Ranked-Choice Voting Reduces Negative Sentiment in Politician Rhetoric*

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Abstract

We study whether implementation of ranked-choice voting (RCV) in local US elections reduces negative sentiment in political candidates' rhetoric. Using an event-study design and a newly collected corpus of candidate voter guide statements, we apply modern transformer-based sentiment analysis tools to the text. Compared to a plurality voting rule, we find RCV causes a significant reduction in negative-sentiment rhetoric. In contrast, an experiment testing for independent demand-side effects finds no evidence RCV reduces the negative sentiment that voters express towards an election winner who is not their top choice (despite actively ranking them next best).

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1 Introduction

Many raise fears that negative rhetoric from political candidates contributes to growing affective polarization in American political life.[1] Explanations for such rhetoric often focus on the personal characteristics of the politician or the broader socioeconomic and media forces that shape politics. In this work, we explore another factor that may be influencing the presence of negative rhetoric in elections: the electoral institution itself. Specifically, we study how the the choice of electoral rule – ranked-choice voting versus the more typical first-past-the-post plurality voting rule – affects politicians' expressed negative sentiment.

Ranked-choice voting (RCV), while somewhat more common in other parts of the globe, has only in the 21st century begun to expand its presence in the United States. Existing scholarship studying RCV has analyzed its effect on the degree of polarization in candidate policy positions (Atkinson et al., 2024), voters' confidence in elections and the democratic process (Nielson, 2017), fiscal outcomes and legislator ideology (Vishwanath, 2025), and racially polarized voting (McDaniel, 2018). In contrast, here we study the outcome of negative sentiment expressed in political candidate speech, seeking to understand if RCV may reduce the corrosiveness of political rhetoric.

The most closely related publication in this regard is by Kropf (2021) who explores the relationship between RCV and civility in candidate statements via lexicon-based sentiment analysis of political candidate Tweets drawn from a single election cycle in three cities with RCV and seven with first-past-the-post (FPP) voting. Our work advances the literature in two important ways: one, in our comprehensiveness – we study almost all instances (as of 2023) where RCV has become the governing election rule in local elections in the United States; and, two, in our research design which uses both spatial and temporal variation and modern event-study methods to overcome the endogeneity issues present in prior work.[2]

[1] Affective polarization is characterized by animus towards those on the opposite side of the political spectrum (Iyengar et al., 2019; Boxell et al., 2024) in contrast to traditional polarization defined over distance in policy or political positioning from the ideological center (Jensen et al., 2012; Longuet-Marx, 2024; DellaVigna and Kim, 2025). See Sood and Iyengar (2016) on the effect of candidate speech on affective polarization and Cagé et al. (2024) on its effect on ideological polarization.

[2] A third, ancillary contribution of this work is in the use of modern transformer-based sentiment analysis tools in the detection of negative sentiment (see Section 2.3 for more on how they differ from older lexicon-based tools). Preceding Kropf (2021) is a noteworthy literature (see Donovan et al. (2016) and John and Douglas (2017) for example) that also explores the civility hypothesis leveraging self-reported perceptions of civility while comparing a few cities with RCV to some without. This work is also without a quasi-experimental research design and is further distinguished from the present manuscript in studying perceptions of incivility rather than the measured behavior of political candidates that is analyzed both here and in Kropf (2021). A working paper by McGinn (2020) also addresses the civility hypothesis using mayoral debate transcripts analyzed with lexicon-based sentiment analysis tools in a sample that includes five cities with RCV. Results are generally

The governing logic of the main hypothesis – that, compared to FPP voting, RCV reduces negative sentiment in political candidate rhetoric – can be simply put. For candidates competing under RCV, there is incentive to refrain from language that is negative so as to not alienate those who aren't their core voters, voters whose second-choice or third-choice votes they may need to eventually cross a majority upon the final round of vote distribution.[3] Under FPP, however, capturing a plurality is often sufficient to win, making the preferences of some fraction of the voting base (those existing between plurality and majority) potentially disposable. This prediction conforms with the formal derivation in Buisseret and Prato (2023) that candidates are more likely to pursue broad campaigns that can appeal to all voters (under conditions when multiple candidates have a reasonable chance of securing voters' second-choice support) provided one understands rhetoric with negative sentiment to be generally less broad in appeal.

To assess this hypothesis we apply modern natural language processing tools in the form of transformer-based sentiment analysis to politicians' candidate statements (of the type found in voter guides). This allows us to identify negative sentiment in a candidate's rhetoric, as well as more specific emotional cues. Utilizing the role out of RCV in local elections (for mayor and city council) across the USA in the last 20 or so years, with nearby cities continuing to use FPP chosen as our controls, we perform an event-study analysis to estimate the effect on negative sentiment induced by the switch in electoral rule. The results indicate significant reductions in the negative sentiment in political candidates' rhetoric caused by the move to ranked-choice voting. Evidence is consistent with a shift away from expressed annoyance with the status quo or political opponents to more anodyne expressions of civic enthusiasm. Besides the direct relevance to scholarship on RCV and negative political rhetoric, this finding also connects with a broader empirical literature showing how electoral institutions affect political candidates' speech (Cagé et al., 2024; Di Tella et al., 2025) and behavior (Gagliarducci et al., 2011).

Additionally, using an online experiment, we also explore whether RCV has an independent and direct effect, unmediated by changes in politician behavior, not just on the negative

insignificant, however, it is unclear if identification assumptions are met as the manuscript does not report the information needed to statistically assess parallel trends and relies on two-way fixed effect specifications known to have methodological issues (Goodman-Bacon, 2021) in contrast to the event-study analysis carried out here.

[3]Under RCV, voters rank all candidates on the ballot by the order of preference. If no candidates receive a majority of first-choice votes in the first ballot count, the election enters multiple stages of runoffs during which candidates with the fewest votes are eliminated and have their votes redistributed to a voter's next most preferred choice. The process is continued until a final round when a candidate receives a majority of distributed votes.

sentiment expressed on the supply side of politics (politicians) but on that of the demand side as well (voters). The specific hypothesis tested is that voters, by considering who to rank as next most preferred after their top choice candidate, may feel less negatively toward a winner they ranked when their top-choice candidate loses (in contrast to FPP selection where a disappointed voter gives no formal consideration to who might be an acceptable next best fit). With random assignment of voting rule, we test this hypothesis measuring voters' reported sentiment toward a winning candidate that was not their most preferred candidate.[4] Unlike with the supply-side effect, however, here we find no effect of RCV in reducing voters' negative sentiment.

2 Data and Methods

2.1 Political Rhetoric Under Study

When seeking to assess the tenor of political candidates' rhetoric, there is no shortage of content to assess. However, there are naturally differences in rhetoric based on the modality of communication. For instance, speech varies significantly whether delivered through targeted mailers, before the faithful at a rally, via paid television advertisements, or in candidate interviews. Thus, when choosing a text corpus to assess for negative sentiment, it is important to ensure it is standardized in at least two ways: one, all candidates running for a given office must be assessed using rhetoric articulated in a common format; two, the format should be one where the volume of, or even access to, speech is not biased towards particular candidates (e.g., by ability to pay for time). These considerations lead us to a common and standardized corpus of political candidate speech for which we assess negative sentiment: candidate election statements such as those typically recorded in official voter guides.

These candidate statements share the following distinctive features relative to other political rhetoric: all official candidates for an office have the right to submit them; they are offered in written format and are typically very constrained in word count, with equal space provided to every candidate; they are not extemporaneous speech; they are statements made in response to a prompt given in common to all candidates for the office; and, the statements

[4] A similar hypothesis is tested in work by Gutiérrez et al. (2022) that asks experimental subjects, in each of three treatment arms, if they would ever support a candidate who was democratically elected in a election but who the subject did not vote for. The three treatment arms are: 1) participation in a hypothetical RCV election 2) participation in a hypothetical FPP election, and 3) a no-election control. However, the paper does not report results for the comparison between the RCV and FPP treatment arms. Furthermore, it may be underpowered to detect any such difference as roughly half of subjects are asked this question after their preferred candidate wins the hypothetical election (something our experimental design addresses).

are intended to speak to the voting public at large. As such, the political speech we study here may be expected to have lower baseline levels of negative sentiment than some other common rhetorical formats, and, the usual questions about external validity to other forms of political speech may apply.

To our knowledge, there is no national database of voter guides (or the candidate statements therein) for the local offices we study. Thus, data collection requires searching out such content at a city or county level on a case by case basis. In many instances, candidate statements are formally recorded and compiled by local registrar offices before subsequently being distributed as official voter guides. In some cases, these voter guides are already available electronically and accessible via the local government website. Often, however, older voter guides are not available online and require requests to local government officials to obtain images of the physical copies they have stored on site. Local government agencies do not always follow up despite repeated outreach over phone and email, leading us to additional avenues of search for the candidate statements in these instances. Sometimes, more responsive local organizations keep record of past candidate statements, such as local civil society groups and local news outlets (examples include the Sun Post in Minnesota and the League of Women Voters in Maine), and, when necessary, we seek out such avenues to try and collect as many years of data as possible (within the parameters defined in the next subsection). In all cases, we focus exclusively on written, published statements, instead of those derived from interview audios or events such as candidate forums. Furthermore, for each individual city, we generally gather statements from one single, consistent provider for all years to ensure the comparability of content and hence sentiment across time.

2.2 Elections Analyzed

In the United States, the use of RCV in elections is uncommon, as most elections at all levels use first-past-the-post (FPP) voting rules that require only a plurality to win office. 21st century reforms to adopt RCV have almost entirely affected non-federal offices. Correspondingly, in this paper we study reforms to RCV in local elections, specifically, in mayoral and city council on-cycle elections in US locales where ranked-choice voting (RCV) has been implemented in the election of these offices by 2023.[5] We rely on news articles, government public archives, and the FairVotes website to record which cities adopted RCV, when they did so, and for

[5]Sometimes, rather than being termed a city council seat, the local legislative seat under study in the RCV-implementing locale is termed a board of supervisors seat, or, in the case of the county of Arlington, VA, a seat on a county board (Arlington, VA is a single unified county with no incorporated cities within it so the county board effectively performs all city functions).

which elected office. In total, there are 19 locations that we identify as "treated" with RCV within this timeframe and whose data is available to be used in our analysis.[6] Table A1 presents these cities. Excluded from our analysis are cities where RCV was introduced in local elections but then revoked, as well as federal elections run using RCV, such as the recent reforms in the states of Alaska and Maine.

