The Decoupling of Demography and Destiny: A Zero-Loss Decomposition of the 2024 U.S. Electorate.

Donald Moratz

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Abstract

Electoral analysis is frequently hindered by methods that conflate shifts in voter preference with changes in the electorate's demographic Composition, leading to significant interpretive errors that misattribute millions of votes. This paper introduces the Rate, Composition, and Volume Decomposition (RCVD), a novel, zero-loss methodology that resolves this issue. The RCVD precisely partitions total vote change into three analytically distinct components: changes in group loyalty (Rate), group size (Composition), and overall participation (Volume). After demonstrating the RCVD's zero-error properties with simulated data and showing how its application reveals systemic data resolution problems through a comparison of ANES and Pew data, I apply the framework to U.S. presidential elections. My analysis of the 2016, 2020, and 2024 cycles uncovers a crucial empirical finding: the 2024 result was determined by a decisive decoupling of Composition and Rate effects. Specifically, a substantial negative Rate swing– the erosion of partisan loyalty among non-White electorates, particularly Hispanic voters-— neutralized the long-predicted Compositional advantage for the Democratic Party. The RCVD is thus a crucial diagnostic tool, fundamentally challenging the "demographics are destiny" narrative and redirecting scholarly attention toward the active defense of coalition loyalty.

1 Introduction

Electoral outcomes are shaped not only by individual vote choices but also by the Composition of the electorate across demographic and identity groups. Ever since Downs (1957) argued for thinking about voting as an economic choice made by individuals, the focus of the discipline has been on individual-level voter behavior. Despite the justifiable nature of this focus, understanding how group-level dynamics shift over time is essential for explaining election outcomes. Individuals belong to specific groups and it is the Composition of the electorate across groups that ultimately determines who wins and loses (Axelrod, 1972). This is particularly relevant to the study of political science since in large elections, candidates must rely on appeals to broad groups rather than tailoring only to individuals. Historically, discussions of group effects were focused on turnout. Conventional wisdom held that conservatives suppress voter turnout amongst the poorest citizens (Piven and Cloward, 1989). To the extent to which that is true, the expectation was that increased turnout would drive more votes to the Democratic party (Lijphart, 1997). However, Citrin et al. (2003) argued that the impacts of changes in turnout could not be so easily identified since the gap between voters and non-voters preferences can change significantly from election to election. As the field turned toward the causal identification revolution, this debate was largely left to lie as research focused more on individual level drivers of voting behavior (Marble et al., 2024).

The discussion of the impact of changes in Composition is not restricted to only academic circles. Recent debates on U.S. demographic trends have focused on the influence of racial Composition and class-based voting patterns on election outcomes (Klein, 2024b). Some argue that demographic trends favor the Democratic Party (Klein, 2024a), while others emphasize the need for Democrats to focus on winning working-class, White voters (Judis and Teixeira, 2023). These debates reflect both public curiosity (Fessenden et al., 2020; Kolko and Monkovic, 2020) and a deeper academic interest in understanding vote share shifts across elections (Zingher, 2019; Hill et al., 2021). However, existing approaches to studying this question often fail to adequately account for the complexities of electoral Composition, particularly when considering both shifts within groups and changes across groups. Recent work by Marble et al. (2024) argues that correctly accounting for votes requires knowing the group's size and its Turnout Rate as well as the Rate at which the group voted for each candidate. The authors provide an exciting new tool for translating voter survey data, like ANES, into estimations of support for parties by racial groups.

Yet, in their work, as well as in other academic studies, authors fail to correctly account for the complex dynamics of electoral change, often conflating true shifts in group loyalty with changes in group size. For example, in Marble et al. (2024), the authors use what I call a derivative-based approach to understand the shifting support of Mitt Romney and Donald Trump from the 2012 to the 2016 election. They attempt to isolate the effect of preference change (which I term Rate) from demographic shifts (which I term Composition). Their method involves fixing the racial Composition of the electorate and then checking the impact of changing preference margins. However, following the same logic and summing across all components shows that their method does not accurately capture the total change in the electorate. Indeed, their approach generates a misspecification of nearly 1.2 million votes, demonstrating a fundamental failure to decompose Rate, Composition, and Volume effects without error.

Currently, there are two main approaches widely used in the literature to study Compositional effects: the derivative-based approach and the regression-based approach as in Hill et al. (2021). I argue that neither approach adequately captures the complex dynamics of the state space of electoral change, primarily because they cannot isolate Rate from Composition effects without generating significant, outcome-altering error. While both the derivative-based approach (e.g., (Marble et al., 2024)) and regression-based methods (e.g., (Hill et al., 2021)) have contributed to understanding vote shifts, they inadequately model how changes in group Composition influence outcomes across elections. To address this gap, I introduce the Rate, Composition and Volume Decomposition (RCVD), a zero-loss[1], non-linear solution that fully and

[1] See Appendix for Discussion on Overfitting

precisely models the dynamic changes across subgroups. By extending the insights of previous authors, RCVD offers a novel solution that fully captures dynamic shifts across both time and subgroups, revealing the critical moments when group loyalty (Rate) decouples from demographic trends (Composition).

The article proceeds as follows. First, I review existing literature and mathematical approaches, with a focus on the derivative-based method. I then introduce RCVD, which more accurately captures Compositional shifts compared to the derivative-based approach. In section 3, I highlight how the RCVD approach changes our interpretation of election outcomes via simulation, introducing situations where reliance on other methods leads to biased estimations. Section 4 features the main analysis. I show how the use of the RCVD method allows researchers to more easily distinguish problems with underlying data by comparing estimates of the 2016 and 2020 election outcomes based on ANES data versus estimates based on PEW data. I show a practical impact: how the use of RCVD combined with PEW data would have done a better job capturing shifting trends among Latino voters in anticipation of the 2024 presidential election. Section 5 concludes.

2 Historical Approaches and the RCVD Framework

Electoral outcomes are shaped not only by individual vote choices but also by the Composition of the electorate across demographic and identity groups. Ever since Downs (1957) argued for thinking about voting as an economic choice made by individuals, the focus of the discipline has been on individual-level voter behavior. Despite the justifiable nature of this focus, understanding how group-level dynamics shift over time is essential for explaining election outcomes. Individuals belong to specific groups and it is the Composition of the electorate across groups that ultimately determines who wins and loses (Axelrod, 1972). This is particularly relevant to the study of political science since in large elections, candidates must rely on appeals to broad groups rather than tailoring only to individuals. Historically, discussions of group effects were focused on turnout. Conventional wisdom held that conservatives suppress voter turnout amongst the poorest citizens (Piven and Cloward, 1989). To the extent to which that is true, the expectation was that increased turnout would drive more votes to the Democratic party (Lijphart, 1997). However, Citrin et al. (2003) argued that the impacts of changes in turnout could not be so easily identified since the gap between voters and non-voters preferences can change significantly from election to election. As the field turned toward the causal identification revolution, this debate was largely left to lie as research focused more on individual level drivers of voting behavior (Marble et al., 2024).

Contemporary academic discussion has taken new interest in the topic. Achen and Bartels (2016) argues that political science needs to rethink how we approach studying democracy, moving away from a focus on individuals and towards a focus on identity groups. Sides et al. (2019) argues that the Trump campaign of 2016 was successful because of changes in the coalitions of both the Republican and Democratic party driven by identity politics. Although recent evidence suggests that demographic sorting is not as strong a predictor of vote choice as one might believe (Kim and Zilinsky, 2024), in an era of increasing polarization, building electoral coalitions based on identity and group membership has become a key strategy for candidates seeking broad-based support (Lemi, 2021). While social media has increased the ability of candidates to engage in micro-targeting of their appeals (E. D. Hersh and Schaffner, 2013), there are limits to the extent to which campaigns can engage in micro-targeting since data availability can vary drastically from state to state (E. Hersh, 2015). However, even if candidates could achieve perfect targeting, electoral success relies on a candidate's ability to build coalitions of voters. This is particularly true as voter persuasion declines and turnout-based strategies gain importance (Hill, 2017).

Recent scholarship has increasingly recognized the importance of these Compositional effects in shaping election outcomes. A variety of approaches have been developed to disentangle how shifts within and across groups impact overall vote shares. Hill et al. (2021) uses a regression-based approach to attribute changes in vote share to either Composition or conversion, while Zingher (2019) focuses on estimating how changes in group size affect party support based on underlying group dynamics.The regression-based approach, though, applies a strict linear specification of the functional form of the equation. A misspecification of the functional form can introduce significant bias in the coefficients from the regression, even if the relationship is otherwise well-specified (Wooldridge, 2010). Additionally, as Engelhardt (2019) points out, distributional shifts across groups within the electorate and attitudinal shifts within groups can mask each other, making interpretations of coefficients from regressions difficult and obscuring the true drivers of electoral change.

There are also several analyses that rely on simple extrapolation to estimate the effect of shifting Compositions. B. L. Fraga, McElwee, et al. (2021) looks at how different Compositions and turnouts across racial groups harmed Clinton in the 2016 election by using 2012 turnout rates and estimating a new vote share. Carmines et al. (2016) argues that shifts between political coalitions and changes in turnout affect vote share. While these studies contribute to our understanding of Compositional effects, they fail to fully capture the dynamic interactions between group shifts and electoral outcomes.

The impact of these shifts is also considered a fundamental feature of election forecasting. While hitherto the realm of newsrooms and podcasts, increasing academic focus is being placed on the difficulties associated with election forecasting. Calvo et al. (2024) discuss how even perfect knowledge of demographic shifts are insufficient information to guarantee accurate forecasts. Similarly, Grimmer, Knox, et al. (2024) argue that evaluating election forecasting requires decades of observations. As the discipline grapples with evaluating and understanding election forecasting, accurately understanding the impacts of demographic shifts on election results takes on increased importance.

Building on this work, the most extensive attempt to propose a clear methodology to segment Compositional effects from Rate effects is provided by Marble et al. (2024). Composition here can be defined as the relative size of groups within the electorate, which contrasts with Rate, which is the percent of voters within a group who support a given candidate. They reject the linearity assumption imposed by earlier regression based approaches to the problem and adopt a non-linear approach. They argue that the difference in votes a group contributes to the election outcome can be captured by:

$$\begin{aligned}\text{Diff Net}_{t,t-1}(x) = &[\text{Vote Share}_t(x, \text{Republican}) - \text{Vote Share}_t(x, \text{Democrat})] \\ &\text{x Turnout}_t(x) \text{ x Group Size}_t(x) \\ &- [\text{Vote Share}_{t-1}(x, \text{Republican}) - \text{Vote Share}_{t-1}(x, \text{Democrat})] \\ &\text{x Turnout}_{t-1}(x) \text{ x Group Size}_{t-1}(x)\end{aligned} \tag{1}$$

Where $\text{Turnout}_t(x)$ x $\text{Group Size}_t(x)$ can be thought of as the Compositional component. This equation refers to the raw votes in the system, where x is the group of interest (such as racial groups) and t is time, but defined by elections rather than years[2] Using this equation, they calculate for each group a different turnout, group size and vote choice component to describe how each individual voting group contributed to the change in total vote share in the two elections for a party. To calculate the Compositional effect and the vote share effect separately, they then first hold Composition fixed from the 2012 election and calculate the impact of the shifted vote share from 2012 to 2016 and then hold vote share fixed at the 2012 election and shift Composition to the 2016 election. The joint sum of these totals is the implied effect of a group on the election outcome. Building on this work, B. Fraga et al. (2023) examine the shift within Latino voters, conducting an analysis of this subgroup, but applying a similar methodology. They find that demographic shifts within the Latino group is a driver for their increased support of Trump in 2020 compared to 2016.

However, this derivative-based approach (hereafter DBA) has two key drawbacks. First, it conflates Composition and Volume. Composition can be thought of as the proportion of the total electorate comprised by each group; i.e. 60 percent White, 40 percent non-White. Whereas Volume is the total size of the electorate. Importantly, the calculation in Marble et al. (2024) allows for changes in group size and Turnout Rate, but does not capture how group sizes do not change equally for all groups.

[2] i.e. the 2016 US presidential election might be defined as $t = 0$ and the 2020 US presidential election might be defined as $t = 1$.

This means that we cannot identify what component of the change is related to a simple increase in the size of the electorate that would have no effect on the share of votes a candidate receives – only the total – and what component of the change is a shift across groups that might have an impact on the outcome. By way of example, consider turnout in the 2008 presidential election. Turnout in that election was at a 40 year high (Woolley and Peters, 2021), but increased turnout was only a part of the story. In particular, turnout amongst Black voters rose by nearly 5%, whereas turnout amongst White voters declined by just over 1% (Lopez and Taylor, 2009). While the formulation from Marble et al. (2024) would show a positive effect from turnout for Black voters and a negative one for White voters, it would understate the importance of these effects because Black voters became a relatively more larger proportion of the electorate compared to 2008.

