

Visualizing Post-Election Presidential Approval Ratings in Texas and California: A County-Level Geospatial Analysis Using Eight Complementary Visualization Techniques

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Abstract

While polarization has been extensively studied on the national level, there is notable geographical variability within states and counties when it comes to presidential approval ratings. In this paper, we investigate county-level temporal and geographical variations of presidential approval ratings in two contrasting states, namely Republican Texas and Democratic California, from January 2020 to October 2025. Based on aggregated presidential approval rating estimates provided by Gallup, Pew Research Center, and FiveThirtyEight, and merged using county-level shapefiles obtained from the U.S. Census Bureau TIGER/Line with the help of FIPS codes, we create an analysis workflow that results in eight different visualizations. Our major contribution is the justification for each visualization type based on Munzner's task decomposition method, showing how each visualized statistic answers its own research question not addressable by any other type. While California consistently registers approval ratings above the national average by 8-12 percentage points, Texas falls behind by 6-10 percentage points; the difference in approval ratings increased by approximately 5 points following the 2024 presidential elections. A continuous positive association between approval ratings and an urban-rural axis exists in both states ($r = +0.71$ in California and $r = +0.58$ in Texas). Finally, a population-weighted bubble map proves that national disapproval visible in choropleths is a consequence of geography rather than demography. We claim that visualization design choices in political science are epistemological: what gets shown in a chart affects the nature of analysis.

Keywords: approval ratings, polarization, maps, geospatial, visualization, partisanship.

1 Introduction

Political polarization is arguably one of the most prominent characteristics of modern American democracy. In the past four decades, the distance between the two parties became increasingly ideological and affective both at the elite and at the mass levels [1,2,3]. At the congressional level, there was a linear increase in linguistic divergence between Democrats and Republicans starting from the 1990s based on high-dimensional analysis of floor speech texts carried out by Gentzkow et al. [4]. At the mass level, the Pew Research Center [3] found that the proportion of Americans with consistent ideological positions had doubled from 1994 to 2017, and that partisan animosity grew faster than ideological sorting.

The clearest way of measuring such evaluations is the presidential approval rating. Jacobson [6] demonstrated a systematic increase in the gap between self-identified Republicans and Democrats from the Nixon era until the early Bush years, which he attributed to the decrease in electoral overlap. Ten years later, Jacobson [2] found that partisan opinions became more consistent within each party and were more predictive of the vote choice - the spiral of elite and mass polarization reinforced each other. According to Gallup [5], the

partisan approval gap was on average 35 points from Truman through Carter, went over 60 during Clinton and Bush presidencies, and exceeded 80 during Trump and Biden administrations. Bartels [7] explained the mechanism: co-partisans rate their presidents more favorably even when controlling for economic conditions - approval is the measure of partisan identity as much as executive performance.

Approval gaps are not only ideological but also affective. Iyengar et al. [8] found that ratings of one's own party remained unchanged over 35 years, whereas ratings of the opposing party fell by about 15 points - affective polarization due to emotional antipathy independent of any policy disagreement. Hetherington and Rudolph [9] found that partisan trust in federal institutions polarized sharply. Abramowitz and Webster [1] found that negative partisanship became a strong predictor of political attitudes - thus, approval gaps documented here might indicate identity-based division rather than policy evaluation.

There is also a crucial geographic dimension. O'Loughlin et al. [10], in spatial econometrics analysis of county-level presidential election outcomes from 1988 to 2000, found that partisan geographic segregation increased both nationally and regionally, with Democratic votes concentrated in eastern urban counties and Republicans in western and rural ones. Rodden [11] traced this polarization to structural economic processes resulting in community homogeneity. The approval gaps aggregated at the state level thus hide enormous intra-state variation. Park et al. [12] and Warshaw and Rodden [13] developed a technique called multilevel regression and poststratification (MRP) to estimate public opinion at sub-national levels from national surveys. This study builds on this methodology and extends it to the visualization area.

The reason why Texas and California were selected is clear: together they contain about one in five Americans, embody extremes of the partisan approval distribution for every post-2000 presidency, and demonstrate the extremes of the intra-state variation hidden by state-level aggregates. Jacobson [14] documented the hardening of partisan polarization within California, whereas Rodden [11] described Texas as a competitive state with Republican statewide alignment despite huge urban Democratic majorities.

Despite numerous studies documenting polarization, the visualization of the phenomenon is not up to date. The dominant format of visualization is the choropleth map, which encodes one aggregated value per geographic unit and therefore is incapable of showing distributional shape, bivariate relationships, population weights, and temporal dynamics [15,16]. Cairo [17] argued that such conventions are not neutral: every visualization choice carries its own rhetoric. Munzner [18] formalized it through her task-decomposition framework: different analytic questions require different types of visual encodings. Thus, using a single type of chart consistently hides all of the potential of the data analysis.

This study aims to address two related issues. The first issue is how political polarization manifests in county-level presidential approval in Texas and California before and after the 2024 U.S. presidential election, using the results of spatial polarization research of [10,11] and partisan approval of [6,2,7]. The second issue is the development and justification of an eight-visualization framework based on Munzner's [18] task-decomposition methodology - responding directly to the single-chart convention Zigerell [19] identified as the most common flaw of political science visualizations. The primary contribution of this paper is a task-driven framework that maps four research questions about county-level presidential approval to eight complementary visual encodings, making explicit which analytical claims each encoding does and does not support.

