Region (region) Geographic region uses the standard four-category Census scheme, which is coded consistently across all ANES waves, so no harmonization was required:

Northeast- New England and Mid-Atlantic states

Midwest - East North Central and West North Central states

South - South Atlantic, East South Central, and West South Central states

West- Mountain and Pacific states

Descriptive Statistics

The final sample after harmonization and cleaning is shown in Table 2. This is 15,608 total cases.

Table 2: Sample sizes by election year

Year	n
2016	4270
2020	8280
2024	5521

Table 3 summarizes year-level variations in turnout and vote choice. Self-reported turnout increased markedly from 2016 (77.8%) to 2020 (86.2%). These shifts, along with sample sizes ranging from 3,456 to 7,287 indicated that pooling data would potentially cause issues on the process, so we used a year-conditioned modeling strategy, preserving the marginal distributions of each election.

Table 3: Year-level baseline summaries (turnout and vote shares among voters)

YEAR	n	Turnout Rate	Dem Share	Repub Share
2016	3456	0.778	0.473	0.433
2020	7287	0.862	0.550	0.401
2024	4865	0.831	0.535	0.421

Methods: Synthetic Data Generation

Architecture

Stage 1: Data Harmonization

As noted above.

Stage 2: Latent Class Analysis

Latent Class Analysis (LCA) was used to identify natural voter segments in each of the three years based on observed behaviors and media consumption patterns. This unsupervised clustering approach created heterogeneous subpopulations, reducing the dimensions of the data. LCA was chosen over k-means clustering after a comparative analysis that found LCA had fewer clusters. More clusters risks model collapse during fitting. 2016 found 3 classes, 2020 found 4 classes, 2024 found 3 classes.

Stage 3: Bayesian Network Specification

For each year, Bayesian Networks (BNs) were then used to encode conditional dependencies and causal assumptions which governed the relationships between voter characteristics and political behavior. The directed acyclic graph (DAG) structure made these causal assumptions explicit. (Figure 1) This pipeline fitted separate models for each election year rather than pooling. This approach was chosen because electoral contexts differ, media environments change, and the effect of media on voting behavior will vary election-to-election.

Stage 4: Bayesian Network Fitting

Conditional probability tables were built for each node in each year, and smoothing was applied to handle sparse cells. This created year-specific, fitted BNs. After this fitting, the networks were validated to ensure they accurately reproduced the observed joint distributions of voter characteristics and behaviors. The fitted networks then served as generative models for the synthetic data generation stage.

Stage 5: Synthetic Data Generation

Synthetic voter datasets were generated by sampling from a fitted Bayesian network. This produced two types of data: observational, mirroring the original

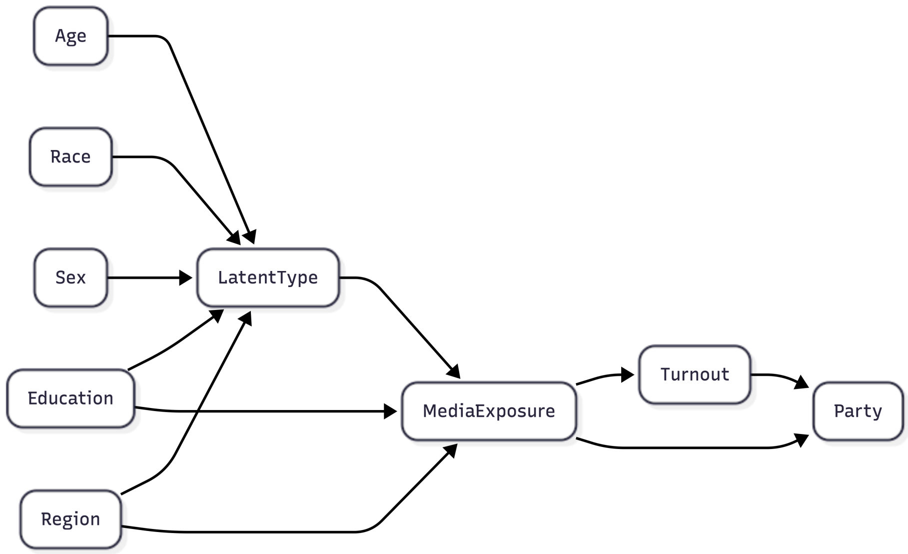

Figure 1: Directed Acyclic Graph

survey relationships, and interventional, simulating possible scenarios. Following generation, logical constraints were enforced, such as preventing non-voters from having candidate preferences, to ensure data consistency for analysis. This is outlined in greater detail below.