For the event-study analysis, we require control cities which are sufficiently similar to the cities experiencing the adoption of RCV in terms of their underlying negative political rhetoric trends and which do not implement RCV during our period of study. Since the acquisition of voter guide candidate statements is a time consuming process and no repository exists for the entire country, we limit our search for control voter guides to those from cities that geographically border a treated city. Whether they are a good counterfactual for RCV-implementing cities in terms of negative political rhetoric is an empirical question that is assessed below. Table A2 lists the cities for which we successfully obtain candidate statement data and which constitute the control cities used in our analysis.

For each treatment city and the neighboring control cities, we attempt to collect candidate statements for at least the four elections preceding the election year when RCV is adopted in the relevant treated city and in the elections following adoption.[7] It is not always possible to find candidate statements in every election year in a location. Most elections under study are held in even-numbered years and are held in November (with a small number of cities holding them in May). Beyond the above, we try and obtain additional years of election data in control cities to ensure there are control observations in all years in which an election in an eventually treated place takes place (relevant for odd-numbered year elections). The full list of all elections with candidate statement data collected, listed by city, year, and office, can be found in Tables A3-A10

Occasionally an election for an office is uncontested. Our analysis excludes such elections as the bite of our theoretical prediction is moot in such cases. Instead, all analysis below focuses only on elections where voters were able to select from three options (at least two official candidates and a write-in option). In total, across all control and treatment locations, we analyze candidate statements from 295 elections occurring in 60 cities across 12 states.

[6] In four additional cases of cities that implemented RCV in mayoral or city council elections by 2023 – Minneapolis and St. Paul, Minnesota, Basalt, Colorado, and Palm Desert, California – repeated outreach to local election officials and a thorough search for supplemental sources of this data (as described in the previous subsection) did not yield voter guides. They, thus, are not included in the present analysis.

[7] We aim for 4 elections post implementation, but, for cities adopting RCV very recently there is obviously a shorter post-period, meaning the dynamic effect two or three elections post-RCV implementation will be estimated from a smaller set of early-adopting treatment cities.

Focusing only on general elections, as is done in the baseline analysis below, yields instead 277 elections occurring in 59 cities across 12 states. The earliest election in the data is 1999 and the latest in 2025. The first election in the data that is run with a newly implemented RCV rule takes place in 2004 and the last takes place in 2023. In the baseline sample there are 1792 candidate statements in total, and in the expanded sample, 1898, with the vast majority of observations coming from candidates that appear only once in the data.

2.3 Sentiment Analysis Tools

To measure the main outcome of interest – the expression of negative sentiment in political rhetoric – we use existing natural language processing tools to assess the compiled candidate statements. Our primary sentiment measure is a variant of RoBERTa, a pretrained, transformer-based sentiment-analysis model that classifies texts based on emotional cues. In an advance from earlier generations of lexicon-based models, which use predefined word dictionaries to assign sentiment values, RoBERTa is trained by interpreting and learning the contextual meanings of languages based on larger bodies of texts. Thus, RoBERTa is capable of capturing and adapting by itself to the nuances of context-dependent meanings (Liu et al. (2019)). Specifically, our study uses the sentiment-roberta-large-english (SieBERT) model developed by Hartmann et al. (Hartmann et al., 2023) which refines an earlier version from Liu et al. (2019). This newer model, tuned on 15 datasets that consist mainly of tweets and online reviews, gives a binary rating (negative or positive) to a text based on its overall display of negative or positive sentiment. The tweet training data in particular is well suited to the analysis of political speech. We implement the SieBERT model using the package found on the Hugging Face Transformers library, which is an open-access online platform on which developers (including those of the sentiment analysis tools discussed here) share and update their models.[8]

To assess the robustness of the main results, we also use the TWEETeval package which provides a modified RoBERTa package that is specifically adapted for social media context (Barbieri et al., 2020).[9] Similar to SieBERT, the TWEETeval model provides sentiment ratings to each of three labels (negative, neutral, positive). The model is trained on approximately 58 million posts from X (previously Twitter), a setting known for emotionally-charged, political speech.

Examples of candidate statements categorized as negative and positive sentiment, re-

[8]The SieBERT package can be found at https://huggingface.co/siebert/sentiment-roberta-large-english
[9]The TWEETeval package can be found at https://huggingface.co/datasets/cardiffnlp/tweet_eval

spectively, are shown in Figures A1-A2. Beyond the general characterization of negative or positive sentiment, we also study the particular types of negative or positive sentiment that may shift. To do so, we use the RoBERTa-based model of roberta-base-go_emotions which is trained with the GoEmotions data set containing 58 thousand comments from Reddit that are manually labeled with 27 emotion categories (Demszky et al., 2020).[10] The output provides a probability score for the analyzed text for each of the emotion categories, proving useful for the study of more detailed, overlapping emotional cues.

2.4 Demand-side Data

We also collect the votes received by each candidate from similar sources as those used to obtain candidate election statements (especially official governmental platforms like Secretary of State websites; on a few occasions, we utilize the City Clerk office's newsletter or local news reports). From the raw votes we compute the vote share a candidate received (between 0 and 100), or, sometimes vote share is directly provided in the sources consulted. For RCV elections the votes and vote share come from first-round votes as 2nd, 3rd, etc. rankings are incompletely provided and limited in availability, making the first round the only one with public information on votes received for each and every candidate. In a few instances, while winners are reported, we cannot find an online source from the local government or local media that records the exact vote share. In such instances, when calls to the local government go unanswered, we drop those elections from the analysis where vote share is used.

To also test demand-side effects of RCV on voter sentiment that are unmediated by changes in politician behavior, we conduct an online experiment on Prolific. Across two sessions, 750 participants take part.[11] The participants were paid $0.50 for about two minutes of their time on average. Participants were presented with an election for governor to be determined by their vote and that of four other voters in a temporary online polity. Three candidates were presented without name but with brief political statements (that were unlikely to be familiar to participants) drawn from real politicians. Each participant was randomly assigned into one of two treatments, RCV and FPP, where the election was determined, as known to the participant in advance of their vote, under the respective voting rule. Unknown to the participant, the other four votes in their online polity were drawn from previous votes elicited prior to their session and selected by the experimenters so that the outcome of the election

[10] The roberta-base-go_emotions package can be found at https://huggingface.co/SamLowe/roberta-base-go_emotions.

[11] Following standard practice, 4 additional observations from the same IP address are dropped.

would be such that the participant's most preferred candidate lost.[12] Following the revelation of the loss, the participant was asked *"Since the candidate you voted for did not win, how do you feel towards the candidate that won?"* and given a seven point Likert scale (running from "strongly negative" to "strongly positive") to answer. This expressed participant sentiment towards the winning candidate is the experimental outcome of interest studied below.

2.5 Empirical Approach

For identification of our main politician sentiment results, we utilize an event-study design. Events are defined by the adoption of ranked-choice voting in a mayoral or city council election as outlined in Section 2.2. These local public offices "treated" with RCV are compared to equivalent offices from nearby locales that have always been elected under traditional first-past-the-post election rules (see details in Section 2.2). We are interested in studying the effect of these events (the introduction of the RCV voting rule) on the expression of negative political rhetoric by candidates competing under the rule. Our primary measure of negative sentiment comes from analysis of the candidate statements described in Section 2.1 using the RoBERTa sentiment analysis methods outlined in Section 2.3. The familiar event-study specification takes the following form

$$NegativeSentiment_{ict} = \sum_{k=-4,k\neq 0}^{k=3} \beta_k \mathbb{1}_{k,c,t} + \lambda_t + \psi_c + \epsilon_{ict} \tag{1}$$

where $NegativeSentiment_{ict}$ in our baseline analysis represents an indicator variable equal to one if candidate *i*'s statement during electoral cycle at time *t* in city c is categorized as expressing negative sentiment using the SieBERT natural language processing model (described in Section 2.3); the treatment dummy $\mathbb{1}_{k,c,t}$ equals 1 if an electoral cycle t occurs k election cycles before/after the adoption of RCV in city c (note that $k = -1$ is the left out category); λ_t represents electoral cycle year fixed effects; ψ_c represents city fixed effects; finally, ϵ_{ict} is the error term, clustered at the city level. Following the influential initial work of Goodman-Bacon (2021), the literature has raised contamination concerns for β_k estimates in a staggered timing event-study design such as that represented in (1).[13] To

[12] For RCV treatment participants, the electorate in their online polity was chosen so that their second choice candidate (known to us by their ballot), won the election, since this is the kind of loss we hypothesize to be best-powered to detect a treatment effect.

[13] In particular, with heterogeneity in the treatment effect across treated cohorts, β_k's from (1) can be contaminated by treatment effects from other relative periods, producing causally uninterpretable results for the event-time-dummy estimates.

avoid this, we estimate the interaction-weighted (IW) estimator version of (1) proposed by Sun and Abraham (2021). This estimator yields a weighted average of the cohort-specific average treatment effects on the treated where the weights are non-negative, sum to 1, and are easily interpretable (equal to the cohort's contribution, relative to other cohorts, to each respective event-time estimate). These IW event-study estimates are immune to the above contamination concerns and allow for heterogeneity in the treatment effect across the cohorts that are treated at different points in time - relying instead only on the identifying assumptions of no anticipation and parallel trends. We use never-treated cities as the control group. The list of these control cities is found in Table A2, while the eventually treated cities are found in Table A1. Figure 1 plots a map of both. Panel (a) of Table A11 presents summary statistics for the election data analyzed in our main sample.

In terms of our experiment testing for independent demand-side effects of RCV on voter sentiment, identification comes from random assignment into RCV and FPP treatments which makes for straightforward statistical analysis. Table A12 presents a balance test across the collected demographic variables. The results are consistent with successful random assignment. Panel (b) of Table A11 presents summary statistics for the experiment.

3 Results

3.1 Main Results on Negative Sentiment of Politician Rhetoric

For a comparable set of elections at baseline, we first focus on general election races, which constitute the vast majority of our sample, while using the SieBERT sentiment scoring. To assess the robustness of these benchmark findings, we also present results when additionally including the primary elections in our data and when using the alternative TWEETeval sentiment scoring method.