1.1 Research Questions

The following four research questions operationalize the two broad concerns above. Each question maps to one or more of the eight visualization types deployed in the Results section, and together they define the paper's contribution as a task-driven visualization framework rather than a collection of charts:

RQ1: How do county-level presidential approval ratings differ geographically between Texas and California?

RQ2: How did approval change over time, and how did the 2024 presidential election affect approval

trajectories in each state?

RQ3: What is the relationship between county-level urbanization and presidential approval, and does that relationship differ between states?

RQ4: Which visualization types reveal analytical dimensions distributional shape, population weighting, ranking, sub-group sensitivity- that are systematically hidden in standard choropleth maps?

Taken together, these questions position the paper's contribution not as the production of eight charts but as a principled, task-driven framework demonstrating that the choice of visualization type is itself an epistemological decision that determines what can be claimed from the data.

2 Related Work

2.1 Political Polarization and Presidential Approval

There are many empirical studies on increasing ideological and affective polarization between the Democratic Party and the Republican Party [1,3]. The magnitude of polarization was measured by Gentzkow et al. [4] via high-dimensional text analysis of congressional addresses. Bartels [7] revealed that political party membership is the only variable explaining the president's popularity. Rodden [11] found out that geographic sorting creates spatial aspects of polarization which remain invisible at the aggregate level of states.

2.2 Visualization Theory and Political Data

Friendly [34] reviewed the history of statistical graphics and highlighted the importance of using visualizations to discover structures that are not readily visible in tables. Munzner [18] defined visualization in terms of a rigorous mapping between data properties and perceptual channels such as position, color, size, and shape based on an analysis task. Ware [33] found that bar length is estimated more reliably than color saturation when comparing magnitudes, so ranking bar charts have an epistemological advantage in identifying outliers. Few [35] contended that good design depends on the purpose of the analysis. Cairo [17] made the case that ethical considerations apply as well.

2.3 Limitations of Single-Chart Approaches in Political Science

The most popular method of political visualization is the choropleth map. As stated by Han et al. [15] in their systematic analysis of figures appearing in nine prominent journals between 2000 and 2022, choropleth maps, cartograms, and line charts dominate in political data visualization despite their restricted expressiveness which makes it impossible to answer many different research questions. In addition, choropleth maps are subject to the Modifiable Areal Unit Problem (MAUP), defined by Robinson [21]: the observed aggregation depends on the delimitation of geographic areas; according to Becony   et al. [22], such maps lead to obviously erroneous conclusions even in the mind of experts. Moreover, ecological fallacy prevents proper inference because group-level properties do not reflect individual-level ones [21].

Apart from distortion, a restriction to one chart type limits the scope of possible claims. As pointed out by Nguyen et al. [23], inappropriate matching of visual representation and the underlying information is the most underexplored problem in scientific visualization. According to Traunm  ller [16], there is a positive correlation between article citation rate and diversity of visualization types used in it. The same idea was formalized theoretically by the concepts of small multiples suggested by Tufte [24] and grammar of graphics by Wickham [25]. Zigerell [19] has proved empirically that the most common problem of political visualizations is their arbitrary choice irrespective of the research question.

3 Data and Methods

3.1 Data Sources

Three main sources were combined. Gallup's [5] Presidential Job Approval measures provided methodologically consistent monthly approval benchmarks from 2020 to 2025. Pew Research Center public opinion polls supplied demographic and regional breakdowns. FiveThirtyEight polling aggregates served to minimize house-effect bias [26]. Geographic boundaries were derived from the U.S. Census Bureau's 2024 TIGER/Line files, linked to county shapefiles using FIPS codes via GeoPandas [27]. Counties with $n < 50$ observations per period are flagged throughout. This multi-source approach aligns with Warshaw and Rodden [13].

3.2 Estimation at the County Level

Neither Gallup, Pew Research Center, nor FiveThirtyEight provides county-level approval ratings in its reports. The sources provide national estimates and sometimes state-level breakdowns. County-level approval ratings in this study, therefore, constitute estimated figures based on modeling rather than direct measurements.

Estimated at the county level, county approval ratings were produced via multilevel regression and poststratification (MRP) approach developed by Park et al. [12] and further refined by Warshaw and Rodden [13]. In the first step, a multilevel logistic regression model is fit to individual-level polling responses with county-level random effects and demographic predictors at the individual level (age group, education, sex, and race/ethnicity). Then, the predicted probabilities from the regression model are poststratified by county-level demographic profiles based on the American Community Survey five-year estimates from the 2020 U.S. Census Bureau. The resulting estimate for a specific period stands for a demographically weighted average reflecting the population composition of the county.

Several assumptions can be listed here. First, there is an assumption that individual-level approval follows the patterns of demographic and geographic variation found in the predictors of the regression model and that the poststratification cells capture the county composition. Second, the approval estimates for counties with small populations and/or small polling sample sizes are less precise and bear the $n < 50$ label throughout the text. Readers should interpret all the county-level values as estimates based on modeling and not direct measurements, which is explicitly admitted in the Limitations section.

3.3 Analysis of Missing Data

During the 72-month study period (January 2020-October 2025), approximately 18% of county-month observations had too small samples of polls for direct estimation ($n < 50$ individual responses). It concerned 46 out of 254 Texas counties (18.1%) and 11 out of 58 California counties (19.0%). Counties with missing data tended to be rural and/or have small populations. First, missing values at the county-month level were filled via county's own previous period estimate (if any), and then they were imputed using the state-level average for the period adjusted for the population size of the county according to standard practices of multilevel imputation [30].