The second drawback of the DBA is that – having already calculated the effect of the shift in vote share within a group – by calculating their Composition effects using the previous elections Rate combining the two becomes difficult. The crux of the issue is that the sum of the two first derivatives will either overstate the impact of the shifts (if the state-space is concave) or understate the impact of the shifts (if the state-space is convex). This is because the correct calculation of the impact of both Rate and Composition requires also adding the cross-partial second derivative. To show this, consider equation 1 for a single group. We can therefore state the variables as a function only of time t and not of group x. For clarity, I will use $r(t)$ to mean [Vote Share$(t, \text{Republican})$ − Vote Share$(t, \text{Democrat})$], ¸(t) to mean Turnout$(t)x$Group Size(t). Finally, define Diff Net$(t, t-1)$ as $\Delta z(t)$ Then we can restate equation 1 as:

$$\Delta z(t) = r(t)c(t) \tag{2}$$

Which is similar to equation 5 in Marble et al. (2024)[3]. Now consider that $\Delta z(t) =$

[3] $C_t(x) = \text{Vote Share}_t(x, C)x\text{Share Voters}_t(x)x\text{Overall Turnout}_t$

$z(t_2) - z(t_1)$. Then we can solve for the role of the change in Rate, $r(t)$, and Composition, $c(t)$ as follows[4]:

$$\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
&= r(t_2)c(t_2) - r(t_1)c(t_1) = [r(t_2) - r(t_1)]c(t_1) + r(t_1)[c(t_2) - c(t_1)] + [r(t_2) - r(t_1)][c(t_2) - c(t_1)]
\end{aligned} \tag{3}$$

Therefore, without accounting for the cross-partial derivative, the resulting combination of the two first derivatives will misrepresent the impact of the shifts[5], understating their impact when the shifts move in the same direction and overstating their impact when they move in opposite directions. Of course, one might argue that therefore the correct approach is to not sum the pieces, but the question of attribution remains. This becomes even more complicated when the equation uses three variables, as in Marble et al. (2024). The correct equation becomes the sum of the first, second, and third cross-partial derivatives. Suppose the third variable is $v(t)$, then the correct specification is:

$$\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
&= r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) \\
&= [r(t_2) - r(t_1)]c(t_1)v(t_1) + r(t_1)[c(t_2) - c(t_1)]v(t_1) + r(t_1)c(t_1)[v(t_2) - v(t_1)] \\
&+ [r(t_2) - r(t_1)][c(t_2) - c(t_1)]v(t_1) + [r(t_2) - r(t_1)]c(t_1)[v(t_2) - v(t_1)] + r(t_1)[c(t_2) - c(t_1)][v(t_2) - v(t_1)] \\
&+ [r(t_2) - r(t_1)][c(t_2) - c(t_1)][v(t_2) - v(t_1)]
\end{aligned} \tag{4}$$

As can be seen, accurately capturing the shifts requires including multiple cross-partial derivatives and tracing through the expected disconnect generated by failing to account for these shifts becomes a significant challenge. By utilizing this approach, one is making the assumption that the cross-partial derivative terms are trivial or zero. In section 4, I will show that this is oftentimes not the case by examining recent U.S. presidential elections. In practice, other work has not directly calculated the impact

[4]Proof in Appendix

[5]Except in the trivial case where the cross-partial derivative is zero

of Volume, generating an unspoken assumption that any remaining votes that are left unaccounted for must be driven by changes in Volume.

As a result, methods that rely on only the simple specification of the component parts do not take into account the simultaneous nature of the problem, which will ultimately result in a misstatement of the total effects of the shifts in Rate and Composition. By assumption, these approaches are drawing a hyper-plane through the space, when the underlying dynamics are better described as a smooth gradient. This generates an error because the specification without the cross-partial derivatives is, in essence, a First-Order Taylor approximation of the underlying function. If the underlying function is linear, or the cross-partial derivatives are trivial, then this specification will be a relatively accurate description of the change between two points. However, as the cross-partial derivatives grow larger, this approximation becomes worse (Reed, 1998). The intuition in 2-dimensional space is shown in Figure 1.

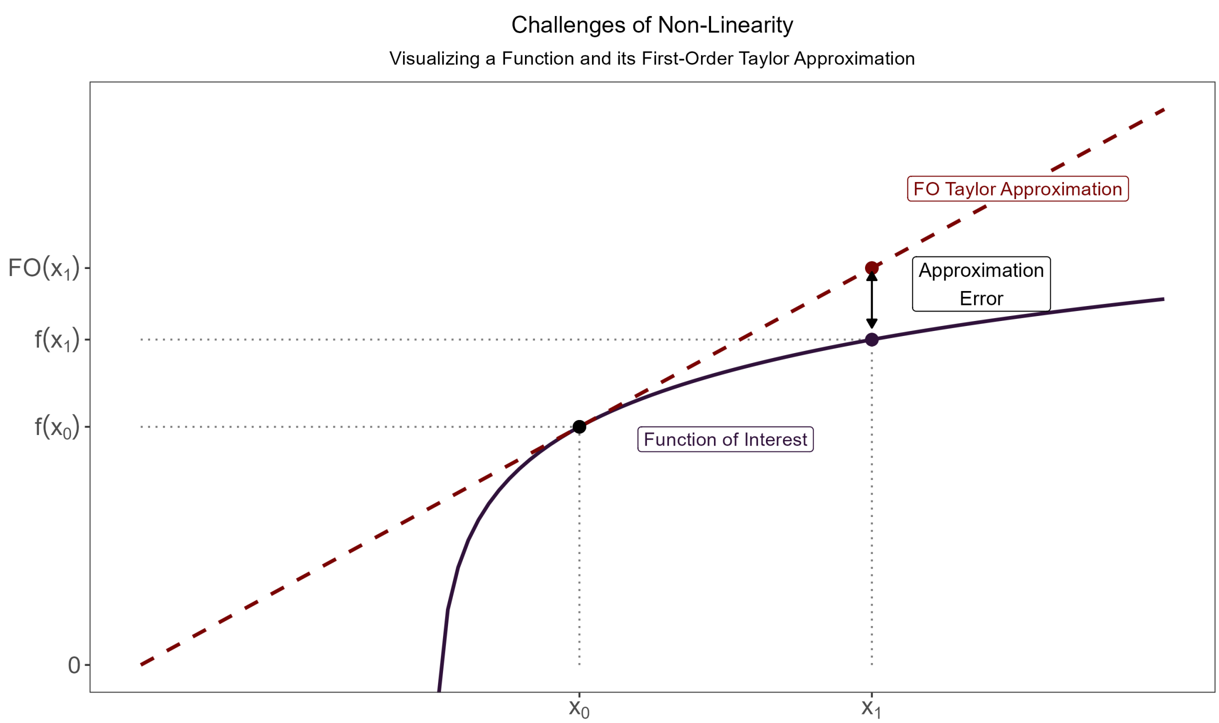

Figure 1: This figure shows that even in a simple 2-dimensional space, first order Taylor approximations can take on significant error sizes as the complexity of the function of interest grows. This figure is based on Figure 4.3.1 in Reed (1998).

I propose an alternative specification of the method for calculating the difference between vote shares that instead treats the problem as sequential. The underlying intuition of why the problem can be described as sequential in nature is more fully developed later but intuitively, by calculating the effects of Composition using prior Rates, the DBA misses that the Rate a group votes for a candidate can be changed fundamentally by who is turning out to vote. The impact of Composition can only be measured by who comprises the new voter pool, not the individuals who composed the prior voting pool. This is particularly important if Citrin et al. (2003) were correct that the difference between non-voters and voters in a given election can be very different than it is in other elections. As the most important takeaway, the bias of the DBA estimate can be both substantial and even yield the wrong sign of the impact of Composition when a candidate goes from winning (losing) a group to losing (winning) that group.

I argue that the specification proposed in Equation 5 in Marble et al. (2024) serves as the best starting point for understanding shifts in the electorate. In order to clearly identify the components of shifts in the electorate though, I will redefine the terms. I begin by defining $z(t)$ as the total number of votes a group gives to a party of a candidate, where t is still defined as an election. I am interested in describing how that group's contribution to the candidate's vote total compares to their contribution in the prior period and I want to show how that contribution is broken into Rate, Composition and Volume. Given that those are the three bins I would like to explain, then $z(t)$ must be defined as a function of those three bins:

$$z(t) = r(t)c(t)v(t) \tag{5}$$

Where $r(t)$ is the Rate at which a group votes for the candidate, $c(t)$ is the proportion of the electorate that the group comprises and $v(t)$ is the total number of voters in the election. This specification differs from the one used in equation 3 in Marble et al.

(2024) and B. L. Fraga, Velez, et al. (2024) in that emphasis is placed on total Volume. This is done for three reasons. First, total votes can, in and of itself, prove meaningful in analysis of election results. Second, total votes provides the only meaningful metric by which we can gauge the plausibility of any analysis. That is to say, since we rely on estimates of group Compositions and vote choice, the only firm vote total against which we can compare our estimates of the group dynamics in an election is the final reported vote tally. I will show the importance of this in section 4. Third, as discussed in Marble et al. (2024), using this specification allows researchers to quickly apply the results of exit polls against vote tallies to understand the shifts in elections almost immediately after their conclusion. Given that this equation is a composite function, we can apply the derivative multiplication rule to find the derivative:

$$z'(t) = r'(t)c(t)v(t) + r(t)c'(t)v(t) + r(t)c(t)v'(t) \tag{6}$$

And indeed this derivative suggests using a formula essentially identical to the one utilized by Marble et al. (2024), whereby the first part of the expression is the impact of the change in Rate, the second part the impact of the change in Composition, and the third part the impact of the change in Volume. However, as shown above, this formula is misleading. As defined, $z(t)$ is a fundamentally non-linear equation in a four dimensional state-space. Therefore, the slope is not constant, and, as a result, adequately describing the changes requires the use of cross-partial derivatives. Instead, to calculate the impact of Rate, Composition, and Volume separately, I propose employing a sequential gradient ascent method to explore the state-space:

$$\begin{aligned} \Delta z(t) =& [r(t_2) - r(t_1)]c(t_1)v(t_1) \\ &+ r(t_2)[c(t_2) - c(t_1)]v(t_1) \\ &+ r(t_2)c(t_2)[v(t_2) - v(t_1)] \end{aligned} \tag{7}$$

While initially counter intuitive, the proof that this is equal to $z(t_2) - z(t_1)$ is presented in the Appendix. I call this the Rate, Composition, and Volume Decomposition (RCVD).

There are two noteworthy constraints to this approach. First, turnout, a fundamentally important feature of election results, affects both $c(t)$ and $v(t)$, as does population growth. To see this for $c(t)$, consider that the percentage of the total voters that a group comprises is a function of both the proportion of the population comprised of the group and the turnout Rate of that group as in equation 1. For $v(t)$, a similar challenge exists- an increase in the total number of potential voters in a group (population size) and the total number of realized voters (turnout) both affect the final total size of the voting population.

While a decomposition of the formula into the component parts of turnout and population change is achievable, I argue it is not necessary for the purposes of this paper for two main reasons. First, across the simple case of two time periods only four years apart, underlying changes in the racial Composition of the potential electorate are unlikely to be meaningful, at least compared to the impact of turnout. Second, turnout changes are only interesting insofar as they are differential. If all groups increase turnout at the same Rate (thus preserving the relative group sizes), then there are no Compositional effects. With this specification, any changes that are universal (overall population growth, increased turnout across all groups) are captured in Volume, while any changes that are differential are captured in Composition.

A second crucial caveat is that this sequence is not unique. The gradient ascent can be calculated by moving any order-combination of Rate, Composition, and Volume. Unless the state-space is defined by a regular cuboid, a shift in the sequencing of the calculation will by necessity change the interpretation of the estimated coefficients. In order to address this, In the next section I highlight how changing the sequencing can have an effect on the interpretation of a simulated election result. There are two key arguments for why this proposed ordering is the most justifiable. First, by moving Rate first, the Rate calculation exactly matches all previous work that has been done on the impact of shifts in Rates- which is to say, calculating the impact of shifts in Rates on the first period's Composition and Volume. Second, by moving Volume third, the impact of Composition is also calculated on the first period's Volumes. This ensures that the final calculation, Volume, reflects only a perfectly proportional shift from the previous period. In essence, this order rearranges all of the components of the calculation according to the levels observed in the first period, and only after rearranging those components, does Volume move last, leaving it as a simple stretching or shrinking of the newly specified outcome. This approach causes the shift in Volume to behave as an eigenvalue, scaling the result, but preserving the underlying relationships.