Stage 6: Validation

Data quality was assessed through tests such as comparing individual and joint variable patterns between real and synthetic data, testing whether statistical models could distinguish synthetic from real cases, evaluating whether the synthetic data reproduced meaningful associations from substantive analyses, confirming all logical and demographic constraints were met, and producing validation metrics with diagnostic visualizations.

Synthetic Data

Generation

We generated synthetic voter microdata using a two-stage modeling pipeline applied separately for each election year. First, for each year, we estimated latent class models (LCA) using poLCA package (Linzer and Lewis (2011)) based on observed demographics, media exposure, turnout, and vote choice to recover heterogeneous voter types. Cross-year alignment of latent classes used the Hungarian algorithm (Hornik (2005)) applied to Euclidean distances between class-conditional response profiles. These latent types were then integrated into a Bayesian network (BN) defined by a fixed causal directed acyclic graph (Figure 1), fitted using the bnlearn package in R (Scutari (2010)). In this, demographics influenced latent tendencies, which shaped media exposure, which in turn affected turnout and vote choice.

Each year's BN was fitted independently, allowing joint distributions and causal effects to be generated for each election. We generated synthetic observations by ancestral sampling from the fitted network under the observational regime, and under hypothetical media exposure regimes using Pearl's graph mutilation procedure for do-operations (Pearl (2009)). This approach preserved observed marginal and conditional distributions, captured heterogeneous voter responses to media, and produced privacy-preserving data suitable for subsequent analysis.

Synthetic Sample Size

Synthetic data were generated by sampling from year-specific Bayesian network models estimated separately for the 2016, 2020, and 2024 election cycles. For validation purposes, 15,000 synthetic observations were generated under the natural (unintervened) regime and 60,000 synthetic observations under interventional regimes that fix media exposure to counterfactual values. Synthetic samples were drawn independently by year from cached model bundles, ensuring reproducibility and allowing joint distributions and causal effects to vary over time. This sampling strategy should have provided sufficient precision for validation while maintaining a strict separation between model estimation and data generation. There is always a possibility that I have done this wrong.

Validation

We assessed synthetic data quality using a multi-dimensional validation framework, incorporating adversarial classification for general utility, Total Variation Distance (TVD) for univariate distributions, chi-square tests for bivariate associations, and coefficient overlap for inferential utility.

Distributional Fidelity: Univariate distributions for turnout and vote choice closely matched observed data. See Figure 2. TVD metrics were negligible, ranging from 0.001–0.003 for turnout and 0.011–0.016 for vote choice2. Chi-square goodness-of-fit tests yielded $p > 0.50$ for turnout across all years3. For vote choice, 2016 and 2020 showed no significant deviation ($p > 0.08$), while 2024 exhibited marginal deviation ($p = 0.039$) that does not compromise analytical validity.

Association Structure: Bivariate associations were preserved with high fidelity. See Figure 3. The Turnout $\times$ VoteChoice relationship achieved perfect preservation (Cramér's V difference $= 0.000$) due to the constraint that non-voters cannot express candidate preference, which the synthetic generation enforces by design.