Figure 2 presents the baseline results of specification 1. We see that the control cities in our sample appear to provide a good counterfactual for those cities eventually treated with ranked-choice voting. The incidence of negative sentiment in candidate rhetoric moves in a parallel fashion among treated and control cities in advance of the adoption of ranked-choice voting in the eventually treated cities. After RCV implementation, there is a clear and statistically significant reduction in the incidence of negative-sentiment speech from political candidates in the treated locations. It manifests itself in the first election using RCV and continues in the subsequent elections with a more moderate effect. Averaged over the three post-implementation elections, there is a significant 6.4 percentage point reduction (p-value of 0.001) in the incidence of negative sentiment, which is quite sizable compared to the pre-event mean incidence of 7.8 percent in eventually treated cities. Column (1) of Table 1 reports this estimate and, for comparison, the average sentiment difference in the pre-period between treatment and control locations, a statistically insignificant and positive 1.1 percentage points in this case.

The addition of the primary elections in the data does little to change the finding. Figure A3 presents these results, again using SieBERT sentiment scoring. Averaged over the three post-implementation elections, as reported in column (2) of Table 1, there is a significant 5.4 percentage point reduction in the incidence of negative sentiment (p-value of 0.005). By comparison, the pre-event mean incidence is 6.4 percent in eventually treated cities.

To assess the robustness of these results to a different method of measuring negative sentiment, we use the alternative NLP model, TWEETeval. Figure A4 presents a version of Figure 2 using the TWEETeval sentiment scoring method instead. Results are broadly consistent with those using SieBERT sentiment scoring. Averaged over the entire post-implementation period, the reduction in the incidence of negative sentiment is estimated at 8.7 percentage points (significant at the 1% level), as seen in column (3) of Table 1. This is again quite large in comparison to a pre-event mean incidence of 10.5 percent in the eventually treated cities. Replicating the analysis of Figure A3 but using TWEETeval outcomes instead also yields very similar results, presented in Figure A5. Again, negative sentiment is estimated to fall precipitously in the first election after RCV implementation, with persistent but more moderate effect sizes in the subsequent elections. Averaged over the entire post-implementation period, as shown in column (4) of Table 1, there is an estimated 6.9 percentage point reduction (significant at the 1% level) in the incidence of negative-sentiment political speech (by comparison, the pre-event mean incidence is 8.7 percent in these eventually treated cities).

While the negative sentiment result is a unique, standalone outcome from politican policy positions or ideology, one might consider reductions in negative sentiment speech to naturally flow from a reduction in politicians' ideological polarization brought on by RCV (a consequence of RCV commonly articulated by its advocates). However, prominent existing work tests for but does not find evidence that RCV in fact reduces political polarization or affects legislator ideology (Atkinson et al., 2024; Vishwanath, 2025), making our finding even more striking.

3.2 Specific Emotional Sentiments That Change

The previous subsection captures broad changes in the nature of political rhetoric brought on by RCV introduction. Namely, the rhetoric becomes less negative in the sentiment it expresses. But what specific kinds of sentiment are altered in response to the change in the electoral system? Here we study a battery of emotional categories using the roberta-base-go_emotions model (Demszky et al., 2020). Across a range of positive and negative emotions, roberta-base-go_emotions provides confidence scores that the text is reflective of that particular emotion. Most of these emotional categories show no change upon RCV implementation. We discuss those that do here.

There are three emotional categories where there is a statistically significant percentage change post-RCV in the confidence score the model assigns to that emotion's presence in a candidate's statement (and for which the identifying assumption of parallel trends in the pre-period is not rejected).[14] In column (5) of Table 1 we see that the model's confidence that the text reflects the negative emotion of *annoyance* goes down after the introduction of RCV (significant at the 5% level), with an 11% reduction in the confidence score. Figure A6 contains text from candidate statements that scored the highest in *annoyance*. They appear to be appropriately categorized by the model. Excerpts that evince such annoyance include: "I hate losing all the land in northwest Plymouth to development"; and "the [property tax] increases over the last couple years have been absurd"; and "San Francisco's Budget and Payroll is Out of Control! I will stop the ridiculous, unending increases."

On the other hand, for the positive emotions of *excitement* and *love* (as in "I love this city" rather than romantic love), we see the model's confidence that the text reflects these emotions going up after RCV implementation, with positive and large increases, significant at the 1% level, as seen in columns (6) and (7) of Table 1.[15] Figures A7-A8 contain text from the candidate statements with the top confidence scores on *excitement* and *love*. They reveal anodyne expressions of enthusiasm for the city and the boosting of municipal political projects. For instance: "I love Fremont and I believe our best days are ahead!" and "Those were exciting days as we worked to establish a new city!"

These combined results offer a more detailed characterization of the shift away from negative-sentiment political speech brought on by RCV. A refined governing mechanism

[14] Additionally, the emotions of *amusement*, *disappointment*, and *joy* show a statistically significant post-period coefficient but also have statistically significant pre-period coefficients violating the identification assumption.

[15] While the results on *annoyance* and *excitement* are robust to the inclusion of primary elections, the pre-event coefficient on *love* becomes statistically significant, indicating less robustness in the specific emotional sentiment results vis-a-vis the findings on the incidence of negative sentiment in the previous subsection.

at play may be something like the following: candidates substitute away from language expressing annoyance with the status quo or political opponents to more positive expressions of enthusiasm for their city or for their political projects because the replaced rhetoric is less likely to get other candidates' voters to transfer their 2nd or 3rd placed vote.

3.3 Demand-side Effects

The above findings show a clear causal effect of the RCV voting rule on changes to political candidates' speech. This supply-side effect on the level of negative sentiment in the political process may also be complemented by an independent demand-side effect that RCV has on those selecting politicians, voters. The online experiment described in Section 2.4 is designed to test whether a voter's sentiment toward a winning candidate, when the winner is not the voter's preferred candidate, is affected by the electoral rule used in selection. Since RCV requires a voter to actively consider their next-best pick for office, the prediction is that under RCV selection a losing voter may feel more positive sentiment toward a winning candidate they ranked but who was not their first choice.

The experimental results do not support this hypothesis. The estimated difference in the Likert scale response to the sentiment question in Section 2.4 is small, negative, and not statistically significant. As shown in column 1 of Table 2, those in the RCV treatment have a minimally reduced Likert score response, by -0.026 units on the 7 point scale, with a standard error of 0.101 (p-value of 0.798). The 95% confidence interval ranges from a -0.225 reduction to a 0.173 increase. For comparison, the estimated coefficient is only 1.8% of a standard deviation in this Likert score for the experimental population and the lower bound of the 95% confidence interval is only about 12% of it, indicating even modest effect sizes are ruled out. If one focuses on the small share of the experimental population that reports that they had not voted in the previous election, less engaged members of the electorate who may be so because of dissatisfaction with the existing plurality rule in the US, the sign on the coefficient changes and becomes considerably larger (see column 2 of Table 2). Although this is more in line with the prediction, the estimate is not statistically significant.

These results indicate that an RCV election rule does not directly reduce the negative sentiment expressed by voters. However, there is still the possibility that voters' sentiment is indirectly affected by RCV through the effect that we document it to have on candidate behavior. Our preferred interpretation of the main results is that, on average, candidates substitute away from negative-sentiment language in an effort to avoid alienating voters who might transfer their 2nd or 3rd ranked votes to them.[16] This change in candidate behavior implicitly presumes candidates know some voters prefer less negative rhetoric, a preference that if satisfied may be reasonably inferred to positively shift the sentiment that these voters have towards the election process. Such a mechanism, however, relies on candidates believing that when they express less negative sentiment, they will actually win over some voters for their efforts. Is this supported by the data? Consistent with this belief, we see in our data that candidates with negative-sentiment statements win fewer votes. As seen in columns 3 and 4 of Table 2, the vote share is lower by a statistically significant 7 to 9 percentage points (significant at the 1% level) for candidates who express negative-sentiment speech.[17]

4 Conclusion

In this paper we show that the introduction of ranked-choice voting lowers the incidence of negative sentiment expressed in politician speech. We offer the best test to date of the prediction that an RCV electoral rule incentives more unifying messaging in campaigns, using modern event study identification methods and a comprehensive study of American jurisdictions that have adopted RCV in local elections. To arrive at our conclusion, our work applies transformer-based sentiment analysis tools to the text of a newly collected corpus of candidate voter guide statements from mayoral and city council elections. The negative sentiment expressed in them is estimated to fall precipitously in the first election after RCV implementation, compared to traditional first-past-the-post plurality voting, with persistent but more moderate effects in subsequent elections. Evidence is consistent with a shift away from expressed annoyance with the status quo or political opponents to more anodyne expressions of civic enthusiasm. In a separate experiment, we also test for direct effects of RCV on the demand side of elections. Here we find no evidence that an RCV electoral rule reduces the negative sentiment that voters express towards an election winner who is not their top choice (despite actively ranking them next best). However, as we see less negative campaign messaging is associated with increased vote shares, RCV may reasonably be thought to indirectly improve voters' general electoral sentiment via the reduction in

[16] It may be that there is no (even subconscious) strategic calculation on the part of the candidates and that the mechanism is instead a selection one – RCV makes it feel more possible to win for some political aspirants who thus decide to enter politics and whose positive outlook is complemented by more positive speech style. We leave distinguishing this from our preferred explanation to further work.

[17] The underlying specification regresses vote share received (taking first-round votes for the RCV elections, given incomplete and limited disclosure of subsequent rounds) on the negative-sentiment indicator and city and year fixed effects, with standard errors clustered at the city level.

negative sentiment it causes in politician rhetoric. Given the known impact that politically charged language has on attitudes in the general population (Djourelova, 2023; Djourelova et al., 2024), it is not far fetched to imagine this reduction in negative sentiment among politicians may reduce affective polarization in the voting public as well.