3 Proof of Concept: Validation through Controlled Simulation

This section moves from theoretical critique to methodological proof. I introduce a set of controlled electoral simulations designed to demonstrate the inherent non-zero error of the DBA and establish the necessity of the RCVD framework. The previous section, Historical Approaches and the RCVD Framework, formally introduced the mathematical structure of RCVD; here, I rigorously apply it. I first quantify the DBA's error in a basic two-group model, demonstrating the magnitude of the Residual term. I then rigorously prove that this misspecification is not caused by the omission of the Volume component, but by the DBA's failure to correctly model the non-linear interaction between Rate and Composition. Finally, I justify the fixed RCVD calculation order based on the preservation of theoretical interpretability.

Two-Group Simulation: Quantifying the Residual

This section presents a basic, two-group simulation designed to isolate and quantify the methodological failure of the existing decomposition literature, thereby establishing the necessity of the RCVD approach. I analyze the total vote change for the Democratic candidate between the 2016 (Clinton) and 2020 (Biden) U.S. presidential elections, utilizing a simplified data structure that collapses racial groups into White and non-White voters. Table 1 provides the baseline data, derived from the framework introduced by Marble et al. (2024) but simplified for this illustration.[6] While survey data has noteworthy biases, for the moment I am assuming away any concerns with the underlying data itself.

Table 1 shows the magnitude of the change we must decompose: a total shift of 9 million votes for the Democratic candidate (Clinton's +8 million margin to Biden's +17 million margin)[7]. This shift is characterized by changes in all three fundamental parameters. With respect to Rate, there was a 7.5% decline in margin within the non-White bloc, countered by a 6.6% improvement in margin within the White bloc. In terms of Composition, there was a 3.6% shift of the electorate towards non-White voters. Finally, there was a large increase in Volume of 26 million additional total votes cast.

Table 1: Comparing Two Elections - Basic Data

Election	**Group**	**Candidate 1**	**Candidate 2**	**Total**	**Margin**	**Margin Rate (%)**	**Composition (%)**
1st Election (2016)	Non-White	29.5	7.5	37.0	22.0	59.5	28.7
	White	39.0	53.0	92.0	−14.0	−15.2	71.3
	Total	68.5	60.5	129.0	8.0	6.2	100.0
2nd Election (2020)	Non-White	38.0	12.0	50.0	26.0	52.0	32.3
	White	48.0	57.0	105.0	−9.0	−8.6	67.7
	Total	86.0	69.0	155.0	17.0	11.0	100.0
Comparing the Two Elections	Non-White	8.5	4.5	13.0	4.0	−7.5	3.6
	White	9.0	4.0	13.0	5.0	6.6	−3.6
	Total	17.5	8.5	26.0	9.0	4.8	0.0

Note: Votes are reported in millions. Candidate 1 refers to Clinton (2016) and Biden (2020); Candidate 2 refers to Trump.

Figure 2 demonstrates how the prevailing method for decomposition fails to fully account for the total 9 million vote change due to its sequential, derivative-based calculation. The core methodological flaw is its inability to account for the multiplicative interactions among the Rate, Composition, and Volume parameters.

As shown in Figure 2, when the DBA is applied to this two-group system, it generates a Mean Absolute Error (MAE) of just over 1.4 million votes. This unallocated

[6] The Democratic party is consistently set as the reference group across all analyses. Positive numbers indicate increased support/votes for Democrats; negative numbers indicate decreased support. No political endorsement should be inferred from this mathematical designation.

[7] I have replicated the process used by Marble et al. (2024) in creating this data. The difference in their reported votes from reality seems to be related to their estimation of voter support for candidates based on the ANES.

portion is the residual term. The traditional method is not a zero-loss approach; the 1.4 million vote residual represents real votes that contributed to the 2020 outcome but are mathematically unassigned to a specific, theoretically meaningful component (Rate, Composition, or Volume).

Figure 2: This figure shows that even in a simple case with only two voter groups, the traditional calculation can yield misattributed votes on an order of magnitude of over one million votes. The underlying numbers reflected in this figure are in Appendix A.

The consequence of this non-zero residual is interpretive confounding. Since previous decomposition studies have left the Volume term unspecified, they have, in essence, folded the residual into an error term that also contained the correctly calculated Volume effect. In doing so, the DBA systematically misattributes the interaction effects, resulting in two key distortions. First: understated Compositional effects. As demonstrated in Figure 3, the benefit Biden received from the change in the racial Composition of the electorate is understated by 650,000 votes using the DBA. Second: misallocated Volume. A large portion of the 1.4 million Residual is incorrectly assigned, masking the true, clean contribution of the Volume effect.

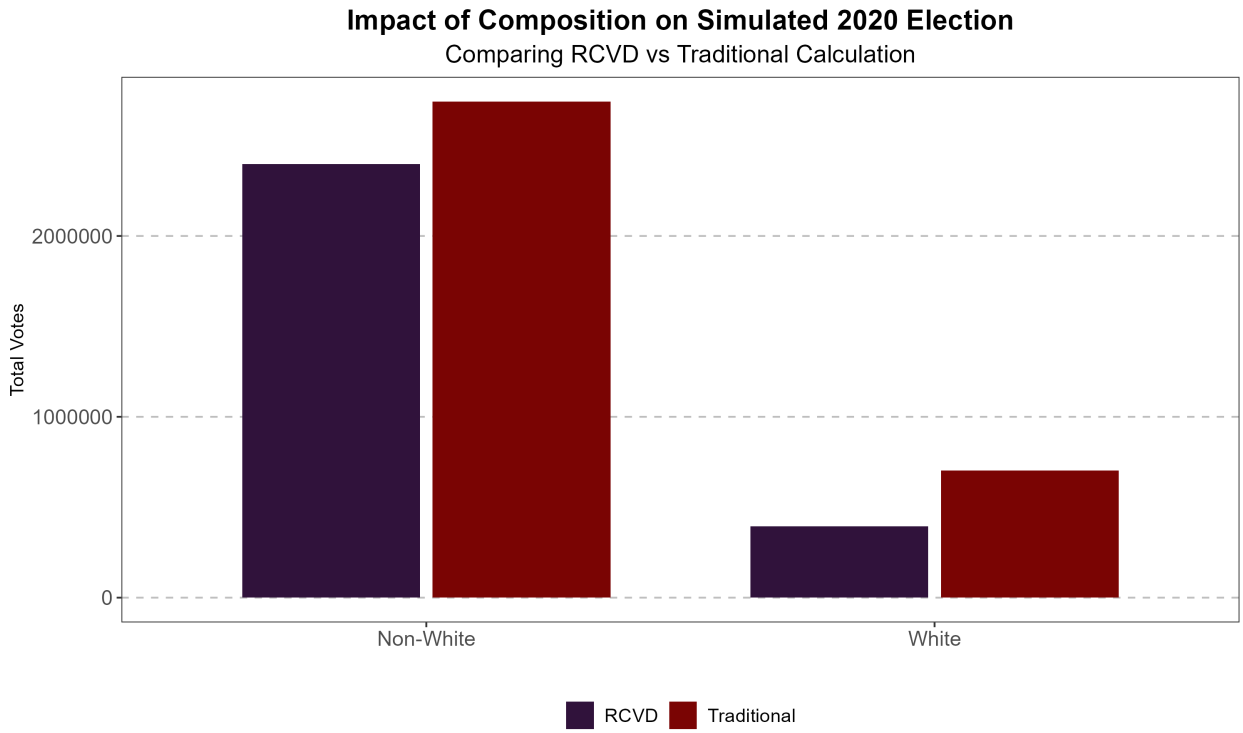

Figure 3: This figure shows that even in a simple case with only two voter groups, the traditional calculation can misattribute the impact of shifts in Composition on an order of magnitude of hundreds of thousands of votes. The underlying numbers reflected in this figure are in Appendix A.

Crucially, the RCVD approach is shown to leave a MAE of 0, precisely accounting for every vote in the system. Furthermore, the RCVD approach retains the highly intuitive property of explaining Rate in a manner identical to the DBA, meaning that the large body of existing work focused solely on Rate changes remains valid, while the problematic Composition and Volume terms are corrected. This robust, zero-loss property is maintained even when the data is partitioned into further subgroups.[8]. In future work, I intend to examine the robustness of the RCVD approach to subpartions of the data.

[8]See Appendix for the robustness of the method to partitions

The Problem is Not Volume: Isolating Rate-Composition Misspecification

In the preceding analysis, the DBA produced a significant Residual, partially driven by unassigned interaction effects and partially by the unmodeled Volume term. The traditional literature often assumes this error is synonymous with unexplainable variance or Volume. In this section, I directly challenge that assumption by demonstrating that the DBA's fundamental flaw lies in its handling of the Rate and Composition interaction, even when Volume is perfectly controlled.

To achieve this isolation, I analyze a hypothetical, zero-sum vote shift that transforms the actual 2020 Biden popular vote victory into a narrow Trump victory. I ensure this shift is achieved by manipulating only the Rate (group vote loyalty) and Composition (group size) parameters, while holding the total Volume of votes constant. Since changes in Volume can be modeled as a linear transformation (an eigenvalue applied to the data that perfectly preserves underlying relationships), controlling Volume to zero ensures that any resulting error must be driven exclusively by the misspecification of the Rate and Composition interaction.

Table 2 presents this hypothetical scenario, utilizing a five-group breakdown of the electorate based on data from Marble et al. (2024). I achieve the synthetic shift by multiplying the Rate of support for the Democratic candidate by a factor of .93 and shifting the Composition of all non-White groups by a factor of .8. The final line of the 'Total' column confirms the successful manipulation: the net change in total votes across the two scenarios is exactly 0.00 million votes. Therefore, in this controlled, synthetic example, the only two theoretical buckets for explaining the resulting ≈ 17.75 million vote margin shift are Rate within groups and Composition between them.

Figure 4 highlights the critical methodological result. Despite the total change in votes being zero, the DBA still produces a massive Mean Absolute Error (MAE) of 1.7 million votes. This unallocated error is caused entirely by the DBA's inability to correctly model the non-linear interaction between Rate and Composition. By com-

Table 2: Hypothetical Data, Both Rate and Composition

Election	Group	Candidate 1	Candidate 2	Total	Gross Margin	Trad Mar (%)	Trad Comp (%)
1st Election (2020)	Black	15.42	1.47	16.89	13.95	82.60	10.89
	Hispanic	13.21	4.47	17.68	8.73	49.40	11.41
	Other	8.64	5.16	13.80	3.48	25.20	8.90
	White	47.95	57.21	105.16	−9.25	−8.80	67.84
	NA	0.80	0.67	1.47	0.13	8.60	0.95
	Total	86.02	68.98	155.00	17.03	10.99	100.00
2nd Election (2020)	Black	11.47	2.04	13.51	9.43	69.82	8.72
	Hispanic	9.83	4.32	14.14	5.51	38.94	9.12
	Other	6.43	4.61	11.04	1.81	16.44	7.12
	White	48.82	66.30	115.13	−17.48	−15.18	74.28
	NA	0.60	0.58	1.18	0.01	1.00	0.76
	Total	77.14	77.86	155.00	−0.71	−0.46	100.00
Comparing the Two Elections	Black	−3.95	0.57	−3.38	−4.52	−12.78	−2.18
	Hispanic	−3.38	−0.16	−3.54	−3.23	−10.46	−2.28
	Other	−2.21	−0.55	−2.76	−1.66	−8.76	−1.78
	White	0.87	9.10	9.97	−8.23	−6.38	6.43
	NA	−0.20	−0.09	−0.29	−0.11	−7.60	−0.19
	Total	−8.87	8.87	0.00	−17.75	−11.45	0.00

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.

parison, the RCVD framework correctly accounts for all votes in the system, yielding an MAE of 0.