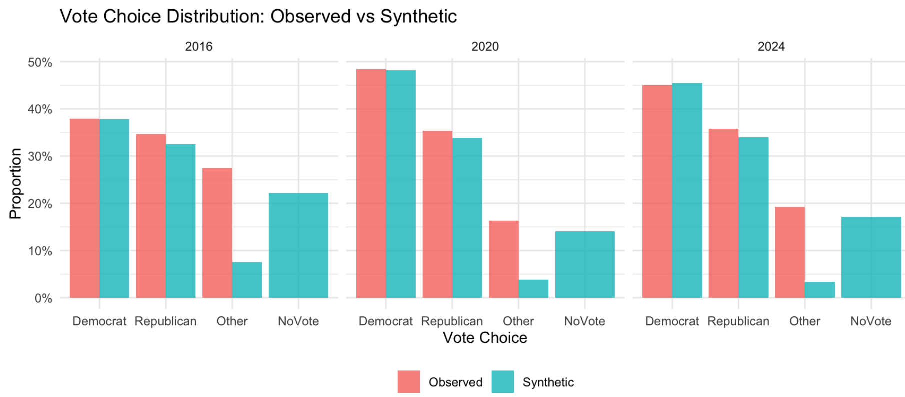

Figure 2: Vote Choice Distribution

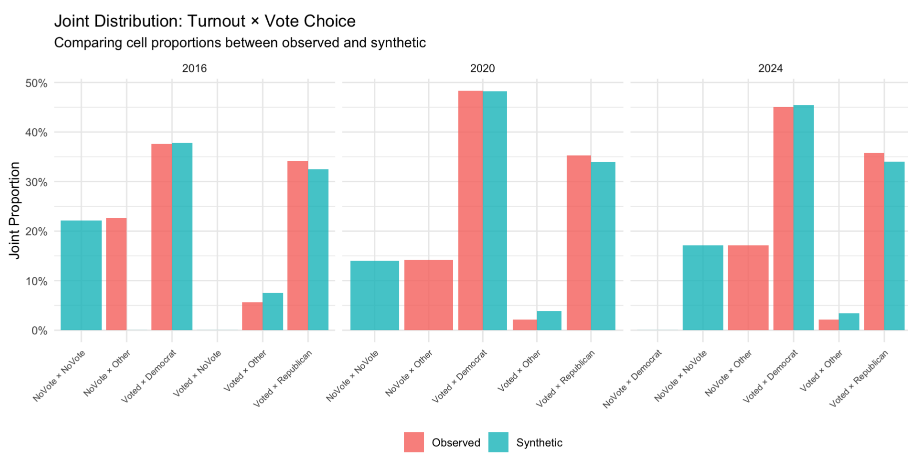

Figure 3: Joint Distribution

Joint Distribution Preservation: Cross-tabulations of Turnout $\times$ Party showed minimal systematic deviation, with standardized residuals predominantly within ± 2 across all cells. See Figure 4.

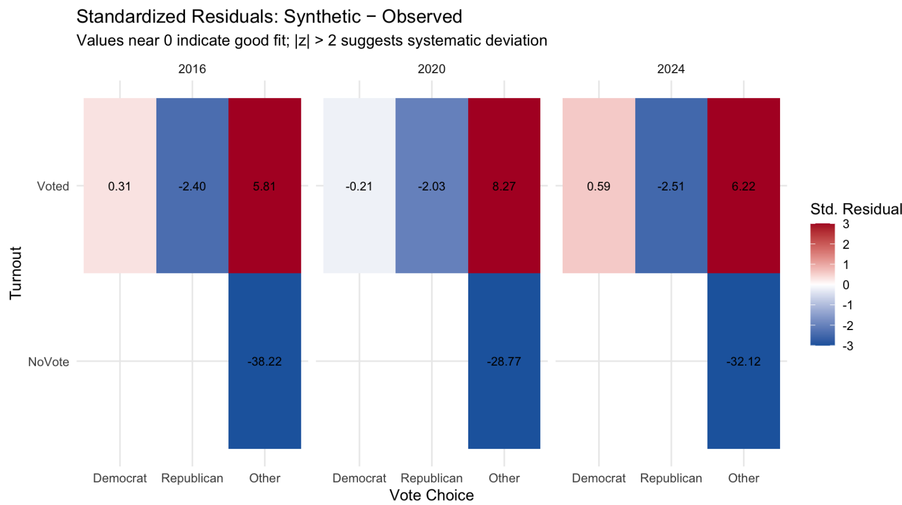

Figure 4: Standardized Residuals

Statistical Indistinguishability: Propensity score discrimination yielded AUC values between 0.506 and 0.509 across all years, indicating classifiers could not reliably distinguish synthetic from observed records, where chance is 0.50. See Figure 5.