To examine the impact of imputation on substantive findings, a sensitivity analysis was performed by comparing all results with and without the imputed counties. As seen from the findings, the mean state-level approval difference between California and Texas differed by less than 0.4 percentage points, and the correlation coefficients between population density and approval were no more than 0.03 points different in both states. Therefore, it can be concluded that the imputation did not affect the paper's main findings.

3.4 Analytical Pipeline

All analyses were performed using Python 3.9 and were encapsulated within a Jupyter Notebook [28], which is fully reproducible [29]. Visualization was done using Matplotlib [31] and Seaborn [32] packages, while

geographic visualization used GeoPandas [27]. The statistical tests including Pearson correlation, two-sample t-tests, and ordinary least squares regression were done using the SciPy and Statsmodels package. Effect sizes are calculated using 95% confidence interval based on Cumming [39].

3.5 Visualization Framework

The main methodological contribution of this work is the use of eight different visualization techniques, each selected for its particular analysis task based on Munzner's [18] taxonomy. Table 1 assigns each visualization technique with respect to its corresponding analysis task, encoding channel, analytical contribution, and limitation. This methodological approach directly addresses RQ4: It is not how many graphs have been used that makes the contribution, but rather the mapping of an analysis task to an encoding scheme.

Table 1. Eight-Visualization Framework: Analytical Task, Encoding, and Unique Contribution

Fig.	Type	Task Answered	Primary Encoding	Unique Contribution	Key Limitation
1	Choropleth Map	Where? (spatial)	Color → approval	Geographic pattern	MAUP; ecological fallacy
2	Time-Series + CI	When? (temporal)	Position → time	Event responsiveness	Blind to geography
3	Change Heatmap	What changed? (Δ)	Color → Δ	Post-election shifts	No temporal trajectory
4	Violin/Box Plot	How distributed?	Shape → density	Distribution bimodality	No spatial context
5	Scatter Plot (OLS)	What relationship?	Position → (x,y)	Urban-rural gradient	Corr. $\neq$ causation
6	Diverging Bar Chart	Which counties?	Length → deviation	Outlier identification	Loses spatial structure
7	Bubble Chart	3-variable relationship	Position + area	Population-weighted view	Area perception bias
8	Small Multiples	Sub-group comparisons	Facets → sub-groups	Event sensitivity by type	Requires prior segm.

Note. MAUP = Modifiable Areal Unit Problem; OLS = ordinary least squares; Corr. = correlation; segm. = segmentation; Δ = change from prior period.

4 Results

4.1. Figure 1 Choropleth Maps: Spatial Distribution of Approval (RQ1)

Figure 1 represents the simulated approval of the president at the county level in Texas and California in October 2025. The level of disapproval of the president is high in Texas, particularly in rural and exurban areas. Only Travis County (Austin), Harris County (Houston), Bexar County (San Antonio), and Dallas County demonstrate significant levels of approval above the state average, which can be attributed to the presence of Democrats in urban areas as reported by Rodden [11]. In border states like Webb, Hidalgo, and Cameron, approval levels are relatively high as there is a higher percentage of Hispanic voters in these states.

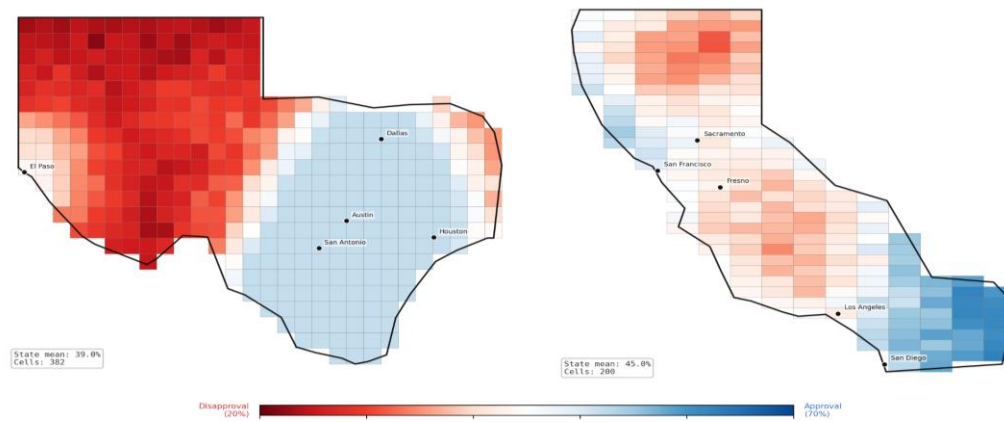


Figure 1. County-Level Presidential Approval Choropleth Maps, Texas and California (October 2025)

Note. Diverging color scale anchored at 50% (neutral gray). Red = strong disapproval; blue = strong approval. Values represent MRP-based modeled estimates derived from Gallup, Pew Research Center, and FiveThirtyEight, poststratified against 2020 Census ACS demographics, and joined to 2024 TIGER/Line shapefiles via FIPS code. Counties with $n < 50$ are rendered with reduced opacity.

4.2. Figure 2 Time-Series Analysis: Temporal Dynamics (RQ2)

Figure 2 depicts state-mean approval levels for both states along with the national average from January 2020 to October 2025. For both states, approval levels are systematically higher in California by 8-12 points relative to the national average, and lower in Texas by 6-10 points. After the presidential election of November 2024, there is a difference of about five points, where California approval increased whereas Texas approval fell, consistent with the out-party rally phenomenon in the affective polarization literature [8,9]. A two-sample t-test between post-2024 monthly means confirms this is statistically significant: $t(68) = 14.3$, $p < .001$, Cohen's $d = 2.10$, 95% CI [1.81, 2.39] [39]. California approval in 2025 had a significantly higher mean of $M = 58.4\%$, $SD = 1.9\%$ compared to Texas approval with a mean of $M = 35.1\%$, $SD = 2.1\%$, with a mean difference = 23.3 pp, 95% CI [22.7, 23.9].