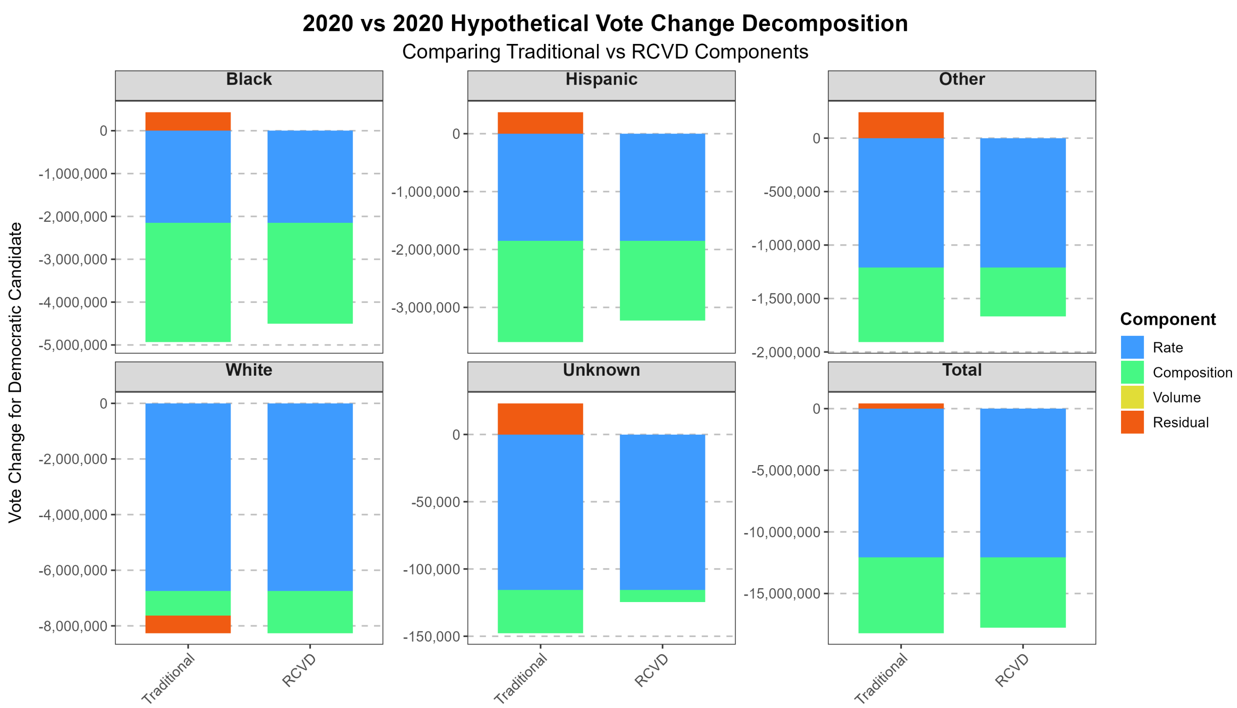

Figure 4: This figure shows that even when Volume is not a factor in evaluating the shifts in an election, the DBA creates significant errors in attribution of vote changes. Here, the total absolute error is 1.7 million votes. The underlying numbers reflected in this figure are in Appendix A.

This finding is definitive: The 1.7 million vote error is not due to the omission of

Volume, but is a direct consequence of the DBA's formula. By comparing the DBA and RCVD, it is clear that all 1.7 million unidentified votes come from a misspecification of the impact of Composition and Rate, distributed across the groups in increments of hundreds of thousands of votes.

In summary, this scenario definitively refutes the implicit assumption that the DBA's unexplained variance is merely Volume or general error. It validates the necessity of the zero-loss RCVD framework by demonstrating that even in a highly controlled environment where Volume is eliminated as a potential explanatory variable, the DBA fundamentally fails to correctly partition the vote change between Rate and Composition.

Non-Uniqueness and the Fixed RCVD Path

As noted in the conclusion of Section 2, the non-linear nature of the Rate, Composition, and Volume Decomposition (RCVD) means that the order of calculation is not unique. Mathematically, there are six possible permutations of the Rate (ΔR), Composition (ΔC), and Volume (ΔV) terms that satisfy the zero-loss property of the RCVD framework. This path-dependence is a necessary artifact of correctly modeling the interaction effects that the DBA previously relegated to the unassigned Residual. Therefore, there needs to be a strong theoretical justification for the chosen order ($\Delta R \rightarrow \Delta C \rightarrow \Delta V$).

Figure 5 illustrates an alternative zero-loss order (Composition $\rightarrow$ Rate $\rightarrow$ Volume) when applied to the simple 2016-2020 simulation. While the total MAE remains 0, the calculated contribution of Rate and Composition shifts: the alternative order assigns a slightly larger role to Composition and a slightly smaller role to Rate.

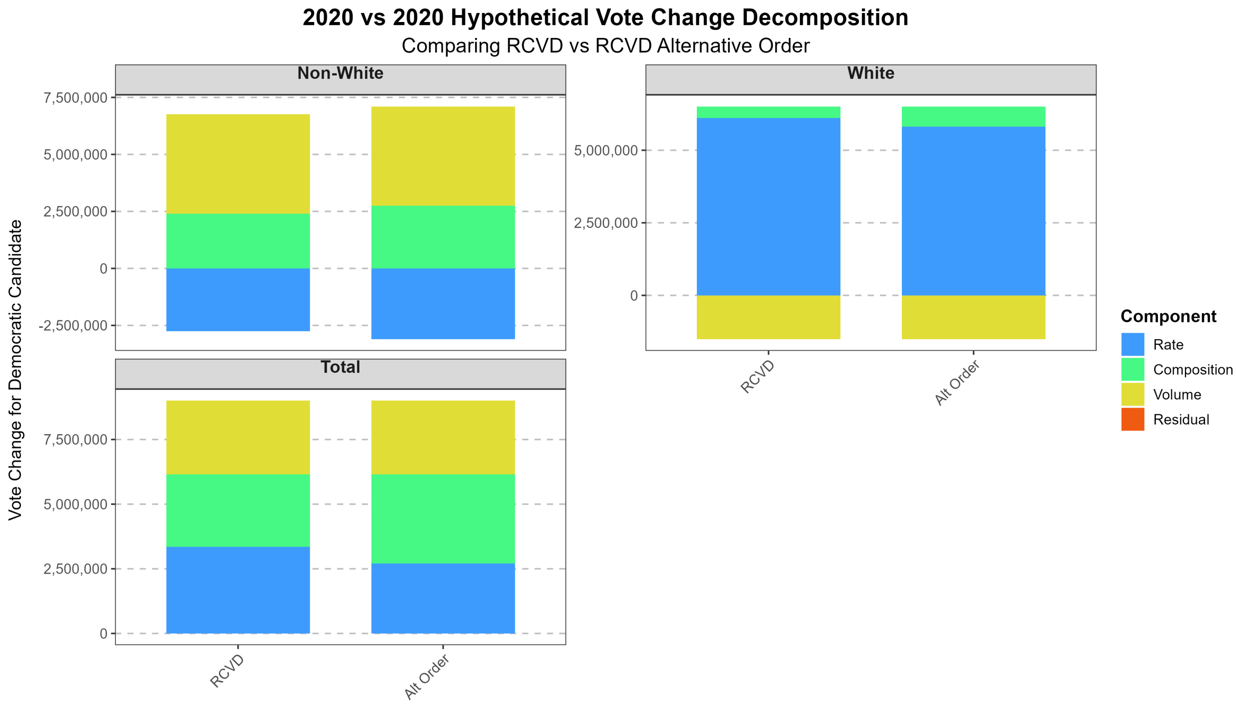

Figure 5: This figure shows that shifting the order in which RCVD is calculated yields no error term, but can shift the interpretation of the impacts of both Rate and Composition.

Despite the relative closeness of these results in the simple case, I adhere to the $\Delta R \rightarrow \Delta C \rightarrow \Delta V$ order for two core reasons related to the underlying political theory. First, this order preserves Rate's causal primacy. The convention in electoral studies has always been to calculate the change in group loyalty (Rate) based on the prior period's data. Maintaining this sequence ensures that the ΔR term represents the clean, unadulterated shift in group preference, free from the simultaneous influence of demographic change. This allows our ΔR term to retain the exact same highly intuitive value calculated by the DBA, validating the existing literature while correcting the other terms.

Second, this order maintains Volume as an eigenvalue. By sequencing Volume last, we ensure it serves as an eigenvalue—a perfect proportional shift that occurs after all components affecting the margin have been calculated. Intuitively, shifting Composition first (e.g., more non-White voters) will ultimately change the final national aggregate Rate, even if the Rates within each group do not change. By placing ΔC before ΔV, we ensure that Volume is purely an increase or decrease in the system's size, distributed proportionally across the new electoral configuration set by Rate and Composition. This preserves the most theoretically clean interpretation of Volume.

In sum, the $\Delta R \to \Delta C \to \Delta V$ ordering is not arbitrary, but a deliberate choice that preserves the most theoretically clean and consistent interpretation of Rate against existing literature, while ensuring Composition and Volume are correctly specified.

4 Real-World Application: ANES, PEW, and the 2024 Hispanic Vote

The preceding section established the theoretical and empirical utility of the Rate, Composition, and Volume Decomposition (RCVD) framework, demonstrating that the DBA significantly obscure the mechanisms driving electoral change. If the RCVD framework is a superior methodological lens, it must offer substantive payoffs by resolving current empirical puzzles and fundamentally reinterpreting established electoral dynamics. This section delivers precisely that by applying the RCVD decomposition across three critical comparisons, leveraging the superior demographic granularity of PEW Research Center data where appropriate.

Our analysis proceeds in three stages. First, I provide a definitive substantive argument for the RCVD method, showing that it yields a fundamentally different interpretation of the American electorate in the 2020 election compared to standard methodological practices that leave Composition effects obscured. Second, I tackle the persistent puzzle of non-White electoral volatility—particularly among Hispanic voters—by comparing the explanatory power of the gold-standard American National Election Studies (ANES) data against an alternative from PEW, demonstrating the superior descriptive accuracy of the latter in capturing real electoral shifts. This lends credence to analysis from B. L. Fraga, Velez, et al. (2024) that emphasizes the persistence of electoral shifts amongst Hispanic voters. Finally, I leverage the full strength of the RCVD framework to analyze the recent volatility in presidential politics, offering a high-resolution view of the 2020 versus 2016, 2024 versus 2020, and 2024 versus 2016 electoral dynamics. This triadic comparative structure permits isolation of the specific shifts in voter support (Rate), group turnout/population dynamics (Composition) and overall votes (Volume) which have shaped the past decade of American elections, culminating in a critical assessment of how the shifting racial and ethnic Composition of the electorate now affects the partisan balance of power.

The 2020 Baseline: Compositional Effects in the ANES

The substantive utility of the Rate, Composition, and Volume Decomposition (RCVD) framework rests on its capacity to offer diagnostic clarity where conventional metrics produce interpretive confounding or unnecessary errors. Political analysis of the 2020 presidential election, often relying on changes in two-party vote share within key demographic groups, remains subject to this issue. A change in a group's aggregate vote margin may be due to a true shift in partisan preference (Rate), a change in that group's share of the total electorate (Composition), or overall population growth/turnout changes (Volume). Standard decomposition methods generally fail to separate Rate and Composition effects cleanly, thus hindering causal inference about the drivers of electoral victory or loss.

I begin my empirical application by using data from the 2020 American National Election Studies (ANES), which, despite its limitations in accurately describing election outcomes in the time-period of interest (addressed later in Section 4), represents the discipline's historical "gold standard." Applying the RCVD framework to the ANES data for the 2020 election reveals a concerning divergence from conventional readings.

A traditional aggregate analysis might conclude that the Democratic victory was driven by a modest shift in Rate among non-White voters combined with significant Compositional advantages (greater non-White share of the electorate). However, the RCVD decomposition offers a far more nuanced picture. By correctly partitioning the total vote shift, I find that Compositional effects are significantly less beneficial to Democrats than traditional analyses would lead researchers to believe. Figure 6 shows how the DBA overstates the positive impact of Compositional shifts for Democrats by roughly 365,000 votes.

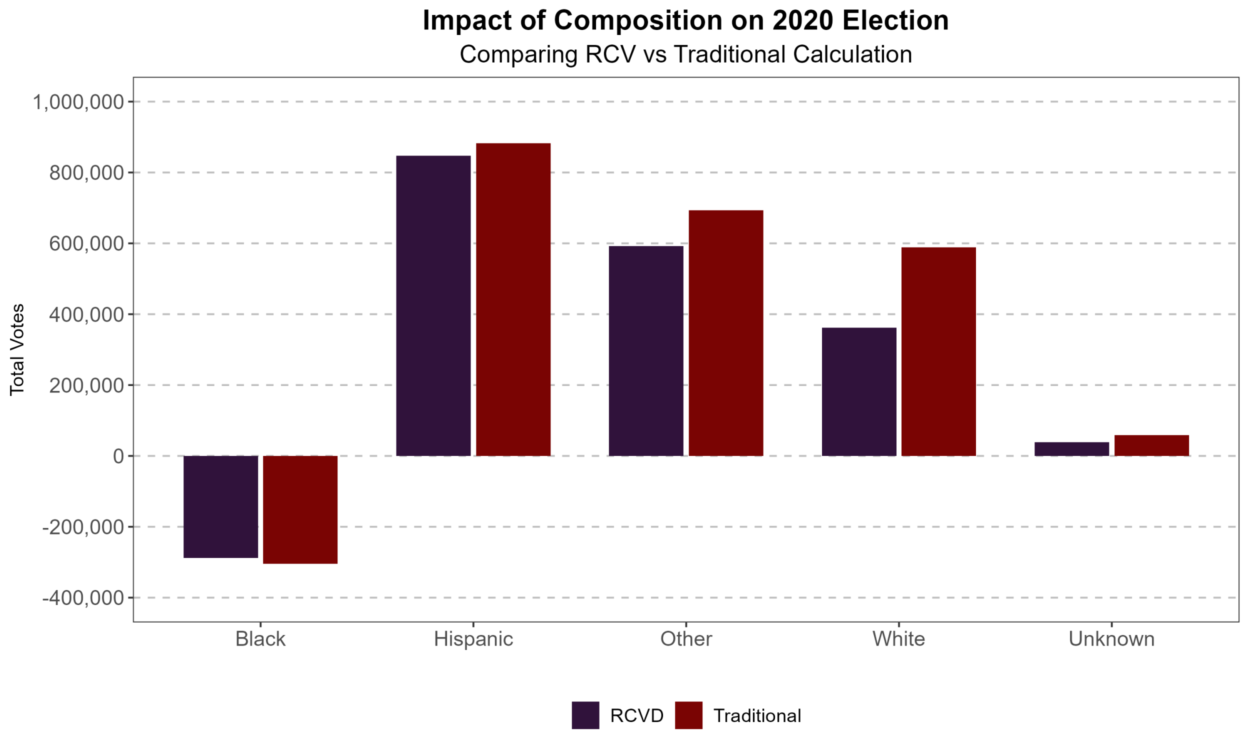

Figure 6: This figure shows how shifting from the traditional calculation to the RCVD calculation changes the evaluation of the impact of Composition on the 2020 election. In particular, the traditional calculation overemphasizes the benefits of Composition towards Democrats by several hundred thousand votes.