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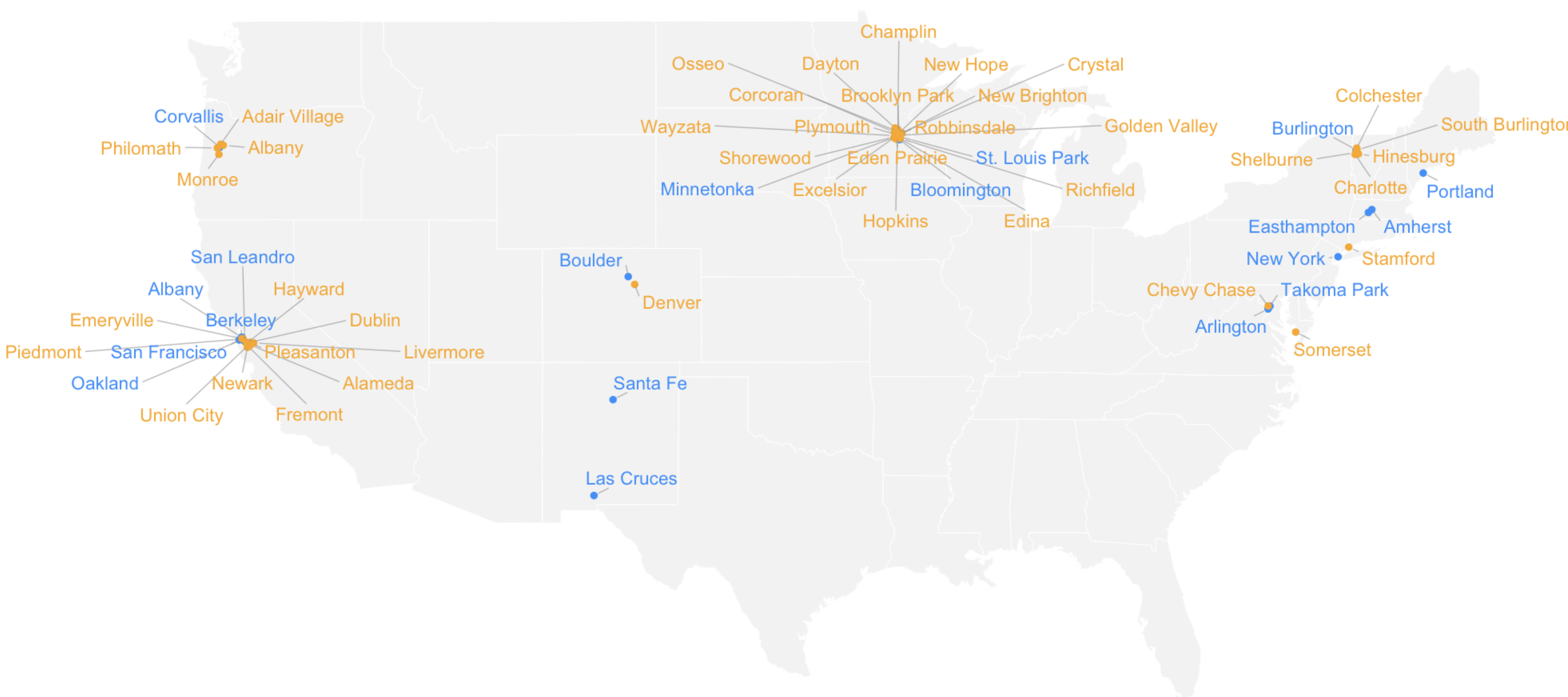
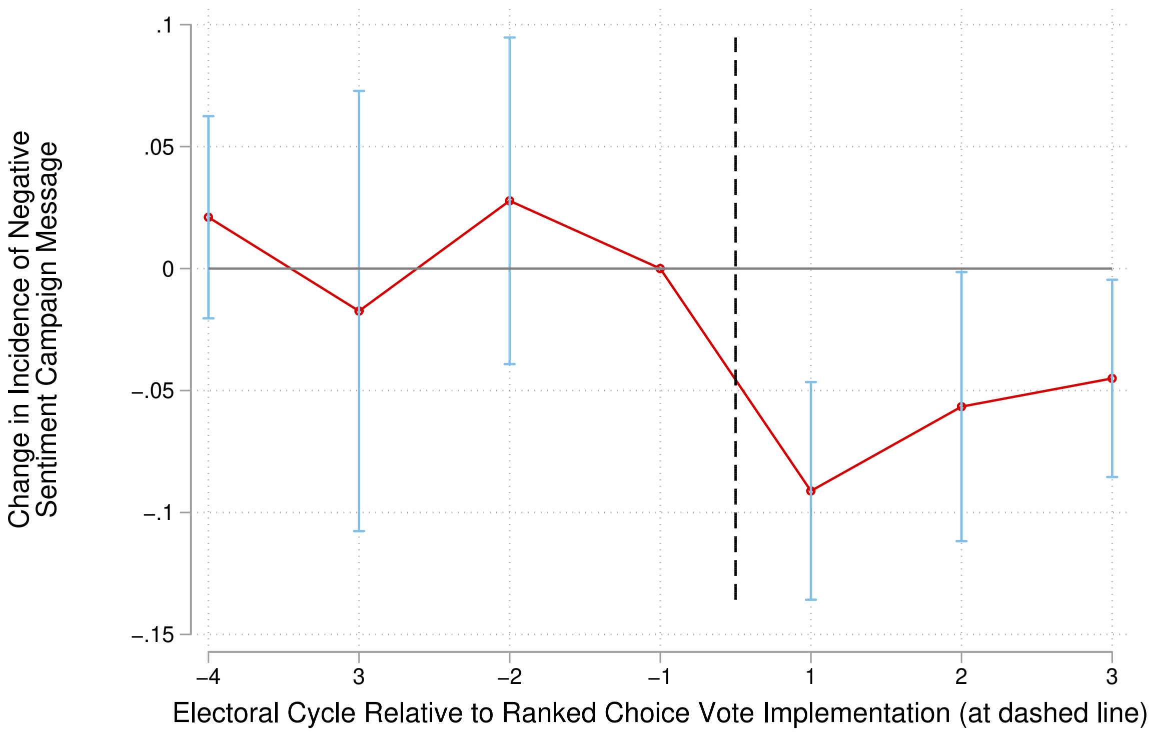
Figure 1: Cities Under Study



Notes: The map identifies all the local jurisdictions that are studied in the paper, with treated municipalities (where ranked-choice voting is implemented for mayoral or city council elections) in blue and control municipalities (that use only first-past-the-post electoral rules for the same offices) in orange. See Section 2.2 for additional details.

Figure 2: Ranked-Choice Voting Lowers the Incidence of Negative Sentiment in Politicians' Speech



Notes: The figure reports event study results based on the Sun and Abraham (2021) IW estimator version of specification 1 described in Section 2.5 using never-treated units as the control group. The outcome is an indicator variable equal to one if a political candidate's speech is categorized as expressing negative sentiment using the SieBERT natural language processing model described in Section 2.3. Candidate speech under study comes from candidates running for mayor or city council. The vertical dashed line represents the implementation of ranked-choice voting in these local elections. In total there are 1772 observations. Standard errors are clustered at the city level.

Table 1: Ranked-Choice Voting's Effect on Politician Rhetoric

	Dependent Variable:						
	Incidence of Negative Sentiment				Log Confidence Score for: Annoyance	Excitement	Love
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post	-0.0643***	-0.0537***	-0.0874***	-0.0688***	-0.110**	0.523***	0.360***
	(0.0188)	(0.0190)	(0.0166)	(0.0164)	(0.0551)	(0.170)	(0.110)
Pre	0.0105	-0.0136	0.000918	-0.0181	0.0131	0.201	0.213
	(0.0269)	(0.0315)	(0.0219)	(0.0293)	(0.0633)	(0.155)	(0.137)
N	1772	1898	1772	1898	1772	1772	1772

Notes: The table presents the effects of the implementation of ranked-choice voting on the sentiment of political candidates' speech. The average of post-event and pre-event coefficients are reported here from event study analysis using the Sun and Abraham (2021) IW estimator version of specification 1 described in Section 2.5, with never-treated units used as the control group and local election RCV implementation being the event in question. In columns 1-4 the dependent variable is an indicator variable equal to one if a political candidate's speech is categorized as expressing negative sentiment. Columns 1 and 2 use the SieBERT natural language processing model (Hartmann et al., 2023) to determine negative sentiment. Columns 3 and 4 use the TWEETeval natural language processing model (Barbieri et al., 2020) to determine negative sentiment. Pre-event mean negative sentiment incidence in the eventually treated cities is 7.8%, 6.4%, 10.5%, and 8.7% in columns 1-4, respectively. Column 1 corresponds to the results presented in Figure 2. Column 2 corresponds to the results presented in Figure A3. Column 3 corresponds to the results presented in Figure A4. Column 4 corresponds to the results presented in Figure A5. See the corresponding figure notes and the main text for further specification details. In columns 5-8 the dependent variable is the log of the confidence score for the emotional categories of "annoyance" (column 5), "excitement" (column 6), and "love" (column 7) determined using the roberta-base-go_emotions model (Demszky et al., 2020). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Demand-side Responses

	Dependent Variable:			
	Voter Sentiment		Vote Share (0-100)	
	(1)	(2)	(3)	(4)
RCV Electoral Rule Treatment	-0.0259	0.346		
	(0.101)	(0.260)		
Negative Sentiment in Candidate Rhetoric			-6.986***	-8.863***
			(2.415)	(1.725)
N	750	76	1743	1743

Notes: Columns 1 and 2 report results from the online experiment described in Section 2.4. The outcome is the participant's Likert score response on a seven point scale (running from "strongly negative" to "strongly positive") to the question *"Since the candidate you voted for did not win, how do you feel towards the candidate that won?"* RCV treatment is an indicator for a voter's random assignment to the RCV voting rule (rather than the FPP voting rule). Column 1 presents results for the full sample and column 2 presents results for the subset that reports they have not voted in the last election. The regressions control for the demographic variables in panel (b) of Table A11 (with column 2 excluding the voted-in-last-election variable, necessarily). The regressions in columns 3 and 4 use the naturally occurring candidate statement data analyzed in Section 3.1. The outcome is the vote share (from 0-100) obtained by a candidate. The specifications regress vote share received (taking first-round votes for the RCV elections, given incomplete and limited disclosure of subsequent rounds) on the SieBERT (column 3) or TWEETeval (column 4) negative-sentiment indicator variable characterizing a candidate's political statement, plus city and year fixed effects, with standard errors clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

APPENDIX A: ONLINE FIGURES AND TABLES

Figure A1: Examples of Negative Sentiment Candidate Statements

(a) Negative Sentiment Example 1

In Corvallis, we have the most noble words on paper but seem to lack the courage to take action and bring those words to life. **Words** minus **Action** equals **Zero !**

Please vote NO on the Corvallis Operating Levy to defeat another attempt by City Government to ask for more money before eliminating waste and cutting expenses. In Corvallis, we have enough money for all of the things we **need**, but we don't have enough money for everything we **want**. I've lived here for 36 years and I have never heard an honest discussion about cutting expenses. I will lead the community through that conversation.