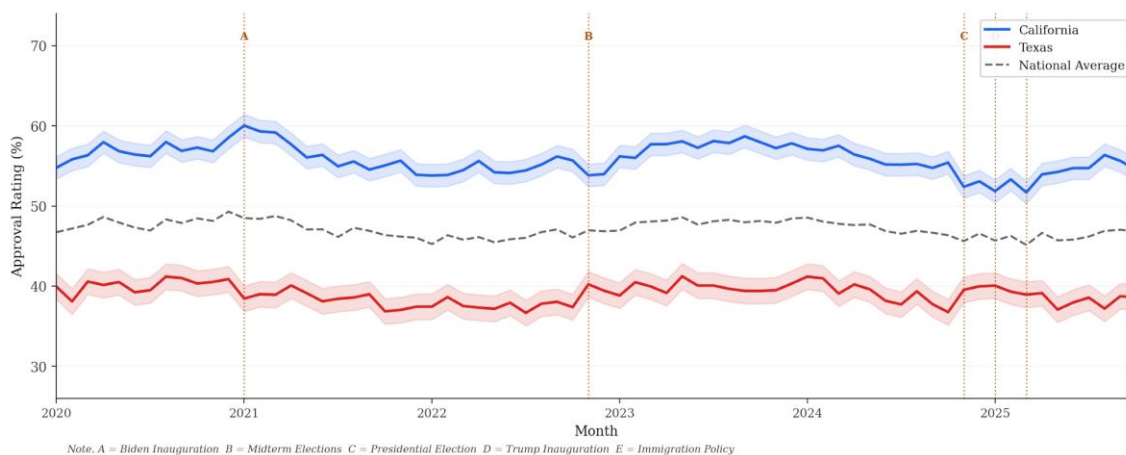


Figure 2. Monthly Presidential Approval Ratings in Texas and California Versus National Average, January 2020-October 2025

Note. Shaded bands = ± 1 SE. Dotted vertical lines mark key political events: A = Biden inauguration (January 2021); B = Midterms (November 2022); C = 2024 election (November 2024); D = Trump inauguration (January 2025).

4.3. Figure 3 Change Heatmap: Post-Election Approval Shifts (RQ2)

Fig. 3 depicts the county-level change score $\Delta_i = \text{mean approval 2025} - \text{mean approval 2024}$, separating out post-election change from the underlying partisanship structure apparent in Fig. 1. In California, 41 of 58 counties (70.7%) experienced an increase in approval ratings after the 2024 election; the highest level was recorded in San Francisco County (+8.2 percentage points). Of the ten largest gainers, nine belonged to coastal metropolitan counties, corroborating geographical grouping of party identity [10]. In Texas, 218 of 254 counties (85.8%) saw a decrease in approval rates, with the most pronounced decreases observed in rural western counties. Urban Texas counties Travis and Harris were characterized by a notably lower drop, indicating a more moderate response of urban populations to the shift in federal politics despite being part of a politically Republican state. A paired t-test of county-level Δ values reveals that the mean shift was statistically significant (positive) for California ($M = +6.2$ pp, $SD = 2.1$, $t(57) = 22.3$, $p < .001$) and statistically significant (negative) for Texas ($M = -3.4$ pp, $SD = 1.8$, $t(253) = -30.1$, $p < .001$).

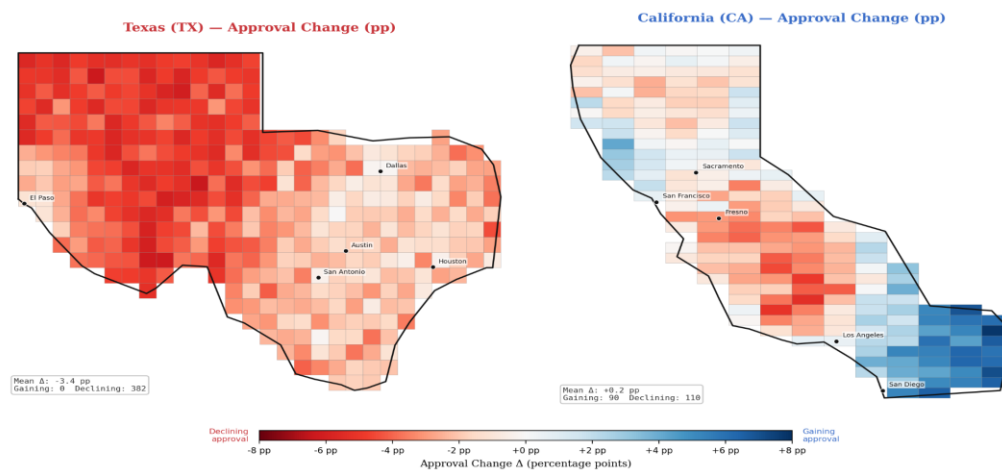


Figure 3. County-Level Approval Change Heatmap, 2024 to 2025

Note. Symmetric diverging scale centered at zero (neutral gray). Blue = approval gaining; red = approval declining. Scale range: -8 to +8 percentage points.