Critically, the RCVD framework provides a zero-loss allocation, ensuring that the sum of the Rate, Composition, and Volume components precisely equals the observed overall change in the national vote margin. This contrasts with traditional methods that often leave unexplained residual terms or produce component estimates that do not cleanly reconcile with the final outcome, thus hindering the robustness of counterfactual claims (e.g., "What if mobilization had been higher?"). Figure 7 shows that in the instance of White voters, the overall error associated with the DBA to the analysis is actually greater than the total impact of Composition on the final outcome. Indeed, the total error across all groups is roughly 700,000 votes versus a total Compositional impact (from RCVD) of roughly 1.5 million votes.

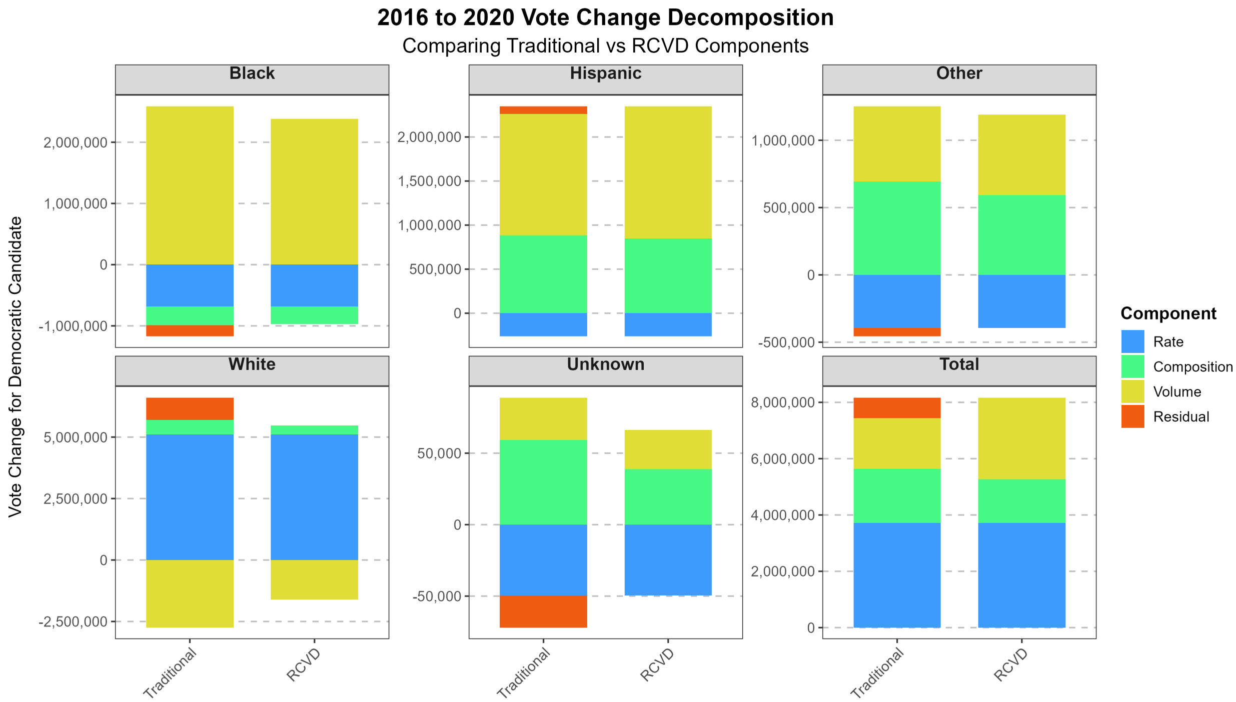

Figure 7: This figure shows how shifting to RCVD shifts interpretations of the 2020 election results when compared to 2016. It highlights that the magnitude of the error associated with the DBA is oftentimes several hundred thousand votes, and in the case of White voters, actually exceeds the total impact of Composition.

In sum, the application of RCVD to the 2020 ANES data serves as a crucial proof of concept. It demonstrates that the interpretive lens of the discipline has risked substantial bias in understanding the dynamic impact of Composition (mobilization and demographic change). This finding provides the foundation for my subsequent substantive analysis, where I argue that within the context of the three most recent elections PEW data has greater accuracy in describing the outcomes. I use this data to refine the empirical claims of this article, particularly concerning the increasingly salient Hispanic electorate.

Survey Divergence: Comparing ANES and PEW

The robustness of any electoral decomposition hinges entirely on the descriptive accuracy of the underlying survey data. While the ANES remains the discipline's preferred benchmark, its ability to capture the fine-grained heterogeneity and rapidly evolving preferences of certain demographic groups, particularly the Hispanic electorate, has been subject to increasing scrutiny (B. L. Fraga, 2016). Low response rates and difficulties in adequate sampling often result in limited statistical power for subgroup analysis.

To address this, we turn to the PEW Research Center's validated voter data (Hartig et al., 2023), which employs a different sampling strategy and potentially achieves superior resolution for non-White sub-populations. This comparison is critical for correcting potentially misleading inferences derived from the ANES data in Section 4.1. I apply the RCVD framework to both the ANES and the Pew data for the 2020 election, focusing specifically on the decomposition of the Hispanic vote shift.

Figure 8 shows the total residuals of the implied election results from the two datasets compared to the actual election outcomes. The lower graph highlights that ANES overstates Democratic support by nearly 4 million votes. In comparison, PEW understates Democratic support by just under 600,000 votes (Wooley and Peters, 2025). While this error term is still substantial, it suggests that PEW paints a much more accurate picture of the electorate than does ANES for these elections. The comparative application of RCVD, visually summarized in the higher graph in Figure 8, yields two profound differences in interpretation with respect to Hispanic voters. First, the ANES data, while showing a modest Republican gain among Hispanic voters in Rate, largely showed an overall Democratic increase in support from this group driven by shifts in Composition– potentially a more persistent, demographic-driven effect. In contrast, the PEW data, when decomposed by RCVD, isolates a significantly larger and statistically more consequential Rate effect (i.e., true partisan preference change) driving net effect of Hispanic voters and shows that Composition is playing a largely inconsequential role. This suggests that ANES may systemically underestimate the degree of preference volatility among the Hispanic electorate, inaccurately muffling a strong, underlying signal of Republican persuasion in support of the argument made in B. L. Fraga, Velez, et al. (2024).

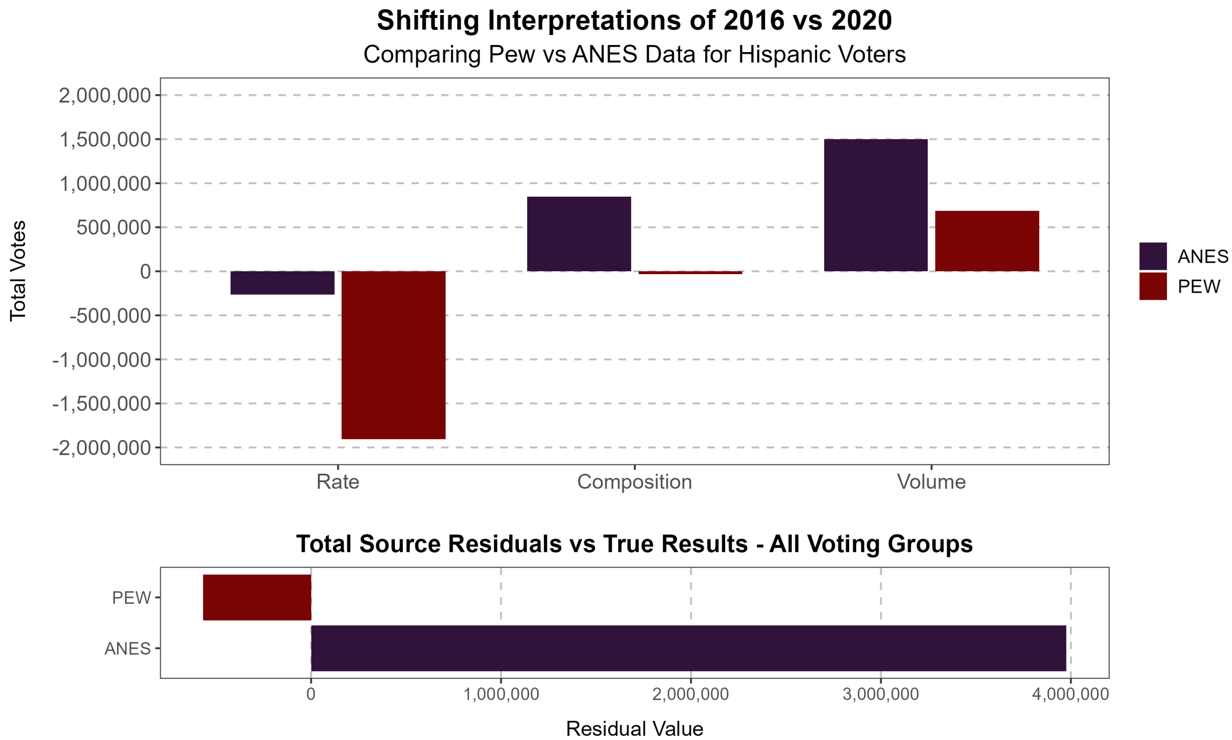

Figure 8: This figure compares the implied election results from ANES data versus PEW data. The upper portion of the figure shows that utilizing PEW data fundamentally alters the interpretation of the impact of Hispanic voters on the 2020 election. In particular, it shows that there is no evidence that Democrats benefited from a shift into Hispanic voters in 2020 and instead suffered a significant Rate decline. The lower portion of the figure shows that the implied error in votes of using ANES data to evaluate the 2020 election is nearly 4 million votes, whereas using the PEW data has an error of less than 600,000.

This has substantial interpretation effects that are not merely statistical, but speak to potentially deep strategic issues amongst Democratic party officials. If, as ANES data suggests, the change is mostly Compositional, the challenge for the Democratic party is primarily organizational (mobilization). If, however, the Pew data and RCVD decomposition are correct in highlighting a larger Rate effect, the challenge is fundamentally one of ideological and issue-based persuasion. This provides evidence to refute a notion expressed in Klein (2024a) that Democrats need not worry about bleeding voters at the edges because they will be saved by demographic changes. This implies a deeper vulnerability to Republican outreach and a greater susceptibility to electoral swings than previously modeled.

In essence, Figure 8 serves as a methodological caution: when conducting any analysis, it is crucial to compare the implications of the data towards measurable real-world outcomes. Rather than a whole hearted endorsement of PEW over ANES, this suggests that researchers should carefully consider whether the data they are building off of reflects a good approximation of reality, as argued in Grimmer, Marble, et al. (2022). In this particular instance, by embracing the superior descriptive validity of the Pew dataset for this key population, the RCVD framework establishes that the volatility of the Hispanic electorate is driven less by passive demographic turnover and more by active, consequential shifts in partisan loyalty. This rectified understanding of the 2020 baseline is essential for analyzing the dramatic shifts observed in the subsequent 2024 election, which I detail next.

The Full Picture: Decomposition Across Three Electoral Cycles

To move beyond the baseline interpretation of the 2020 election established in the preceding sections, I now leverage the RCVD framework to analyze the decade-spanning trajectory of vote change across three critical electoral cycles: 2016–2020, 2020–2024, and the full 2016–2024 interval. This dynamic analysis demonstrates how the compounding effects of Rate and Composition ultimately determined the 2024 electoral outcome.