Inferential Utility: Logistic regression models predicting Democratic vote from year produced nearly equivalent coefficient estimates on synthetic versus observed data, with all 95% confidence intervals overlapping. See Figure 6.

Minor deviations were observed in variance ratios (range: 0.61–1.79), suggesting occasional over- or under-estimation of dispersion. However, these differences do not substantively affect point estimates, and the overall validation confirms synthetic data adequately reproduce the statistical properties of the observed ANES data.

Analysis of Media Consumption

To estimate causal effects of media exposure on political behavior, we applied Pearl's do-calculus using graph mutilation (Pearl (2009)). This approach distinguishes causal effects from observational associations by simulating interventions that fix media exposure to specific values while removing confounding pathways. For each election year, we compared outcomes under the natural (observational) regime with outcomes under hypothetical interventions $do(MediaExposure = m)$ for each media regime where $m \in \{Left, Right, Both, None\}$.

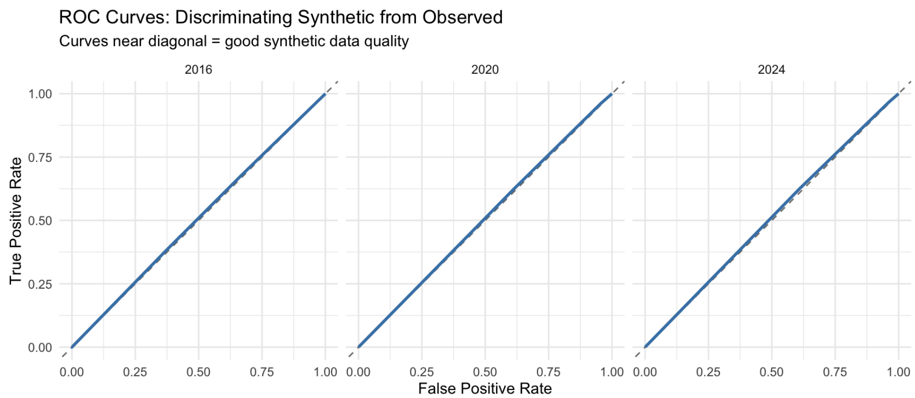

Figure 5: ROC Curves

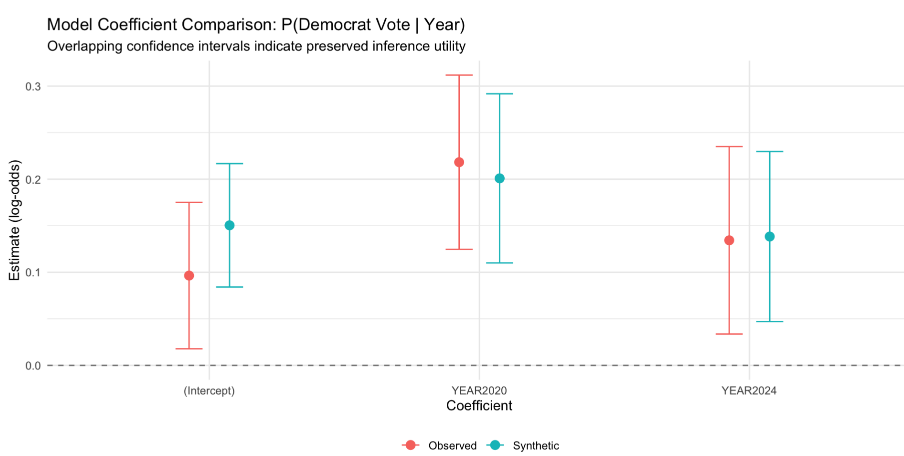

Figure 6: Model Coefficient Comparison

We estimated two primary quantities: mobilization effects which are the changes in turnout probability and persuasion effects (changes in party among voters). For each intervention, we computed ΔTurnout = P(Voted | $do(MediaExposure = m)$) − P(Voted | natural) and analogous contrasts for Democratic and Republican votes.