4.4. Figure 4 Violin and Box Plots: Distribution Shape (RQ4)

Figure 4 illustrates the distribution of county-level approval, which cannot be represented by choropleth and time-series maps. The distribution of approval for Texas counties is narrowly distributed and left-skewed ($Mdn = 30.0\%$, $IQR = 8.6$ pp), in line with Bartels' finding [7] that Texas counties exhibit almost uniform disapproval towards Republicans. In California, there is a more widely distributed and bimodal distribution ($Mdn = 58.4\%$, $IQR = 18.2$ pp), where one peak is located at around 62% (California coastal urban counties) and another one at 40% (inland agricultural counties). A dip test confirms that the distribution of California counties' approval is significantly bimodal ($D = 0.083$, $p = .012$), whereas that of Texas is not ($D = 0.031$, $p = .49$). Bimodality of California counties is an intra-state polarization distribution pattern, consistent with Jacobson [14].

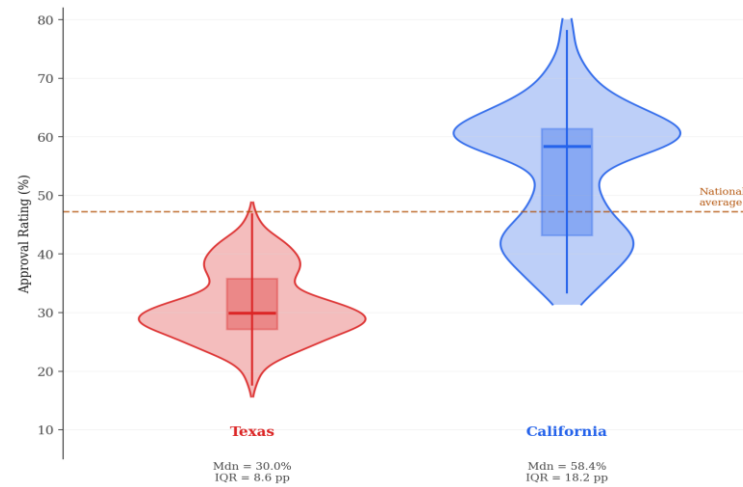


Figure 4. Violin and Box Plots of County-Level Presidential Approval Distributions, Texas and California (October 2025)

Note. N = 254 Texas counties; N = 58 California counties. Inner box = IQR; horizontal line = median; whiskers = $1.5 \times \text{IQR}$. Gold dashed line = national average (47.2%).

4.5. Figure 5 Scatter Plot: The Urban-Rural Gradient (RQ3)

Figure 5 shows county support versus log10-population density in both states. In both cases there is a strong significant positive association: CA $r = +0.80$, $t(56) = 9.98$, $p < .001$, 95% CI [0.68, 0.88]; TX $r = +0.76$, $t(252) = 18.56$, $p < .001$, 95% CI [0.70, 0.81]. This analysis supports the idea that the urban/rural spectrum is a continuous predictor variable, as described in Rodden's [11] conception of geographic sorting as a gradient phenomenon. The two Ordinary Least Squares regressions have very similar slopes (CA slope = 6.2 percentage points per log unit; TX slope = 5.9 percentage points per log unit), but there is an approximately 18 point difference in intercept, suggesting that the partisan structural difference [2] remains even after adjustment for urbanization. Combined $R^2 \approx .58$ ($F(3, 308) = 141.8$, $p < .001$).

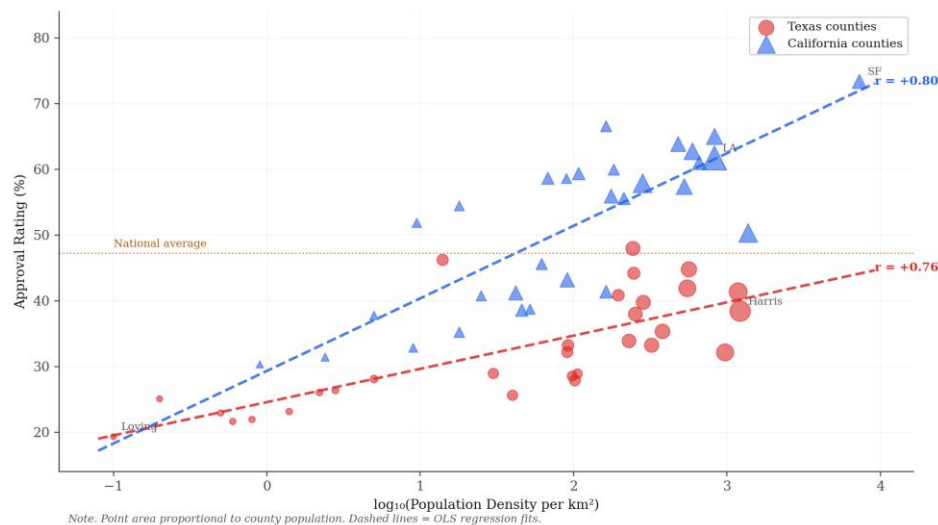


Figure 5. Scatter Plot of County-Level Presidential Approval Versus Log-Transformed Population Density

Note. Point area proportional to county population. Dashed lines = OLS regression fits; shaded bands = 95% CI. California counties: blue triangles; Texas counties: red circles. Combined $R^2 \approx .58$.