The 2016 to 2020 Cycle– Figure 9

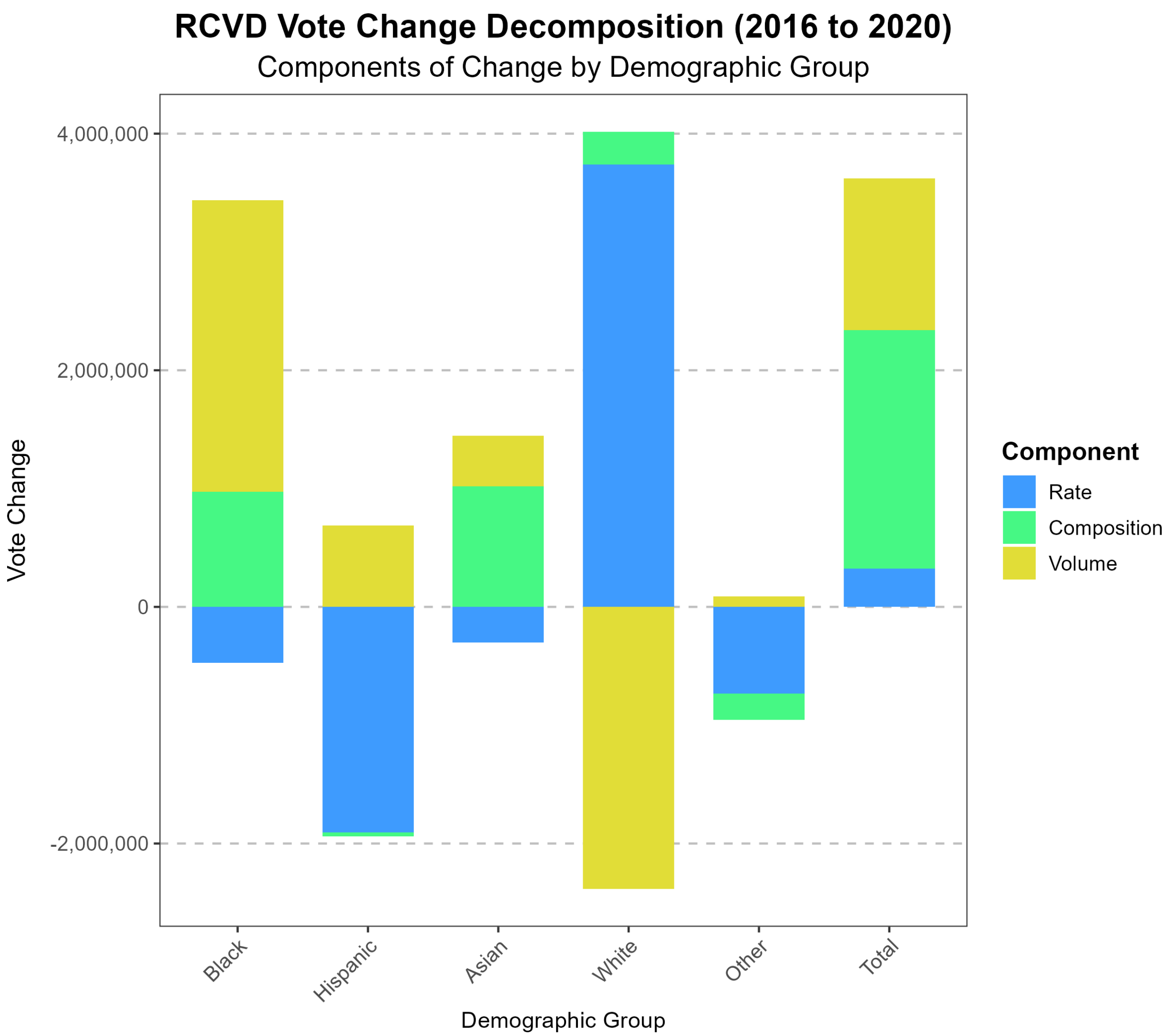

Figure 9: This figure provides an evaluation of the 2020 election compared to the 2016 election using PEW data and the RCVD approach. It shows that Composition had a large positive impact for Democrats as a result of shifting out of White voters and into Black and Asian voters. There was also a large positive impact for Democrats driven by an increase in White support. However, this impact was almost entirely offset by a loss of support amongst Hispanic voters, and to a lesser extent amongst Black, Asian and other voters.

The change observed from 2016 to 2020 shown in Figure 9 established the initial pattern of Democratic bounce-back from the disappointing 2016 election results. While Democrats had won the popular vote, they had failed to capture the presidency. While accounting for the translation of the popular vote to the election outcome involves some challenges (Grimmer, Knox, et al., 2024), it is undoubtedly the case that Democrats performed much better in 2020 versus 2016. The victory was characterized by a powerful combination of favorable Compositional forces (the increasing share of non-White voters, particularly Black and Asian voters) and significant, positive Rate effects across several key Democratic coalition groups (captured here in Rate amongst White voters). The RCVD decomposition during this period confirms that mobilization efforts and passive demographic trends worked synergistically with preference shifts to yield a substantial net gain for the Democratic ticket. This period represents the high-water mark of the conventional wisdom that demographic change inherently favors one party. Even in 2020, though, the cracks that manifested in 2024 were beginning to show amongst non-White voters, as all non-White groups voted for Democrats at a lower Rate, and in particular Democratic support declined noticeably amongst Hispanic voters (from 72% to 61%).

The Critical 2020 to 2024 Swing- Figure 10

The subsequent swing between 2020 and 2024 shown in Figure 10 represents a period of critical realignment and directly challenges established assumptions about the stability of the non-White Democratic coalition. The RCVD analysis reveals a dramatic reversal: Democrats suffered a severe, net negative loss attributable overwhelmingly to the Rate component across all non-White voting groups.

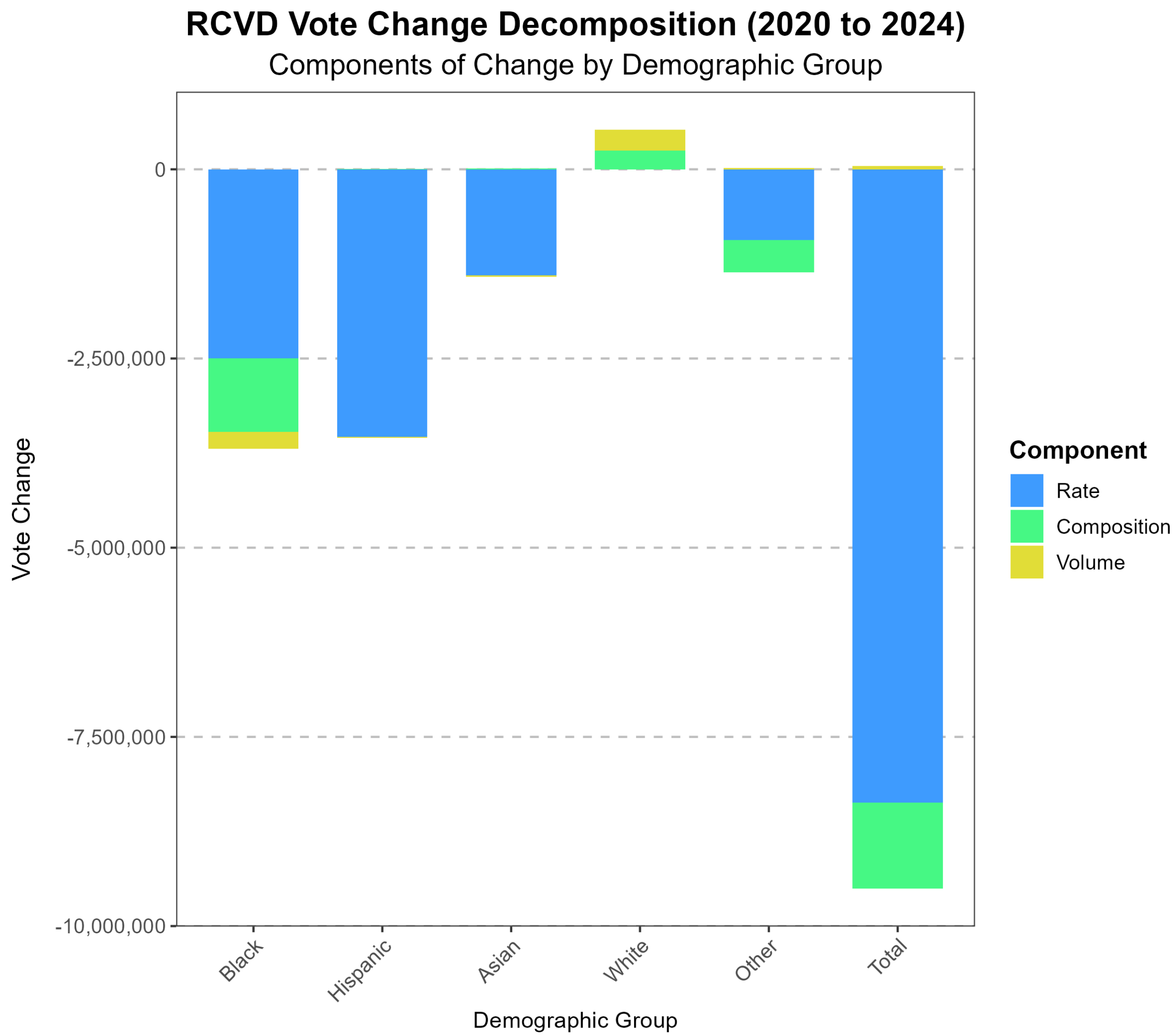

Figure 10: This figure provides an analysis of the 2024 election compared to the 2020 election. It shows that Democrats suffered a dramatic decrease in support amongst all non-White voting groups, most prominently amongst Hispanic voters. The decline in support was so significant that even with continued shifts away from White voters amongst the Composition of the electorate, the total impact of Composition in 2024 was a net negative for Democrats.

Specifically, the Rate effect—the pure change in partisan preference—was negative and substantial among Hispanic and Black voters, signaling a profound erosion of loyalty and successful Republican persuasion. This negative Rate swing was so significant that, even with continued underlying shifts away from White voters in the Composition of the electorate, the total impact of the Composition component in 2024 was a net negative for Democrats. This finding is unprecedented in recent electoral history and underscores the core mechanism of the 2024 result: an accelerating decay in base loyalty (Rate) that entirely neutralized and then overcame the structural advantages of demographic change (Composition).

The Cumulative 2016 to 2024 Arc–Figure 11

The eight-year view from 2016 to 2024 shown in Figure 11 provides the final synthesis. The decomposition highlights the structural dilemma for the Democratic Party. While the overall analysis demonstrates some favorable impacts from Composition over the long run, this benefit was dwarfed by the cumulative negative trend in the Rate component.

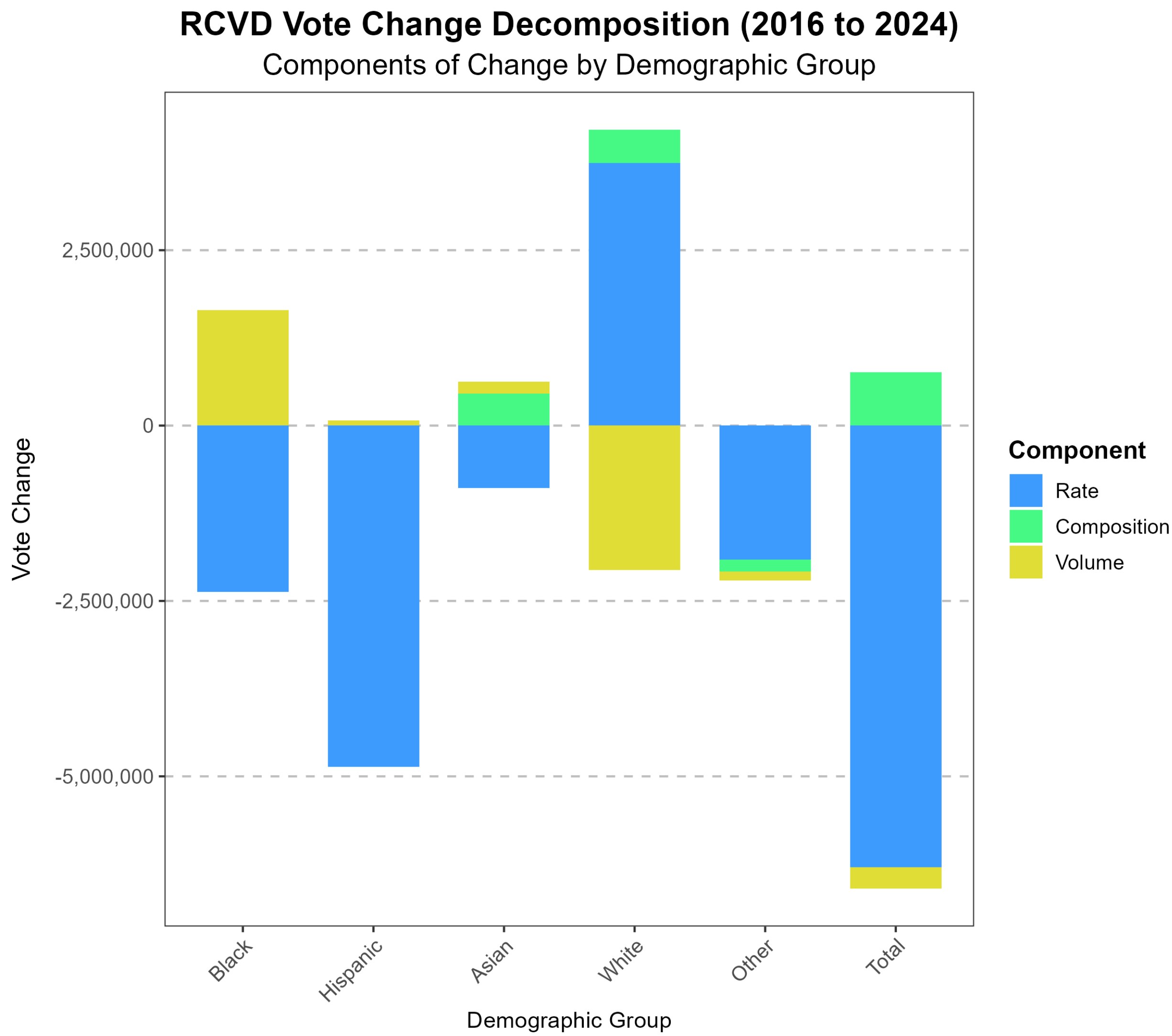

Figure 11: This figure compares the 2024 election to the 2016 election. It highlights the strong negative trend in support amongst Hispanic voters, and to a lesser extent amongst other non-White voters. While this analysis demonstrates some favorable impacts from Composition, it highlights the shortcomings of a reliance on these demographic shifts to promote future success for the Democratic party.