There are **5 issues** that I will address :

- Enhance Community Livability by muffling the exhaust Noise of street racing vehicles
- Replace the Public Works Director

(b) Negative Sentiment Example 2

9. I came to California to attend Stanford. I will settle here in Berkeley to raise a family. There's lots of fake talk nowadays about helping our children get the best education that the world has to offer. Never before have more of our youth been abused, raped, drugged, shot, and, worst of all, drained of any hope to create anything of permanent value in the world. Berkeley needs a Mayor with a solution to this crisis, and the courage and principle to make it happen. The root of the problem is deliberate deception. I will work diligently to make such harmful deceit impossible in Berkeley. Under my leadership, I will transform City Hall into an open, transparent, and solving democratic institution. I am for the people of Berkeley, not the developers. With all my powers, I will work to remove the stranglehold that these profit-hungry real estate agents have over the City Council and staff. Even without public office, I've already turned back fee hikes aimed against the public. Help me do even more. Let's put an end to the waste of your tax dollars, and accomplish these

Note: The figure presents text excerpts from two (randomly selected) candidate statements assigned a "negative sentiment" classification by both the SieBERT and TWEETeval models (Hartmann et al., 2023; Barbieri et al., 2020). Highlighted parts are added by the authors.

Figure A2: Examples of Positive Sentiment Candidate Statements

(a) Positive Sentiment Example 1

My qualifications are:
Union organizer, legislative aide, elections advocate, ethics attorney.

For 15 years, I have promoted progressive values here in our city and around the world:

- With former President Carter's The Carter Center in Africa, I fostered negotiations between warring factions and facilitated free elections.

- As a union organizer and political party official, I fought for workers' rights.

- As a legislative aide, I helped create jobs and improve the quality of life in San Francisco.

As Supervisor, I will improve our quality of life by:

- Ensuring safe streets. Crime and violence are on the rise and I will make it a priority to fight for more beat cops, cameras in high crime areas, and better technology for our police department.

- Reducing homelessness and aggressive panhandling. I'll work with Mayor Gavin Newsom to improve Care Not Cash and get the homeless off the streets and into supportive housing and rehabilitative services.

- Promoting family housing. I'll expand home ownership and rental opportunities for middle and low-income families, artists, and first responders.

(b) Positive Sentiment Example 2

Our city has a vibrant business community, excellent schools, parks, trails and roads. We have outstanding police and fire departments that work extremely hard to keep our community safe.

However, we are still in the process of recovering from the Great Recession. The council must always be vigilant when spending taxpayer's money.

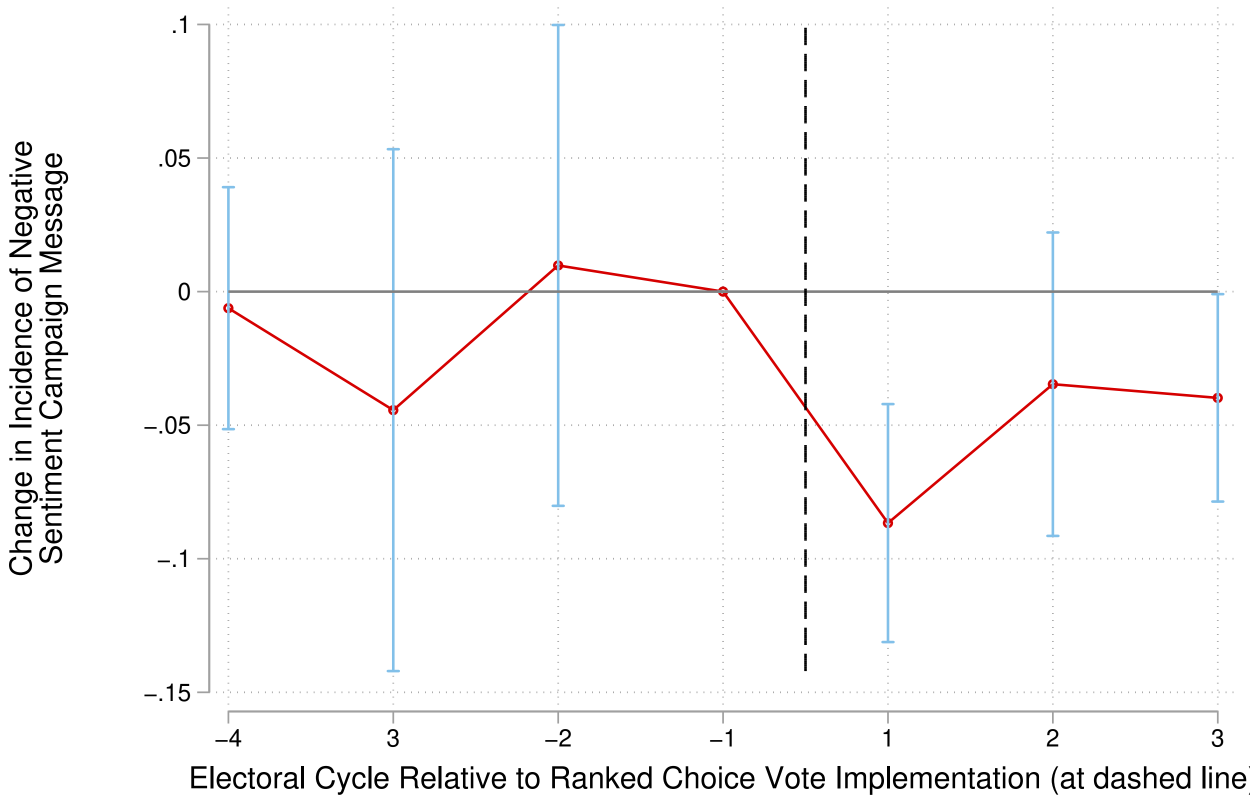
I am fiscally responsible and respectfully ask Eden Prairie citizens for their vote.

The city council recently approved a $21 million upgrade to the Community Center's pool. This upgrade is funded with $17 million of bonded debt which adds $7.3 million in interest costs to the project. Support it or not, Eden Prairie voters should have been asked by referendum if they thought spending $28 million on an amenity was appropriate or if they would have preferred a less expensive option and lower taxes.

I understand budgets, debt and finance. Over my career I have held various auditor, accounting and financial controller positions, and was VP and Chief Financial Officer of a $500 million company for 10 years before I retired. Eden Prairie no longer has a citizen Budget Advisory Committee, and the city council needs the kind of financial expertise that I can provide.

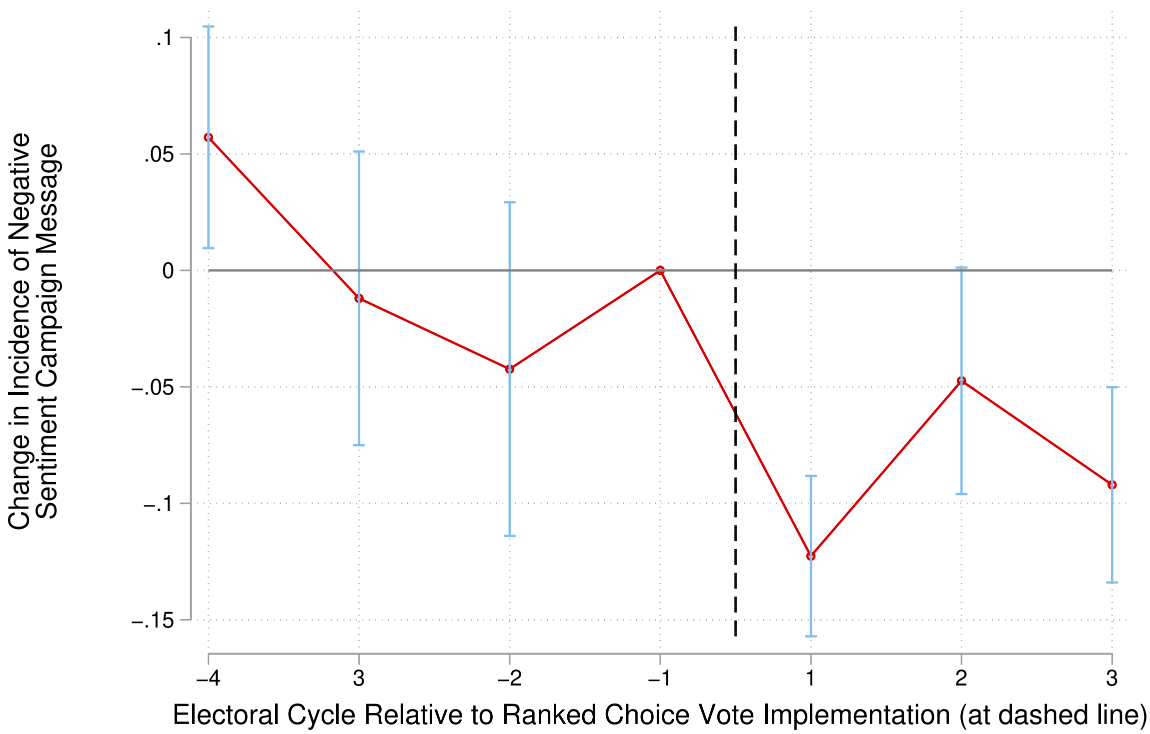
Note: The figure presents text excerpts from two (randomly selected) candidate statements assigned a "positive sentiment" classification by both the SieBERT and TWEETeval models (Hartmann et al., 2023; Barbieri et al., 2020).