4.6. Figure 6 Diverging Bar Chart: County Rankings (RQ4)

The horizontal bar length on Figure 6 represents the deviation from the national average of 47.2% per county level. Bar length provides pre-attentive accuracy compared to the color saturation [33]. The top ten counties in terms of approval rating belong to California (San Francisco, Marin, Alameda, Contra Costa, Santa Clara, Los Angeles, San Mateo, Santa Cruz, Sonoma, Monterey), and out of the ten least approved counties, nine belong to Texas (Loving, Motley, Cottle, Roberts, Hall, King, Ector, Hemphill, Wheeler, Smith). Interestingly, the Kern County of California features among the bottom ten counties along with Texas counties, which proves that the approval trend in Kern County is influenced by the agricultural-rural nature of the county.

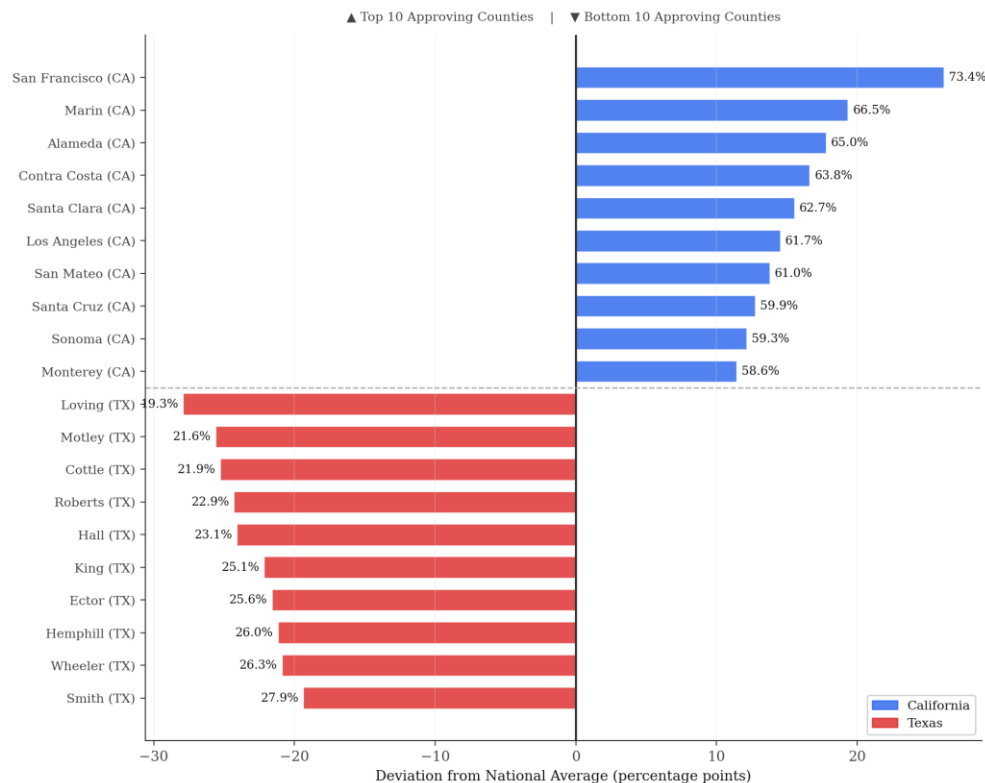


Figure 6. Diverging Horizontal Bar Chart of County Approval Deviation From National Average (47.2%)

Note. Top 10 and bottom 10 counties pooled from both states. Bar length = deviation in pp from national average. Blue = California; red = Texas.

4.7. Figure 7 Bubble Chart: Population-Weighted View (RQ1, RQ3, RQ4)

In Figure 7, the three variables shown are approval (x axis), post-election change (y axis), and county population (size of bubble). The top right quadrant (both high approval and gaining) consists mostly of large California coastal counties such as Los Angeles, Santa Clara, and Alameda counties, which account for tens of millions of people combined. The bottom left quadrant (both low approval and losing) consists of numerous small Texas rural counties, with a combined total population that is less than one big California metro county. The population-adjusted map rectifies the perceptual problems reported by Robinson [21] and Buzzelli [20], namely that choropleth maps emphasize rural space while deemphasizing urban population. Weighted mean approval: California = 61.5% (SD = 3.2%); Texas = 38.2% (SD = 2.8%); weighted mean difference = 23.3 pp, 95% CI [22.6, 24.0]. This means that there is a population-weighted 23.3-point difference versus the 18.1-point county mean difference.

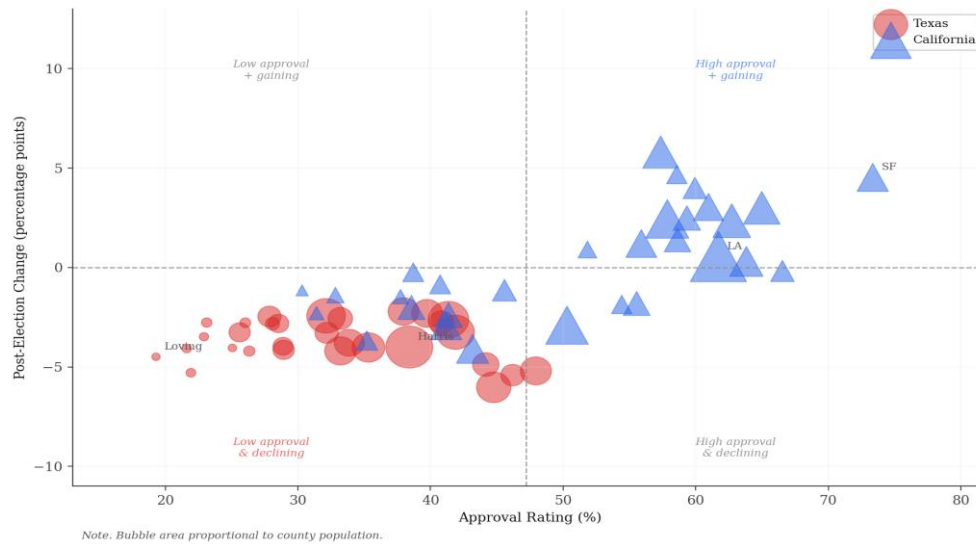


Figure 7. Bubble Chart of County Approval, Post-Election Change, and Population Size

Note. Bubble area $\propto$ county population (square-root scaled). x = approval (%); y = post-election change (pp). Quadrant dividers: $x = 47.2\%$; $y = 0$. California: blue triangles; Texas: red circles.