The strong negative Rate trend in support amongst Hispanic voters, and to a lesser extent amongst other non-White voters, is the single most important factor identified by the RCVD framework over this period. While Democrats showed positive growth in support amongst White voters, the framework cleanly partitions the positive effect of an increasing non-White share of the electorate from the negative effect of these groups becoming less reliably Democratic. The final outcome is explained not by a failure of the electorate to grow (Volume) or shift demographically (Composition), but by a failure of the Democratic Party to retain the loyalty of the electorate that did grow (Rate).

In conclusion, the application of RCVD across these three cycles provides unequivocal evidence that the 2024 result was driven by a decisive decoupling of Composition and Rate effects. The long-predicted demographic dividend (Composition) was rendered irrelevant by a swift and brutal collapse of partisan preference (Rate) within the fastest-growing segments of the electorate, a phenomenon masked by aggregate analysis and only revealed by the precision of the Rate, Composition, and Volume Decomposition.

5 Conclusion

As demographic shifts reshape the U.S. voting landscape, understanding how changes between groups affect election outcomes is crucial for both scholars and policymakers. Previous methods for explaining these shifts have often introduced significant interpretive errors, frequently amounting to millions of misallocated votes, due to the conflation of preference shifts with Compositional change. The Rate, Composition, and Volume Decomposition (RCVD) approach, as defined and applied in this paper, resolves this fundamental ambiguity. It provides a zero-loss methodology that precisely specifies how changes in true partisan preference (Rate), the relative size of groups (Composition), and overall participation (Volume) influence electoral outcomes. Critically, the RCVD framework is broadly applicable, extending beyond U.S. elections to any context where subdividing an electorate or population into distinct groups—whether based on ethnicity, geography, age, education, or income—helps explain dynamics in time-series cross-sectional data.

My empirical application of RCVD to the 2016, 2020, and 2024 presidential elections yields a core finding that fundamentally reconfigures the prevailing ”demographics are destiny” narrative. I demonstrate that the 2024 election was driven not by the expected long-term Compositional benefit for the Democratic Party, but by a sudden and decisive decoupling of Composition and Rate effects. Specifically, the framework isolates a substantial, negative Rate effect—the loss of underlying partisan loyalty—among the fastest-growing non-White electorates, particularly Hispanic voters. This preference volatility neutralized the structural Compositional advantage, confirming that electoral success depends less on passive demographic shifts and more on the active defense of coalition loyalty. The RCVD is thus crucially diagnostic, directing attention away from organizational success (Volume/Composition) toward the strategic failure of persuasion (Rate) amongst the Democratic party.

Future work will explore the robustness and granularity of the RCVD approach in two key areas. First, I will investigate its ability to account for nested subgroups, demonstrating how shifts within smaller partitions—such as regional or age-based splits within the Hispanic electorate—contribute to broader electoral changes, building on the work of B. L. Fraga, Velez, et al. (2024). Second, I will extend the analysis across multiple non-presidential time periods to capture long-term trends, showing how the RCVD approach can reveal the evolving durability and fragility of group shifts over time. These studies will further validate RCVD as an indispensable tool for analyzing both historical shifts in political support and for providing a refined, error-free basis for extending our understanding of electorate dynamics for predicting future electoral outcomes.

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Appendix

On Overfitting

While zero-error terms in regression models often raise concerns about overfitting (Wooldridge, 2010), the RCVD approach is not subject to these risks. As it is not a regression or estimation technique, but rather an accounting framework, zero-error reflects the accurate decomposition of shifts rather than problematic estimation.

Proof of Equation 3

$$
\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
&= r(t_2)c(t_2) - r(t_1)c(t_1) \\
r(t_2)c(t_2) - r(t_1)c(t_1) &= r(t_2)c(t_2) + r(t_1)c(t_1) - r(t_1)c(t_1) + r(t_2)c(t_1) - r(t_2)c(t_1) + r(t_1)c(t_2) - r(t_1)c(t_2) - r(t_1)c(t_1) \\
&= [r(t_2)c(t_1) - r(t_1)c(t_1)] + [r(t_1)c(t_2) - r(t_1)c(t_1)] + [r(t_2)c(t_2) - r(t_1)c(t_2) - r(t_2)c(t_1) + r(t_1)c(t_1)] \\
r(t_2)c(t_2) - r(t_1)c(t_1) &= [r(t_2) - r(t_1)]c(t_1) + r(t_1)[c(t_2) - c(t_1)] + [r(t_2) - r(t_1)][c(t_2) - c(t_1)]
\end{aligned}
$$

Proof of Equation 4

$$
\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
&= r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) \\
r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) &= r(t_2)c(t_2)v(t_2) - r(t_2)c(t_1)v(t_1) + r(t_2)c(t_1)v(t_1) \\
&- r(t_1)c(t_2)v(t_1) + r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_2) + r(t_1)c(t_1)v(t_2) \\
&- r(t_2)c(t_2)v(t_1) + r(t_2)c(t_2)v(t_1) - r(t_2)c(t_1)v(t_2) + r(t_2)c(t_1)v(t_2) \\
&- r(t_1)c(t_2)v(t_2) + r(t_1)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) \\
&= 3r(t_1)c(t_1)v(t_1) - 3r(t_1)c(t_1)v(t_1) \\
&+ r(t_2)c(t_1)v(t_1) - 2r(t_2)c(t_1)v(t_1) \\
&+ r(t_1)c(t_2)v(t_1) - 2r(t_1)c(t_2)v(t_1) \\
&+ r(t_1)c(t_1)v(t_2) - 2r(t_1)c(t_1)v(t_2) \\
&+ r(t_2)c(t_2)v(t_1) + r(t_2)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_2) \\
&+ [r(t_2)c(t_2)v(t_2) - r(t_2)c(t_2)v(t_1) - r(t_2)c(t_1)v(t_2) + r(t_2)c(t_1)v(t_1) \\
&- r(t_1)c(t_2)v(t_2) + r(t_1)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
&= [r(t_2)c(t_1)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
&+ [r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)]
\end{aligned}
$$

$$
\begin{aligned}
&+ [r(t_1)c(t_1)v(t_2) - r(t_1)c(t_1)v(t_1)] \\
&+ [r(t_2)c(t_2) - r(t_2)c(t_1) - r(t_1)c(t_2) + r(t_1)c(t_1)]v(t_1) \\
&+ [r(t_2)v(t_2) - r(t_2)v(t_1) - r(t_1)v(t_2) + r(t_1)v(t_1)]c(t_1) \\
&+ [c(t_2)v(t_2) - c(t_2)v(t_1) - c(t_1)v(t_2) + c(t_1)v(t_1)]r(t_1) \\
&+ [r(t_2)c(t_2)v(t_2) - r(t_2)c(t_2)v(t_1) - r(t_2)c(t_1)v(t_2) + r(t_2)c(t_1)v(t_1) \\
&- r(t_1)c(t_2)v(t_2) + r(t_1)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)]
\end{aligned}
$$

$$
\begin{aligned}
r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) &= [r(t_2) - r(t_1)]c(t_1)v(t_1) + r(t_1)[c(t_2) - c(t_1)]v(t_1) + r(t_1)c(t_1)[v(t_2) - v(t_1)] \\
&+ [r(t_2) - r(t_1)][c(t_2) - c(t_1)]v(t_1) + [r(t_2) - r(t_1)]c(t_1)[v(t_2) - v(t_1)] + r(t_1)[c(t_2) - c(t_1)][v(t_2) - v(t_1)] \\
&+ [r(t_2) - r(t_1)][c(t_2) - c(t_1)][v(t_2) - v(t_1)]
\end{aligned}
$$

Proof of Equation 4 with Description and Color Coding:

$$
\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
&= r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1)
\end{aligned}
$$

The core expansion begins here. I begin by color coding terms which are introduced that cancel

$$
\begin{aligned}
r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) &= r(t_2)c(t_2)v(t_2) + 2[r(t_2)c(t_1)v(t_1) - r(t_2)c(t_1)v(t_1)] \\
&+2[r(t_1)c(t_2)v(t_1) - r(t_1)c(t_2)v(t_1)] + 2[r(t_1)c(t_1)v(t_2) - r(t_1)c(t_1)v(t_2)] \\
&+[r(t_2)c(t_2)v(t_1) - r(t_2)c(t_2)v(t_1)] + [r(t_2)c(t_1)v(t_2) - r(t_2)c(t_1)v(t_2)] \\
&+[r(t_1)c(t_2)v(t_2) - r(t_1)c(t_2)v(t_2)] + 3[r(t_1)c(t_1)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
&- r(t_1)c(t_1)v(t_1)
\end{aligned}
$$

After rearranging, I drop colors for terms that will be completely reconfigured, only maintaining color groupings for terms that are essentially finalized

$$
\begin{aligned}
&= 3r(t_1)c(t_1)v(t_1) - 3r(t_1)c(t_1)v(t_1) \\
&\quad + r(t_2)c(t_1)v(t_1) - 2r(t_2)c(t_1)v(t_1) \\
&\quad + r(t_1)c(t_2)v(t_1) - 2r(t_1)c(t_2)v(t_1) \\
&\quad + r(t_1)c(t_1)v(t_2) - 2r(t_1)c(t_1)v(t_2) \\
&\quad + r(t_2)c(t_2)v(t_1) + r(t_2)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_2) \\
&\quad + [r(t_2)c(t_2)v(t_2) - r(t_2)c(t_2)v(t_1) - r(t_2)c(t_1)v(t_2) + r(t_2)c(t_1)v(t_1) \\
&\quad -r(t_1)c(t_2)v(t_2) + r(t_1)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)]
\end{aligned}
$$

After additional rearranging, I apply color groupings for terms as they will appear in the final proof

$$
\begin{aligned}
&= [r(t_2)c(t_1)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
&\quad + [r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
&\quad + [r(t_1)c(t_1)v(t_2) - r(t_1)c(t_1)v(t_1)] \\
&\quad + [r(t_2)c(t_2) - r(t_2)c(t_1) - r(t_1)c(t_2) + r(t_1)c(t_1)]v(t_1) \\
&\quad + [r(t_2)v(t_2) - r(t_2)v(t_1) - r(t_1)v(t_2) + r(t_1)v(t_1)]c(t_1) \\
&\quad + [c(t_2)v(t_2) - c(t_2)v(t_1) - c(t_1)v(t_2) + c(t_1)v(t_1)]r(t_1) \\
&\quad + [r(t_2)c(t_2)v(t_2) - r(t_2)c(t_2)v(t_1) - r(t_2)c(t_1)v(t_2) + r(t_2)c(t_1)v(t_1) \\
&\quad -r(t_1)c(t_2)v(t_2) + r(t_1)c(t_1)v(t_2) + r(t_1)c(t_2)v(t_1) - r(t_1)c(t_1)v(t_1)] \\
r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) &= [r(t_2) - r(t_1)]c(t_1)v(t_1) + r(t_1)[c(t_2) - c(t_1)]v(t_1) + r(t_1)c(t_1)[v(t_2) - v(t_1)] \\
&\quad + [r(t_2) - r(t_1)][c(t_2) - c(t_1)]v(t_1) + [r(t_2) - r(t_1)]c(t_1)[v(t_2) - v(t_1)] \\
&\quad + r(t_1)[c(t_2) - c(t_1)][v(t_2) - v(t_1)] \\
&\quad + [r(t_2) - r(t_1)][c(t_2) - c(t_1)][v(t_2) - v(t_1)] \Rightarrow \\
\Delta z(t) &= \Delta r(t)c(t_1)v(t_1) + r(t_1)\Delta r(t)v(t_1) + r(t_1)c(t_1)\Delta v(t) \\
&\quad + \Delta r(t)\Delta c(t)v(t_1) + \Delta r(t)c(t_1)\Delta v(t) \\
&\quad + r(t_1)\Delta c(t)\Delta v(t) \\
&\quad + \Delta r(t)\Delta c(t)\Delta v(t)
\end{aligned}
$$