Figure A3: Ranked-Choice Voting Lowers Incidence of Negative Sentiment in Politicians' Speech (Full Sample)



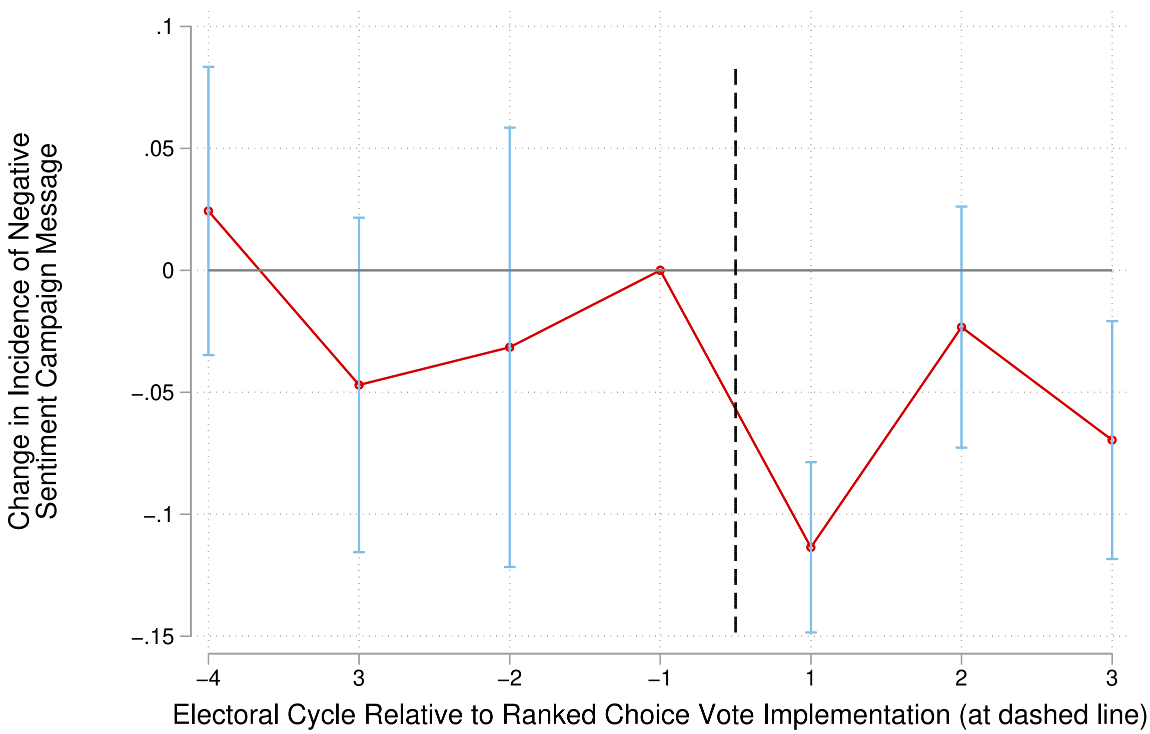
Notes: The figure is the same as Figure 2 except here primary elections are also included. The figure reports event study results based on the Sun and Abraham (2021) IW estimator version of specification 1 described in Section 2.5 using never-treated units as the control group. The outcome is an indicator variable equal to one if a political candidate's speech is categorized as expressing negative sentiment using the SieBERT natural language processing model described in Section 2.3. Candidate speech under study comes from candidates running for mayor or city council. The vertical dashed line represents the implementation of ranked-choice voting in these local elections. In total there are 1898 observations. Standard errors are clustered at the city level.

Figure A4: Ranked-Choice Voting Lowers Incidence of Negative Sentiment in Politicians' Speech (Alternative Sentiment Measure)



Notes: The figure is the same as Figure 2 except an alternative measure of negative sentiment is used (TWEETeval). The figure reports event study results based on the Sun and Abraham (2021) IW estimator version of specification 1 described in Section 2.5 using never-treated units as the control group. The outcome is an indicator variable equal to one if a political candidate's speech is categorized as expressing negative sentiment using the TWEETeval natural language processing model described in Section 2.3. Candidate speech under study comes from candidates running for mayor or city council. The vertical dashed line represents the implementation of ranked-choice voting in these local elections. In total there are 1772 observations. Standard errors are clustered at the city level.

Figure A5: Ranked-Choice Voting Lowers Incidence of Negative-Sentiment Politician Speech (Alternative Sentiment Measure Full Sample)



Notes: The figure is the same as Figure A4 except here primary elections are also included. The figure reports event study results based on the Sun and Abraham (2021) IW estimator version of specification 1 described in Section 2.5 using never-treated units as the control group. The outcome is an indicator variable equal to one if a political candidate's speech is categorized as expressing negative sentiment using the TWEETeval natural language processing model described in Section 2.3. Candidate speech under study comes from candidates running for mayor or city council. The vertical dashed line represents the implementation of ranked-choice voting in these local elections. In total there are 1898 observations. Standard errors are clustered at the city level.

Figure A6: Examples of Candidate Statements with High Scores for Expression of "Annoyance"

(a) Annoyance Example 1

We have a substantial amount of green space in the city (parks, Northwest Greenway, playfields, trails), but we could add more. I hate losing all the land in northwest Plymouth to development. The issue is if you are taking a parcel out of the hands of developers that usually means you have to purchase it. Which in Plymouth means, big dollars. I try to balance the benefits versus the cost.

(b) Annoyance Example 2

I feel like a major concern right now is property taxes. The increases over the last couple years have been absurd. I believe the way perceived property values are used to determine tax rates needs to be reassessed.

I also think becoming more environmentally conscious should be a focus. Being environmentally friendly can also be more fiscally responsible, so it's important that we explore these options.

The world has changed significantly over the last few years, and I think it's important that all the programs and projects of the city are being challenged on a regular basis. I am hoping for the opportunity to help the city of New Hope and all of its residents continue to thrive.

(c) Annoyance Example 3

My occupation is Florist/Coffee Farmer.

My qualifications are:
San Francisco's Budget and Payroll is Out of Control!
I will stop the ridiculous, unending increases.
In 1987, our city budget was less than $1 billion.
Today, it is over $6 billion. That's an increase of over 500%!
That period the Bay Area Cost of Living increased only 85%.
Our budget has increased at a rate of over 5 TIMES inflation!
What are we getting for it? More debt! Less Service! Higher Fees!
San Francisco's Budget and Payroll is Out of Control!
I will stop the ridiculous, unending increases.

San Francisco Deserves Better:
Infrastructure and Transporation will come before new programs.
I will reduce the number of city employees wherever possible.
I will Use Zero Based Budgeting (justify every dollar, every year).
I will Use Common Sense Governance and Enforce All Existing Laws.

Note: The figure presents the candidate statements receiving the highest confidence score for the emotional category of "annoyance" using the roberta-base-go_emotions model (Demszky et al., 2020). Highlighted parts are added by the authors.

Figure A7: Examples of Candidate Statements with High Scores for Expressions of Two Kinds of Enthusiasm ("Excitement" and "Love")

(a) Excitement Example 1

I had the privilege of serving as the first mayor of Adair Village following the city's incorporation in 1976. Those were exciting days as we worked to establish a new city! As a 33 year resident and homeowner of Adair Village I have seen, in recent years, some development of the infant city of 30 years ago. The future may bring additional homes and families as well as a possible business district. Adair Village could be a city with a library, a restaurant or two, a larger grocery market, a gas station and other shopping opportunities. Some businesses could offer jobs for our citizens. If any of this does occur we will face some new challenges in our city such as a safer access onto Highway 99, public transportation and enhanced police and fire protection. I was involved in the formation and history of Adair Village. I would like the opportunity to work with you to meet the challenges of the future of our city. Together we can do it. Exciting days are ahead!

(b) Excitement Example 2

Becker Park is also an underutilized asset. We have an opportunity to leverage funding partners to make Becker Park the crown jewel in our park system, and create a destination park that will serve Crystal residents year round.

The plans for Becker Park will be driven by what the community wants, and I'm excited to see what they come up with.

(c) Love Example 1

Occupation: Business Owner
Age: 43
My education and qualifications are: I love Fremont, and I believe our best days are ahead! Being a local business owner with a degree in Business Economics from UCLA aids me in navigating the complexities of the city's budget and economy. As an immigrant and a mother of autistic children, I understand the hardships faced by people with special needs, people of color and immigrants in our society. And through my beloved Marine husband, I have come to know the values of dedication and perseverance. I am running to build a city with safer, cleaner, and vibrant neighborhoods that offer everyone opportunities. As your councilwoman, I will bring about pragmatic and collaborative solutions, such as: Community Centers, places of neighborhood engagement, extending services to our senior citizens and children. Improved traffic corridors, with additional public transportation options for our workforce and sustained development. Reduction in property crime, with resources and facilitation between police and our communities. I believe residents must have access in order to actively participate in shaping neighborhood-based solutions. That's why my door will always be open to you, and you can count on me to be your voice in city hall. Vote Teresa Keng for a better Fremont!

Notes: The figure presents the candidate statements receiving the highest confidence score for the emotional categories of "excitement" and "love", respectively, using the roberta-base-go_emotions model (Demszky et al., 2020). Highlighted parts are added by the authors.

Figure A8: Examples of Candidate Statements with High Scores for Expressions of Two Kinds of Enthusiasm ("Excitement" and "Love") – Continued

(a) Love Example 2

Occupation: Engineer
Age: 49
My education and qualifications are: I love Newark; I love the people who live here and the communities which make up our city. In the past 20 years I have served on citizen committees, been a school parade coordinator for the Newark Days Parade, restarted/chartered Boy Scout Troop 101, served on the Waterford Board of Directors, served on St. Edward School PTG, and coached my daughters in the Newark Soccer Club. Newark is our home, and we all want Newark to remain a safe place to live. We also want vibrant communities where people walk their dogs along tree lined avenues and where people have access to great retail and resources right here in Newark. We need to re-invent our retail spaces while integrating our public into public safety. What will be the next chapter of Newark's story? With your help, I hope to see Newark as a more vibrant and safe place to live. Vote for me, Mark Gonzales, this election and we'll make it happen.

Notes: The figure presents the candidate statements receiving the highest confidence score for the emotional categories of "excitement" and "love", respectively, using the roberta-base-go_emotions model (Demszky et al., 2020). Highlighted parts are added by the authors.

Table A1: Treatment Cities

State	City	Treatment or Control	First Election Under RCV
CA	Albany	Treatment	2022
CA	Berkeley	Treatment	2010
CA	Oakland	Treatment	2010
CA	San Francisco	Treatment	2004
CA	San Leandro	Treatment	2010
CO	Boulder	Treatment	2023
MA	Amherst	Treatment	2023
MA	Easthampton	Treatment	2021
MD	Takoma Park	Treatment	2007
ME	Portland	Treatment	2011
MN	Bloomington	Treatment	2021
MN	Minnetonka	Treatment	2021
MN	St. Louis Park	Treatment	2019
NM	Las Cruces	Treatment	2019
NM	Santa Fe	Treatment	2018
NY	New York City	Treatment	2021
OR	Corvallis	Treatment	2022
VA	Arlington	Treatment	2023
VT	Burlington	Treatment	2022

Notes: The table lists the cities "treated" with ranked-choice voting that are studied in the paper, listing the first election in which RCV was used for local elections.