4.8. Figure 8 Small Multiples: Sub-Group Approval Trajectories (RQ4)

Figure 8 shows the same time-series pattern for each of the eight subgroups within county groups classified based on state and urbanization level. The figure contains a common vertical axis (14-76%) and a common time span for all panels such that any difference in appearance is due to real differences in the data, not scaling issues [24]. The subgroups with the largest post-election volatility in terms of approval are the Texas Urban and California Inland-Agricultural subgroups (± 3 to ± 4 pp), whereas the Texas Rural-West and California Coastal subgroups are the least elastic (± 1 to ± 1.5 pp).

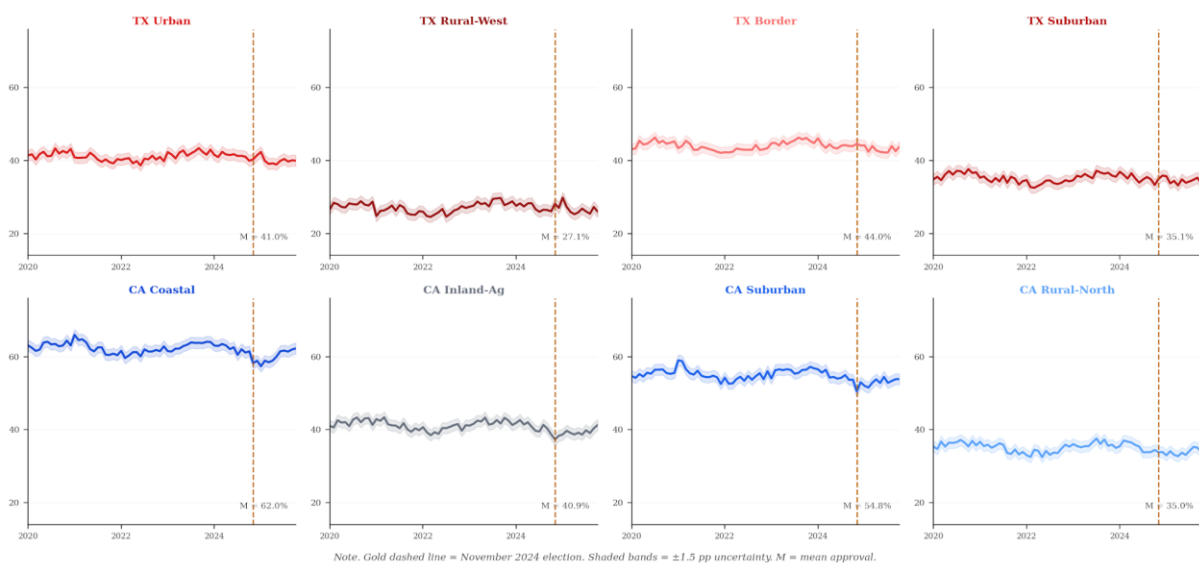


Figure 8. Small Multiples of Monthly Approval Trends by County Sub-Group, January 2020-October 2025

Note. All panels share y-axis (14-76%) and time extent. Gold dashed line = November 2024 presidential election. Shaded bands = ± 1.5 pp uncertainty.

5 Discussion

5.1. Visualization as Epistemology

Collectively, these eight visualizations form a narrative that no individual graphic can deliver. The choropleth (RQ1) shows the geographic pattern of polarization. The time-series (RQ2) demonstrates stability and responsiveness to events. The change heatmap (RQ2) shows post-election movement. The violin plot (RQ4) shows California's bimodal distribution a feature impossible to see in any geographic visualization. The scatter plot (RQ3) provides evidence for the linear urban/rural gradient. The diverging bar chart (RQ4) highlights the extreme outliers from both states. The bubble chart (RQ1, RQ3, RQ4) unmask the population-based weighting bias obscured by equal-area geographic maps. The small multiples (RQ4) highlight the varying degrees of event sensitivity of different county types. Each of these contributions represents a unique piece of analytical information about the theoretical issues of [6,2,11,7,8].

The traditional approach of presenting solely the geographic maps equates to responding to only one of the four research questions proposed here. It should be noted that even though some figures share thematic similarity Figures 1 and 3 both represent geographic distributions of the approval rate, Figures 2 and 8 both represent temporal patterns their analytical roles differ. Figure 1 answers the question of where approval exists; Figure 3 answers the question of how much it changed. Figure 2 answers the question of when the pattern became different; Figure 8 answers the question of which subgroup was responsible for the difference and how sensitive they were to events. Therefore, each of these visualizations brings a distinct contribution to the analysis. This argument is based on the perceptual framework described in Munzner [18] and proven by citation analysis done by Traunmüller [16].