Results indicate modest mobilization effects across all media regimes, with turnout differences relative to baseline generally within ± 2 percentage points. Exposure to right-leaning media showed slight positive mobilization effects in 2016 and 2020, while 2024 exhibited a different pattern with exposure to both left and right media associated with higher turnout. Persuasion effects were similarly modest: Democratic vote share among voters varied by approximately 2–4 percentage points across media regimes, with left-leaning media exposure associated with higher Democratic support and right-leaning exposure with lower Democratic support, as expected.

Heterogeneous treatment effects (HTE) by latent voter type revealed that media effects are not uniform across the electorate. Certain latent types—particularly those characterized by lower baseline political engagement—showed larger mobilization responses to media exposure, while highly engaged voter types exhibited minimal responsiveness. However, the magnitude of these differential effects remained modest, suggesting that media exposure operates as a weak treatment across most voter segments.

Cross-year comparisons revealed limited temporal stability in media effects. The pattern of mobilization and persuasion effects shifted across election cycles, consistent with the year-specific nature of latent class structures identified in the modeling stage. This supports the decision to fit separate models for each election year rather than pooling across cycles.

An exception to the generally modest media effects happened in the 2020 election. Under the $do(MediaExposure = Right)$ intervention, there was a negative mobilization effect, with turnout declining by approximately 15–20 percentage points. This effect is not seen under other interventions, and does not appear in the 2016 or 2024 elections. Importantly, the decline in turnout under $do(Right)$ is accompanied by an increase in Republican vote share among voters, indicating selective demobilization rather than persuasion. This suggests that right-leaning media exposure in 2020 disproportionately discouraged participation among certain voter segments rather than shifting partisanpreferences. The absence of comparable effects in other election years implies that media exposure alone is insufficient to induce large behavioral changes. Its causal impact appears contingent on broader contextual conditions such as COVID, which were unique to the 2020 election cycle.

Discussion

This study demonstrates the viability of Bayesian network-based synthetic data generation as a complement to traditional survey research in studying media effects on partisan volatility. Our validation results indicate that the synthetic voter microdata closely reproduce the statistical properties of observed ANES data across multiple dimensions: marginal distributions, bivariate associations, and regression coefficient estimates. The near-chance performance of adversarial classifiers (AUC 0.506–0.509) confirms that the synthetic records are statistically indistinguishable from observed cases—a key benchmark for synthetic data quality that LLM-based approaches have struggled to achieve (Bisbee et al. (2024)).

The causal analysis using Pearl's do-calculus reveals modest but theoretically meaningful media effects. Mobilization effects—changes in turnout probability under hypothetical media exposure interventions—generally fall within ± 2 percentage points of baseline, consistent with the "minimal effects" tradition while acknowledging that small effects can be consequential in close elections. Persuasion effects on vote choice are similarly modest (2–4 percentage points), with the expected directional patterns: left-leaning media exposure associated with increased Democratic support, right-leaning exposure with decreased Democratic support. The heterogeneous treatment effect analysis reveals that media effects are not uniform across the electorate. Latent voter types characterized by lower baseline political engagement show larger mobilization responses to media exposure, while highly engaged partisans exhibit minimal responsiveness. This finding aligns with Zaller (1992)'s prediction: moderately aware citizens receive sufficient exposure to be affected but lack the partisan anchoring to resist counter-attitudinal messages."