Proof of Key Equation 7

$$
\begin{aligned}
\Delta z(t) &= z(t_2) - z(t_1) \\
z(t_2) - z(t_1) &= r(t_2)c(t_2)v(t_2) - r(t_1)c(t_1)v(t_1) \\
&= r(t_2)[c(t_1)v(t_1) - c(t_1)v(t_1) + c(t_2)v(t_1) - c(t_2)v(t_1) + c(t_2)v(t_2)] - \\
&r(t_1)c(t_1)v(t_1) \\
&= r(t_2)c(t_1)v(t_1) - r(t_1)c(t_1)v(t_1) + r(t_2)c(t_2)v(t_1) - \\
&r(t_2)c(t_1)v(t_1) + r(t_2)c(t_2)v(t_2) - r(t_2)c(t_2)v(t_1) \\
&= [r(t_2) - r(t_1)]c(t_1)v(t_1) + \\
&r(t_2)[c(t_2) - c(t_1)]v(t_1) + \\
&r(t_2)c(t_2)[v(t_2) - v(t_1)]
\end{aligned} \tag{8}
$$

Simple Example Data

Table A1: Concept Demonstration

Method	Group	Rate	Composition	Volume	Calc Mar Chng	Var to Act	Variance %
Derivative Calculation	Non-White	−2.76	2.74	4.43	4.42	0.42	10.4
	White	6.11	0.70	−2.82	3.99	−1.01	−20.1
	Total	3.35	3.44	1.61	8.41	−0.59	−6.5
RCV Calculation	Non-White	−2.76	2.40	4.36	4.00	0.00	0.0
	White	6.11	0.40	−1.51	5.00	0.00	0.0
	Total	3.35	2.79	2.85	9.00	0.00	0.0
Comparing the Two Approaches	Non-White		0.34	0.07	0.42		
	White		0.31	−1.31	−1.01		
	Total		0.65	−1.24	−0.59		

Note: All numbers are in millions. Variance percentages are shown with one decimal place.

Rate Only and Composition Only

Table A2 shows how Rates would have had to have shifted in order to guarantee a win for Trump in 2020 without any Composition shifts. To achieve this effect, I multiplied Biden's margin Rate within each group by a factor of .9, preserving the relative Rates at which each group voted for Biden, but reducing his vote totals. As can be seen, this shift is sufficient to shift just over 17.2 million votes to Trump versus the actual reported result.

Table A2: Hypothetical Data, Only Rate Changes

Election	Group	Candidate 1	Candidate 2	Total	Gross Margin	Margin Rate (%)	Composition (%)
1st Election (2020)	Black	15.42	1.47	16.89	13.95	82.60	10.89
	Hispanic	13.21	4.47	17.68	8.73	49.40	11.41
	Other	8.64	5.16	13.80	3.48	25.20	8.90
	White	47.95	57.21	105.16	−9.25	−8.80	67.84
	NA	0.80	0.67	1.47	0.13	8.60	0.95
	Total	86.02	68.98	155.00	17.03	10.99	100.00
2nd Election (2020)	Black	13.88	3.01	16.89	10.86	64.34	10.89
	Hispanic	11.89	5.79	17.68	6.09	34.46	11.41
	Other	7.78	6.03	13.80	1.75	12.68	8.90
	White	43.16	62.00	105.16	−18.84	−17.92	67.84
	NA	0.72	0.75	1.47	−0.03	−2.26	0.95
	Total	77.41	77.59	155.00	−0.17	−0.11	100.00
Comparing the Two Elections	Black	−1.54	1.54		−3.08	−18.26	0.00
	Hispanic	−1.32	1.32		−2.64	−14.94	0.00
	Other	−0.86	0.86		−1.73	−12.52	0.00
	White	−4.80	4.80		−9.59	−9.12	0.00
	NA	−0.08	0.08		−0.16	−10.86	0.00
	Total	−8.60	8.60		−17.20	−11.10	0.00

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.

Conversely, Table A3 demonstrates how Composition would have had to shift, without any changes in the underlying Rates within groups, in order to deliver a Trump popular vote win. In this specification, to achieve the desired result, I had to multiply the size of each of the non-White voting blocs by a factor of .44, essentially reducing them by more than half. This leads to a shift in the Composition of the electorate from just under 68% White to nearly 86% White, an enormous shift. The impossibility of this shift highlights the importance that Republicans will need to place on changing Rates within minority groups in future elections, especially as demographic changes continue to accelerate in the future. However, as will be shown in Section 4, there is significant reason to believe that Republicans have succeeded at changing Rates in recent elections, suggesting that demographics driving elections towards Democrats is not an assured outcome.

Table A3: Hypothetical Data, Only Composition Changes

Election	Group	Candidate 1	Candidate 2	Total	Gross Margin	Margin Rate (%)	Composition (%)
1st Election (2020)	Black	15.42	1.47	16.89	13.95	82.60	10.89
	Hispanic	13.21	4.47	17.68	8.73	49.40	11.41
	Other	8.64	5.16	13.80	3.48	25.20	8.90
	White	47.95	57.21	105.16	−9.25	−8.80	67.84
	NA	0.80	0.67	1.47	0.13	8.60	0.95
	Total	86.02	68.98	155.00	17.03	10.99	100.00
2nd Election (2020)	Black	6.78	0.65	7.43	6.14	82.60	4.79
	Hispanic	5.81	1.97	7.78	3.84	49.40	5.02
	Other	3.80	2.27	6.07	1.53	25.20	3.92
	White	60.68	72.39	133.07	−11.71	−8.80	85.85
	NA	0.35	0.30	0.65	0.06	8.60	0.42
	Total	77.43	77.57	155.00	−0.14	−0.09	100.00
Comparing the Two Elections	Black	−8.63	−0.82	−9.46	−7.81	0.00	−6.10
	Hispanic	−7.40	−2.50	−9.90	−4.89	0.00	−6.39
	Other	−4.84	−2.89	−7.73	−1.95	0.00	−4.99
	White	12.73	15.18	27.91	−2.46	0.00	18.01
	NA	−0.45	−0.38	−0.83	−0.07	0.00	−0.53
	Total	−8.59	8.59	0.00	−17.18	−11.08	0.00

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.

I have not produced a table comparing the RCVD approach and the DBA for either Table A2 or Table A3, as either specification produces identical results.

Rate and Composition Shift Data

Robustness

To demonstrate the robustness of the method, I present Appendix Tables 1 and 2. Table A1 splits votes out from the Non-White category into Black and All Others, leaving the White category untouched. Table A2 shows that both the DBA as well as the

Table A4: Hypothetical Data, Both Rate and Composition

Method	Group	Rate	Composition	Volume	Calc Mar Chng	Var to Act	Variance %
Derivative Calculation	Black	−2.16	−2.79	0	−4.95	−0.43	9.6
	Hispanic	−1.85	−1.75	0	−3.60	−0.37	11.5
	Other	−1.21	−0.70	0	−1.91	−0.24	14.5
	White	−6.71	−0.88	0	−7.59	0.64	−7.7
	NA	−0.11	−0.03	0	−0.14	−0.02	19.5
	Total	−12.04	−6.13	0	−18.18	−0.43	2.4
RCV Calculation	Black	−2.16	−2.36	0	−4.52	0.00	0.0
	Hispanic	−1.85	−1.38	0	−3.23	0.00	0.0
	Other	−1.21	−0.45	0	−1.66	0.00	0.0
	White	−6.71	−1.51	0	−8.23	0.00	0.0
	NA	−0.11	0.00	0	−0.11	0.00	0.0
	Total	−12.04	−5.71	0	−17.75	0.00	0.0
Comparing the Two Approaches	Black		−0.43	0	−0.43		
	Hispanic		−0.37	0	−0.37		
	Other		−0.24	0	−0.24		
	White		0.64	0	0.64		
	NA		−0.02	0	−0.02		
	Total		−0.43	0	−0.43		

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.

RCVD approach correctly leave the specification of the impact of Rate, Composition, and Volume to White voters (the unchanged category) unchanged from Table 2. This highlights the robustness to irrelevant alternatives of the RCVD approach, showing how it behaves comparably to the DBA.

Table A5: Comparing Two Elections, Robustness to Irrelevant Alternatives

Election	Group	Candidate 1	Candidate 2	Total	Margin	Margin Rate (%)	Composition (%)
1st Election (2016)	Black	13.25	0.90	14.15	12.35	87.3	11.0
	All Others	16.25	6.60	22.85	9.65	42.2	17.7
	White	39.00	53.00	92.00	−14.00	−15.2	71.3
	Total	68.50	60.50	129.00	8.00	6.2	100.0
2nd Election (2020)	Black	15.40	1.50	16.90	13.90	82.2	10.9
	All Others	22.60	10.50	33.10	12.10	36.6	21.4
	White	48.00	57.00	105.00	−9.00	−8.6	67.7
	Total	86.00	69.00	155.00	17.00	11.0	100.0
Comparing the Two Elections	Black	2.15	0.60	2.75	1.55	−5.0	−0.1
	All Others	6.35	3.90	10.25	2.45	−5.7	3.6
	White	9.00	4.00	13.00	5.00	6.6	−3.6
	Total	17.50	8.50	26.00	9.00	4.8	0.0

Note: Votes are reported in millions. Candidate 1 refers to Clinton (2016) and Biden (2020); Candidate 2 refers to Trump.

Table A6: Concept Demonstration, Robustness to Irrelevant Alternatives

Method	Group	Rate	Composition	Volume	Calc Mar Chng	Var to Act	Variance %
Derivative Calculation	Black	−0.71	−0.07	2.49	1.70	0.15	9.9
	All Others	−1.30	1.98	1.94	2.63	0.18	7.4
	White	6.11	0.70	−2.82	3.99	−1.01	−20.1
	Total	4.11	2.61	1.61	8.33	−0.67	−7.4
RCV Calculation	Black	−0.71	−0.07	2.33	1.55	0.00	0.0
	All Others	−1.30	1.72	2.03	2.45	0.00	0.0
	White	6.11	0.40	−1.51	5.00	0.00	0.0
	Total	4.11	2.04	2.85	9.00	0.00	0.0
Comparing the Two Approaches	Black		0.00	0.16	0.15		
	All Others		0.27	−0.08	0.18		
	White		0.31	−1.31	−1.01		
	Total		0.57	−1.24	−0.67		

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.

Table A7: Concept Demonstration for Trump, Real Data from Marble et al. (2024)

Method	Group	Rate	Composition	Volume	Calc Mar Chng	Var to Act	Variance %
Derivative Calculation	Black	0.68	0.04	−0.82	−0.11	1.48	−93.1
	Hispanic	0.26	−0.40	−0.45	−0.59	1.44	−71.0
	Other	0.41	−0.35	−0.18	−0.11	0.69	−85.8
	White	−5.52	−0.31	0.91	−4.92	−0.56	12.9
	NA	0.02	−0.02	−0.01	0.00	0.03	−86.4
	Total	−4.14	−1.04	−0.55	−5.73	3.07	−34.9
RCV Calculation	Black	0.68	0.07	−2.34	−1.59	0.00	0.0
	Hispanic	0.26	−0.83	−1.46	−2.03	0.00	0.0
	Other	0.41	−0.63	−0.58	−0.80	0.00	0.0
	White	−5.52	−0.39	1.55	−4.35	0.00	0.0
	NA	0.02	−0.03	−0.02	−0.03	0.00	0.0
	Total	−4.14	−1.81	−2.86	−8.81	0.00	0.0
Comparing the Two Approaches	Black		−0.04	1.52	1.48		
	Hispanic		0.43	1.02	1.44		
	Other		0.28	0.40	0.69		
	White		0.08	−0.65	−0.56		
	NA		0.01	0.01	0.03		
	Total		0.77	2.31	3.07		

Note: Votes are reported in millions. Variance percentages are shown with one decimal place.