Table A2: Control Cities

State	City	Treatment or Control	First Election Under RCV
CA	Alameda	Control	.
CA	Dublin	Control	.
CA	Emeryville	Control	.
CA	Fremont	Control	.
CA	Hayward	Control	.
CA	Livermore	Control	.
CA	Newark	Control	.
CA	Piedmont	Control	.
CA	Pleasanton	Control	.
CA	Union City	Control	.
CO	Denver	Control	.
CT	Stamford	Control	.
MD	Chevy Chase	Control	.
MD	Somerset	Control	.
MN	Brooklyn Park	Control	.
MN	Champlin	Control	.
MN	Corcoran	Control	.
MN	Crystal	Control	.
MN	Dayton	Control	.
MN	Eden Prairie	Control	.
MN	Edina	Control	.
MN	Excelsior	Control	.
MN	Golden Valley	Control	.
MN	Hopkins	Control	.
MN	New Brighton	Control	.
MN	New Hope	Control	.
MN	Osseo	Control	.
MN	Plymouth	Control	.
MN	Richfield	Control	.
MN	Robbinsdale	Control	.
MN	Shorewood	Control	.
MN	Wayzata	Control	.
OR	Adair Village	Control	.
OR	Albany	Control	.
OR	Monroe	Control	.
OR	Philomath	Control	.
VT	Charlotte	Control	.
VT	Colchester	Control	.
VT	Hinesburg	Control	.
VT	Shelburne	Control	.
VT	South Burlington	Control	.

Notes: The table lists control cities used in the paper, which use FPP not RCV in local elections.

Table A3: List of Elections Included in the Analysis

State	City	Year	Office
OR	Adair Village	2002	Council Member
OR	Adair Village	2012	Council Member
CA	Alameda	2002	Council Member, Mayor
CA	Alameda	2006	Council Member, Mayor
CA	Alameda	2008	Council Member
CA	Alameda	2010	Council Member, Mayor
CA	Alameda	2012	Council Member
CA	Alameda	2014	Council Member
CA	Alameda	2016	Council Member
CA	Alameda	2018	Council Member, Mayor
CA	Albany	2010	Council Member
CA	Albany	2012	Council Member
CA	Albany	2016	Council Member
CA	Albany	2018	Council Member
CA	Albany	2020	Council Member
CA	Albany	2022	Council Member
CA	Albany	2024	Council Member
OR	Albany	2006	Council Member (D1), Mayor
OR	Albany	2010	Council Member (D1-A), Mayor
OR	Albany	2022	Council Member (D1-A), Mayor
OR	Albany	2024	Council Member (D1-B)
MA	Amherst	2021	Council Member (At-Large, D2, D3, D4, D5, D1)
MA	Amherst	2023	Council Member (At-Large, D1, D2, D4, D5)
VA	Arlington	2015	County Board Primary Dem
VA	Arlington	2018	County Board Primary Dem
VA	Arlington	2021	County Board Primary Dem
VA	Arlington	2023	County Board Primary Dem
VA	Arlington	2024	County Board Primary Dem
VA	Arlington	2025	County Board Primary Dem
CA	Berkeley	2002	Council Member (D1, D4, D7, D8), Mayor
CA	Berkeley	2004	Council Member (D2, D3, D5, D6)
CA	Berkeley	2006	Council Member (D1, D4, D7, D8), Mayor
CA	Berkeley	2008	Council Member (D2, D4, D5, D6), Mayor
CA	Berkeley	2010	Council Member (D1, D4, D7, D8)
CA	Berkeley	2012	Council Member (D2, D3, D5), Mayor
CA	Berkeley	2014	Council Member (D1, D7, D8)
CA	Berkeley	2016	Council Member (D2, D3, D5, D6), Mayor
MN	Bloomington	2013	Council Member (At-Large, D1, D2, D3, D4)
MN	Bloomington	2015	Council Member (At-Large, D1, D2), Mayor
MN	Bloomington	2017	Council Member (At-Large, D2, D3, D4)

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A4: List of Elections Included in the Analysis (continued)

State	City	Year	Office
MN	Bloomington	2019	Council Member (At-Large, D1, D2), Mayor
MN	Bloomington	2021	Council Member (At-Large, D3, D4)
MN	Bloomington	2023	Council Member (At-Large 2yr, D1, D2, D3, D4), Mayor
CO	Boulder	2023	Mayor
MN	Brooklyn Park	2014	Council Member (East District), Mayor
MN	Brooklyn Park	2016	Council Member (Central District, East District, West District)
MN	Brooklyn Park	2018	Mayor
MN	Brooklyn Park	2020	Council Member (Central District, West District)
MN	Brooklyn Park	2022	Mayor
VT	Burlington	2018	Council Member (D3, D5, D6, D7, D8)
VT	Burlington	2022	Council Member (D1, D5, D7)
VT	Burlington	2023	Council Member (South, Central, D8)
VT	Burlington	2024	Council Member (D1, D4, D6)
VT	Burlington	2025	Council Member (East, South)
MN	Champlin	2014	Council Member (D1), Mayor
MN	Champlin	2016	Council Member (D4), Mayor
MN	Champlin	2018	Council Member (D1)
MN	Champlin	2020	Council Member (D3, D4)
MN	Champlin	2022	Council Member (D2), Mayor
MN	Champlin	2024	Council Member (D4)
NC	Charlotte	2023	Council Member
MD	Chevy Chase	2007	Council Member
MD	Chevy Chase	2008	Council Member
MD	Chevy Chase	2009	Council Member
MD	Chevy Chase	2011	Council Member
MD	Chevy Chase	2012	Council Member
MD	Chevy Chase	2013	Council Member
VT	Colchester	2019	Council Member
VT	Colchester	2022	Council Member
VT	Colchester	2024	Council Member
VT	Colchester	2025	Council Member
MN	Corcoran	2014	Council Member, Mayor
MN	Corcoran	2016	Council Member, Mayor
MN	Corcoran	2018	Council Member, Mayor
MN	Corcoran	2020	Council Member, Mayor
MN	Corcoran	2022	Council Member
MN	Corcoran	2024	Council Member
OR	Corvallis	2014	Council Member (D6, D7, D8)
OR	Corvallis	2016	Council Member (D2, D8)
OR	Corvallis	2018	Council Member (D1, D3, D5, D9), Mayor

Notes: The table lists city, year, and offices inclueded in the analysis (continued).

Table A5: List of Elections Included in the Analysis (continued)

State	City	Year	Office
OR	Corvallis	2020	Council Member (D7)
OR	Corvallis	2022	Council Member (D2, D9), Mayor
OR	Corvallis	2024	Council Member (D1, D2, D3, D6, D7, D9)
MN	Crystal	2014	Council Member (D1, D2, SectionII)
MN	Crystal	2016	Council Member (D3, D4, Section I), Mayor
MN	Crystal	2018	Council Member (D1, D2, Section II)
MN	Crystal	2020	Council Member (D4)
MN	Crystal	2022	Council Member (D1, Section II)
MN	Crystal	2024	Council Member (D3), Mayor
MN	Dayton	2014	Council Member
MN	Dayton	2016	Council Member
MN	Dayton	2018	Council Member, Mayor
MN	Dayton	2020	Council Member, Mayor
MN	Dayton	2022	Council Member, Mayor
MN	Dayton	2024	Council Member, Mayor
CO	Denver	2023	City Council (D10, D2, D4, D5, D7, D8, D9)
CA	Dublin	2002	Council Member
CA	Dublin	2006	Council Member
CA	Dublin	2008	Council Member, Mayor
CA	Dublin	2010	Council Member
CA	Dublin	2012	Council Member
CA	Dublin	2014	Council Member, Mayor
CA	Dublin	2016	Council Member, Mayor
CA	Dublin	2018	Council Member, Mayor
MA	Easthampton	2021	Council Member (At-Large)
MN	Eden Prairie	2014	Council Member
MN	Eden Prairie	2020	Council Member
MN	Eden Prairie	2022	Council Member
MN	Eden Prairie	2024	Council Member
MN	Edina	2014	Council Member
MN	Edina	2016	Council Member
MN	Edina	2018	Council Member
MN	Edina	2020	Council Member
MN	Edina	2022	Council Member
MN	Edina	2024	Council Member
CA	Emeryville	2011	Council Member
CA	Emeryville	2014	Council Member
CA	Emeryville	2016	Council Member
CA	Emeryville	2018	Council Member
MN	Excelsior	2016	Council Member

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A6: List of Elections Included in the Analysis (continued)

State	City	Year	Office
MN	Excelsior	2018	Council Member, Mayor
MN	Excelsior	2020	Mayor
MN	Excelsior	2022	Council Member, Mayor
MN	Excelsior	2024	City Council, Mayor
CA	Fremont	2002	Council Member
CA	Fremont	2006	Council Member
CA	Fremont	2008	Council Member, Mayor
CA	Fremont	2010	Council Member
CA	Fremont	2012	Council Member, Mayor
CA	Fremont	2014	Council Member
CA	Fremont	2016	Council Member, Mayor
CA	Fremont	2018	Council Member (D1, D2, D3, D4)
MN	Golden Valley	2013	Council Member
MN	Golden Valley	2015	Council Member, Mayor
MN	Golden Valley	2017	Council Member
MN	Golden Valley	2019	Council Member, Mayor
MN	Golden Valley	2021	Council Member
MN	Golden Valley	2023	Council Member, Mayor
CA	Hayward	2000	Council Member (Primary)
CA	Hayward	2002	Council Member (Primary), Mayor Primary
CA	Hayward	2006	Council Member (Primary), Mayor Primary
CA	Hayward	2010	Council Member
CA	Hayward	2012	Council Member
CA	Hayward	2014	Council Member, Mayor
CA	Hayward	2018	Council Member, Mayor
VT	Heinesburg	2020	Council Member
MN	Hopkins	2015	Council Member, Mayor
MN	Hopkins	2017	Council Member, Mayor
MN	Hopkins	2019	Council Member
NM	Las Cruces	2009	Council Member (D3, D5, D6)
NM	Las Cruces	2011	Council Member (D1, D2, D4), Mayor
NM	Las Cruces	2013	Council Member (D6)
NM	Las Cruces	2017	Council Member (D3, D5, D6)
NM	Las Cruces	2019	Council Member (D1, D2, D4), Mayor
NM	Las Cruces	2021	Council Member (D3, D5, D6)
NM	Las Cruces	2023	Council Member (D1, D2, D4), Mayor
CA	Livermore	2011	Council Member, Mayor
CA	Livermore	2014	Council Member
CA	Livermore	2016	Council Member
CA	Livermore	2018	Council Member, Mayor

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A7: List of Elections Included in the Analysis (continued)