Implications for Public Opinion Research

This approach enables four extensions of conventional survey research:

Hypothesis generation. Large synthetic populations allow examination of rare voter profiles—young, disengaged voters consuming mixed media—with sufficient statistical power for reliable inference. By generating large synthetic populations, we can examine rare voter profiles—such as young, politically disengaged voters who consume mixed media—with sufficient statistical power for reliable inference. These exploratory analyses can generate theoretically motivated hypotheses for subsequent validation against human survey data.

Counterfactual simulation. The Bayesian network framework enables principled counterfactual analysis that observational data alone cannot support. Questions like "What would turnout look like if all voters consumed only left-leaning media?" are inherently counterfactual—the factual world contains selection effects that conflate media choice with political predisposition. Graph mutilation provides a formal procedure for simulating such interventions while removing confounding pathways, offering a bridge between the limitations of observational research and the artificiality of laboratory experiments.

Methodological validation. Comparison between synthetic and observed data provides a diagnostic tool for evaluating whether our theoretical assumptions—encoded in the DAG structure—adequately capture the joint distribution of voter characteristics and behaviors. Discrepancies between synthetic and observed patterns can point to model misspecification or unmodeled heterogeneity, guiding refinement of theoretical frameworks.

Privacy-preserving data sharing. Synthetic microdata generated from fitted probability models contain no actual individual records, offering a path toward broader data sharing while protecting respondent confidentiality. This is particularly valuable for ANES and similar surveys that face increasing pressure to balance scientific utility against privacy concerns. National statistical agencies have already adopted similar approaches for administrative data release Kinney et al. (2011); Benedetto et al. (2018)), suggesting a viable model for academic survey programs.

Limitations

Several limitations bear on interpretation:

Structural assumptions. The DAG imposes strong assumptions about causal direction. The assumption that demographics → latent type → media exposure → vote choice may oversimplify feedback processes; vote choice in previous elections likely influences subsequent media consumption. The assumption that demographics cause latent type, which causes media exposure, which causes vote choice, may oversimplify complex feedback processes. In reality, vote choice in previous elections likely influences subsequent media consumption patterns, creating cycles that our DAG cannot represent. Future work should explore sensitivity of results to alternative structural specifications and consider dynamic Bayesian networks that can accommodate temporal feedback.

Latent class interpretation. The latent voter types identified by our LCA are statistical constructs that emerge from observed response patterns, not directly observable entities. While we interpret these types as capturing heterogeneous political predispositions, they may also reflect measurement artifacts or sampling variation. The cross-year alignment procedure using the Hungarian algorithm assumes that latent types are comparable across elections—an assumption that becomes tenuous if the underlying political landscape shifts fundamentally between cycles. The different number of latent classes identified in different years (3 in 2016, 4 in 2020, 3 in 2024) suggests that voter segmentation may itself be temporally unstable.

ANES representativeness. Our synthetic data inherit whatever biases exist in the observed ANES samples. If politically engaged voters are systematically overrepresented—as nonresponse research suggests (Pew Research Center, 2017;

Sciarini and Goldberg, 2016)—our synthetic populations will also overrepresent engaged voters. Bayesian network-based synthesis preserves the joint distribution of observed data; it does not correct for selection bias in the underlying sample. The challenge of reaching volatile, disengaged voters that motivated this research thus remains incompletely addressed.

Media exposure measurement. The harmonized media exposure variable, while necessary for cross-wave comparison, involves substantial simplification of a complex media environment. Collapsing diverse media sources into four categories (Left, Right, Both, None) obscures important distinctions—consuming MSNBC and reading the New York Times are both coded as "Left," despite potentially different effects. Moreover, media consumption is self-reported and subject to recall bias, social desirability effects, and the difficulty of tracking exposure across proliferating platforms. The rapid transformation of the media landscape between 2016 and 2024—including the rise of streaming services, algorithmic social media feeds, and podcast ecosystems—may not be adequately captured by harmonized measures designed for comparability.