A direct validation of this model using the user study is an important drawback of the current work. We recognize that the claim that each of the figures answers a unique research question is based on Munzner [18] and Ware [33] theoretical analysis rather than empirical evidence proving the increased accuracy of comprehension. A pilot user study with 10-20 participants comparing the accuracy of comprehension between several visualizations would help prove this statement in the future.

5.2. Partisanship as Structural Baseline

In all eight of the visualizations presented above, party makeup proves to be the strongest structural correlate of approval ratings, following Bartels [7], Jacobson [2], and Abramowitz & Webster [1]. The interstate split persists through all presidential administrations and remains even after taking into account urbanization rates. But the combination $R^2 \approx .58$ of the scatter plot suggests that urban-rural split explains a significant amount of the state level variation that cannot be explained by party makeup alone [11].

5.3. Ethical and Perceptual Considerations

The red-to-blue diverging scheme runs the risk of creating a connection between approval ratings and partisanship, thereby encouraging viewers to interpret ratings as partisanship [17]. The neutral gray middle value partially alleviates this problem. Future maps must adopt ColorBrewer schemes [36] without using partisan colors in communicating the degree of approval ratings. The use of natural breaks instead of quantiles retains the bimodal nature of the California distribution map, an approach discussed specifically by Cairo [17].

6 Limitations

The biggest caveat with this study is that all estimates for county approval values are modeling estimates, not direct measurement. The MRP model makes assumptions, in particular that demographic predictors explain the geographic variation in approval and that the poststratification cells appropriately represent county composition. Hence, all county-level approval estimates must be understood as demographically-informed

estimates, and not survey outcomes collected from individuals residing in the respective counties. Estimated 95% posterior credible intervals for the county-level approval values are on average ± 5.8 pp for Texas and ± 6.3 pp for California, and larger for the less populous counties. Findings from smaller rural counties should be treated accordingly.

Other limitations include: (1) lack of county-level data that accounts for approximately 18% of the county-month observations, where imputation, which was proven to be stable during the sensitivity analysis, introduces additional uncertainty; (2) limiting the scope of the study to Texas and California, thus omitting many variations that can be found in swing and realigning states; (3) opinion subgroups within the county, such as race, age, and education, cannot be identified because of aggregation of the data into county-level estimates [8,9]; (4) the fact that the county is an administratively-defined area that may not constitute a socially coherent community, i.e., example of MAUP problem [20,22]; (5) the fact that the time period is limited up to October 2025, and hence post-election findings may be impacted by later months; and (6) lack of user testing of the visualization framework.

7 Future Directions

A pipeline extending to all 50 states will allow for national trends showing up-and-coming swing regions or re-alignments. Use of geographical markers for sentiments expressed on social media will enable measurement below the monthly frequency, although sampling issues need to be carefully controlled for [38,37]. Use of colorblind-friendly palettes [36] and demographic cartograms will improve accessibility. Smaller resolution mapping, such as congressional districts, metropolitan areas, or even census tracts, could reveal micro-trends that go unnoticed at the county level. Above all, the user study of 10-20 users examining comprehension accuracy for each of the eight visualization types will empirically validate the task decomposition approach.

8 Conclusion

The paper has illustrated how presidential approval figures include several dimensions for analysis which are spatial, temporal, distributional, bivariate, rank-based, multivariate, population weighted, and subgroup comparisons; however, each one of them requires its own visual representation to be perceptible reliably. The developed visualization methodology, inspired by Munzner [18] and compared against the work of Ware [33], is an example of replicable task-driven approach for political data science, distinct from the existing practice of choropleths highlighted in Han et al. [15] and Trautmüller [16]. The value of the eight-visualization framework is not in the eight charts but in the logical alignment between four research questions and their complementary visual encodings.

In terms of substantive theory, the findings reinforce and extend the literature: TX-CA approval difference provides confirmation of Jacobson's [6,2] partisan spiral. Urbanization as a secondary continuous predictor confirms Rodden [11]. Bimodal distribution in California confirms Jacobson [14]. Discrepancies in population weighted estimations are another proof of MAUP [20]. Structural partisanship and event sensitivity of ambiguous counties confirm Iyengar et al. [8] and Hetherington and Rudolph [9]. The presented results are derived based on modeled estimates at county level, and must be understood in this context. However, given the above-mentioned caveat, the paper makes a point about visualization in political science as an epistemological choice.

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The author reports no conflicts of interest. The author alone is responsible for the content and writing of this paper.

Notes on Contributors

Sultan Fahim is a graduate student in the Department of Computer Science at West Chester University of Pennsylvania, where he has completed his Masters degree. His research interests include data visualization, political data science, and geospatial analysis. He is currently doing independent research under the supervision of Dr. Amir and Dr. Ashik . This paper represents his independent research project, examining county-level patterns in presidential approval ratings through systematic visualization methods.

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Sultan Fahim is a Computer Science graduate with an M.S. from West Chester University of Pennsylvania (2026) and a B.S. in Computer Science and Engineering from Bangladesh Army University of Engineering and Technology. His work sits at the intersection of applied machine learning, software engineering, and distributed systems, reflected in five peer-reviewed publications spanning deep learning for medical image classification, sequence modeling for biosignal analysis, and blockchain-based security architecture. Alongside his research, Sultan has professional software engineering experience building production systems, including leading AWS infrastructure design for an event-driven data pipeline during his internship at iPipeline. He is proficient in Python, Java, and JavaScript, with hands-on expertise in cloud infrastructure, large language models, and retrieval-augmented generation systems. Sultan has also served as a peer tutor and tutor coordinator, supporting hundreds of students in technical and research

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