State	City	Year	Office
MN	Minnetonka	2015	Council Member (Ward 1, Ward 2)
MN	Minnetonka	2017	Council Member (At-Large Seat A, At-Large Seat B), Mayor
MN	Minnetonka	2019	Council Member (Ward 3, Ward 4)
MN	Minnetonka	2021	Council Member (At-Large Seat A, At-Large Seat B), Mayor
MN	Minnetonka	2023	Council Member (Ward 1, Ward 2, Ward 3, Ward 4)
WA	Monroe	2020	Council Member
WA	Monroe	2022	Council Member, Mayor
WA	Monroe	2024	Council Member
MN	New Brighton	2013	Council Member
MN	New Brighton	2017	Council Member, Mayor
MN	New Hope	2014	Council Member
MN	New Hope	2016	Council Member
MN	New Hope	2018	City Council
MN	New Hope	2020	City Council, Mayor
MN	New Hope	2022	City Council
MN	New Hope	2024	City Council
NY	New York City	2013	Mayor
NY	New York City	2015	City Council (D23)
NY	New York City	2019	City Council (D45)
NY	New York City	2021	City Council (D11, D12, D15)
NY	New York City	2023	City Council (D1, D4, D5)
NY	New York City	2025	Mayor
CA	Newark	2011	Council Member, Mayor
CA	Newark	2014	Council Member, Mayor
CA	Newark	2016	Council Member
CA	Oakland	2002	Council Member (D4 Primary, D6 Primary), Mayor Primary
CA	Oakland	2006	Council Member (D2, D6), Mayor Primary
CA	Oakland	2010	Council Member (D2, D4, D6), Mayor
CA	Oakland	2012	Council Member (At-Large, D1, D3, D5, D7)
CA	Oakland	2014	Council Member (D2, D4, D6), Mayor
CA	Oakland	2016	Council Member (At-Large, D1, D3, D5, D7)
MN	Osseo	2014	Council Member
MN	Osseo	2016	Council Member
MN	Osseo	2018	Council Member
MN	Osseo	2020	Council Member, Mayor
MN	Osseo	2022	Mayor
MN	Osseo	2024	Council Member
OR	Philomath	2002	Council Member, Mayor
OR	Philomath	2004	Council Member, Mayor
OR	Philomath	2006	Council Member, Mayor

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A8: List of Elections Included in the Analysis (continued)

State	City	Year	Office
OR	Philomath	2008	Council Member
OR	Philomath	2010	Council Member
OR	Philomath	2012	Council Member
OR	Philomath	2018	Council Member, Mayor
OR	Philomath	2020	Council Member, Mayor
OR	Philomath	2022	Council Member, Mayor
CA	Piedmont	2000	Council Member (Primary)
CA	Piedmont	2002	Council Member (Primary)
CA	Piedmont	2010	Council Member
CA	Piedmont	2012	Council Member
CA	Piedmont	2014	Council Member
CA	Piedmont	2016	Council Member
CA	Piedmont	2018	Council Member
CA	Pleasanton	2002	Council Member, Mayor
CA	Pleasanton	2006	Council Member, Mayor
CA	Pleasanton	2008	Council Member, Mayor
CA	Pleasanton	2010	Council Member, Mayor
CA	Pleasanton	2012	Council Member, Mayor
CA	Pleasanton	2014	Council Member
CA	Pleasanton	2016	Council Member
CA	Pleasanton	2018	Council Member
MN	Plymouth	2014	Council Member (D4)
MN	Plymouth	2016	Council Member (At-Large, D3)
MN	Plymouth	2018	Council Member (At-Large, D2, D4), Mayor
MN	Plymouth	2020	Council Member (At-Large, D1)
MN	Plymouth	2022	Council Member (At-Large, D2, D4)
MN	Plymouth	2024	Council Member (At-Large, D1, D3)
ME	Portland	2011	Mayor
ME	Portland	2015	Mayor
Me	Portland	2019	Mayor
MN	Richfield	2014	Council Member (At-Large), Mayor
MN	Richfield	2016	Council Member (D2, D3)
MN	Richfield	2020	Council Member (D1, D2)
MN	Richfield	2022	Council Member (At-Large)
MN	Richfield	2024	Council Member (D1)
MN	Robbinsdale	2014	Council Member (D3)
MN	Robbinsdale	2016	Council Member (D1), Mayor
MN	Robbinsdale	2018	Council Member (D3, D4)
MN	Robbinsdale	2020	Council Member (D2), Mayor
MN	Robbinsdale	2022	Council Member (D3)

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A9: List of Elections Included in the Analysis (continued)

State	City	Year	Office
MN	Robbinsdale	2024	Council Member (D1, D2)
CA	San Francisco	1999	Mayor
CA	San Francisco	2000	Board of Supervisors D1
CA	San Francisco	2002	Board of Supervisors (D2, D4, D6, D8)
CA	San Francisco	2003	Mayor
CA	San Francisco	2004	Board of Supervisors (D1, D2, D3, D5, D7, D9, D11)
CA	San Francisco	2006	Board of Supervisors (D2, D4, D6, D8, D10))
CA	San Francisco	2007	Mayor
CA	San Leandro	2002	Mayor
CA	San Leandro	2006	Council Member (D3 Primary), Mayor Primary
CA	San Leandro	2008	Council Member (D2)
CA	San Leandro	2010	Council Member (D1, D5), Mayor
CA	San Leandro	2012	Council Member (D2, D4, D6)
CA	San Leandro	2014	Council Member (D1, D3, D5), Mayor
CA	San Leandro	2016	Council Member (D2)
NM	Santa Fe	2018	Council Member (D1, D2, D4), Mayor
NM	Santa Fe	2021	Council Member (D1, D3, D4), Mayor
NM	Santa Fe	2023	Council Member (D1, D2, D3, D4)
NM	Santa Fe	2025	Mayor
VT	Shelburne	2022	Council Member
MN	Shorewood	2014	Council Member
MN	Shorewood	2016	Council Member
MN	Shorewood	2018	Council Member
MN	Shorewood	2020	Council Member, Mayor
MN	Shorewood	2024	Council Member, Mayor
MD	Somerset	2003	Council Member
MD	Somerset	2005	Council Member
MD	Somerset	2006	Council Member
MD	Somerset	2007	Council Member
VT	South Burlington	2022	Council Member
VT	South Burlington	2023	Council Member
VT	South Burlington	2024	Council Member
MN	St. Louis Park	2015	Council Member (At-Large Seat B), Mayor
MN	St. Louis Park	2017	Council Member (Ward 1, Ward 2, Ward 3)
MN	St. Louis Park	2019	Council Member (At-Large Seat A, At-Large Seat B), Mayor
MN	St. Louis Park	2021	Council Member (Ward 3)
MN	St. Louis Park	2023	Council Member (At-Large Seat B), Mayor
CT	Stamford	2017	Mayor
CT	Stamford	2021	Mayor
MD	Takoma Park	2005	Council Member (D2), Mayor

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A10: List of Elections Included in the Analysis (continued)

State	City	Year	Office
MD	Takoma Park	2007	Council Member (D3)
MD	Takoma Park	2009	Council Member (D4, D6), Mayor
MD	Takoma Park	2011	Council Member (D2, D3, D6)
MD	Takoma Park	2013	Council Member (D4)
CA	Union City	2006	Council Member
CA	Union City	2010	Council Member
CA	Union City	2014	Council Member
CA	Union City	2016	Council Member, Mayor
CA	Union City	2018	Council Member
MN	Wayzata	2014	Council Member
MN	Wayzata	2016	Council Member
MN	Wayzata	2018	Council Member
MN	Wayzata	2020	Council Member
MN	Wayzata	2022	Council Member
MN	Wayzata	2024	Mayor

Notes: The table lists city, year, and offices inclueded in the analysis.

Table A11: Summary Statistics

	(1) mean	(2) sd	(3) max	(4) min
Panel (a): Election Data (N=1772)				
Candidate's Electoral Office Ever Treated with RCV	0.471	0.499	1.000	0.000
Candidate's Statement Has Negative Sentiment (SieBERT classification)	0.042	0.200	1.000	0.000
Pre-Event Negative Sentiment in Eventually Treated Cities (SieBERT classification)	0.078	0.268	1.000	0.000
Candidate's Statement Has Negative Sentiment (TWEETeval classification)	0.056	0.230	1.000	0.000
Pre-Event Negative Sentiment in Eventually Treated Cities (TWEETeval classification)	0.105	0.307	1.000	0.000
Log Annoyance Confidence Score	-0.066	0.719	4.293	-1.437
(raw score, 100 point scale)	(1.423)	(3.054)	(73.20)	(0.238)
Log Excitement Confidence Score	-0.867	1.177	4.302	-3.413
(raw score, 100 point scale)	(1.299)	(5.827)	(73.83)	(0.033)
Log Love Confidence Score	-1.088	1.375	4.409	-3.204
(raw score, 100 point scale)	(3.033)	(12.08)	(82.17)	(0.041)
Panel (b): Experiment Data (N=750)				
RCV Treatment	0.515	0.500	1.000	0.000
Sentiment Toward Winning Candidate (1-7 Likert Score; 1 = most negative)	3.972	1.406	7.000	1.000
White	0.687	0.464	1.000	0.000
Male	0.489	0.500	1.000	0.000
Low Income	0.424	0.495	1.000	0.000
Have Ever Voted (Self Report)	0.953	0.211	1.000	0.000
Voted in Last Election (Self Report)	0.899	0.302	1.000	0.000

Notes: The table reports summary statistics. Panel (a) presents them for the baseline election sample (only general elections), where each observation is a candidate statement in a given election cycle (see Section 2). Panel (b) presents them for the online experiment (Section 2.4), where each observation is a voter in an election in a hypothetical online polity. In Panel (b), treatment status is either RCV or FPP and low income is categorized as household income below $63,100.

Table A12: Experimental Balance Table

	(1) Mean of RCV	(2) Mean of FPP	(3) Rank-Sum Test
Percent male	49.7	48.1	z = -0.455 p = 0.6489
Percent white	68.7	68.7	z = 0.008 p = 0.9933
Percent low income	43.3	41.5	z = -0.493 p = 0.6221
Percent ever voted	94.6	96.2	z =1.034 p = 0.3012
Percent voted in last election	91.2	88.5	z = -1.237 p = 0.2159
N	386	364	

Notes: The table reports the mean values of demographic variables for the RCV and FPP treatment arms (in columns 1 and 2, respectively) of the online experiment described in Section 2.4. In column 3 the z-statistics and p-values are reported for a Wilcoxon-Mann-Whitney test comparing the underlying distributions of each variable for the RCV and FPP treatment groups. Low income is categorized as household income below $63,100. Voting history variables rely on self reported information not actual election registers.