Causal identification. While Pearl's do-calculus provides a formal framework for causal inference from observational data, its validity depends on the correctness of the assumed causal structure. Our DAG assumes that all confounding pathways between media exposure and political behavior are blocked by conditioning on demographic variables and latent type. If unmeasured confounders exist—such as personality traits, geographic context, or social network characteristics that influence both media choice and vote choice—our causal effect estimates may be biased. The synthetic data framework does not inherently solve the fundamental problem of causal inference from observational data; it provides a tool for exploring implications of causal assumptions, not for validating those assumptions.

External validity. Our findings are specific to the American electoral context across three presidential election cycles (2016, 2020, 2024). The media environment, partisan landscape, and voting behavior may differ substantially in other democracies or in subnational American elections. The candidate-specific effects of Trump's presence in all three elections may also limit generalizability to future cycles featuring different candidates. Cross-national replication using comparable surveys (such as the Comparative Study of Electoral Systems) would help assess the generalizability of our methodological approach and substantive findings.

Future Directions

This study suggests several promising directions for future research.

Dynamic modeling. Our cross-sectional, year-specific approach treats each election as independent. A natural extension would be dynamic Bayesian networks that model transitions in voter characteristics and behaviors across election cycles. Panel components of the ANES could support such analysis, enabling examination of how media exposure in one cycle affects partisan stability in subsequent cycles.

Experimental validation. The counterfactual predictions from our causal analysis—such as the estimated effect of shifting all voters to left-leaning media—are inherently untestable against observational data. However, they could inform the design of randomized media exposure experiments that test specific predictions. Such experiments would provide external validation of the causal effect estimates derived from our synthetic data framework.

Conclusion

This study demonstrates Bayesian network-based synthetic data generation as a viable complement to traditional survey research on media effects. Building on the foundational work of Argyle et al. (2023) on silicon samples while addressing the documented limitations of LLM-based approaches (Bisbee et al., 2024), we have developed what we term "silicon-augmented survey research"—a methodology that uses synthetic data generated from fitted probabilistic models to complement, rather than replace, traditional survey analysis.

Our approach offers several advantages over both conventional survey methods and LLM-based alternatives. The Bayesian network framework provides transparency and interpretability through its graphical representation of causal assumptions. The conditional probability tables fitted to observed ANES data preserve the variance structure and higher-order associations present in human survey responses—a critical property that LLM-generated samples often fail to maintain. The formal apparatus of Pearl's do-calculus enables principled counterfactual analysis, estimating the causal effects of media exposure interventions that cannot be directly observed. The year-specific fitting procedure accommodates temporal heterogeneity in the media-politics relationship, while constraint enforcement guarantees logical consistency in the generated data.

The substantive findings reinforce several conclusions from the media effects literature while offering new insights. Media effects on both mobilization and persuasion are modest in magnitude, consistent with the "minimal effects" tradition, but exhibit meaningful heterogeneity across voter segments. Voters with lower baseline political engagement—precisely those most difficult to reach with conventional surveys—show the largest responsiveness to media exposure, suggesting that the methodological challenges in studying volatile voters have obscured effects that may be consequential for electoral outcomes.

We acknowledge significant limitations. Our causal estimates depend on the correctness of structural assumptions encoded in the DAG, which may oversimplify complex feedback processes. The synthetic data inherit whatever biases exist in the observed ANES samples. The harmonized media exposure measure obscures platform-specific effects. And the American electoral context may limit generalizability to other democracies.

Despite these limitations, we believe this study makes a meaningful contribution to the methodological toolkit available to political communication scholars. The framework we have developed is fully replicable—the DAG structure, fitting procedures, and generation algorithms can be documented and shared, unlike closed-source LLM approaches. The approach is flexible, accommodating different theoretical structures and survey instruments. And it opens new analytical possibilities—counterfactual simulation, heterogeneous treatment effect estimation, privacy-preserving data sharing—that extend the reach of traditional survey research.

As traditional polling faces mounting challenges, computational approaches to public opinion research will grow in importance. The framework developed here—replicable, flexible, and empirically grounded—offers one path forward.

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