Racial redistricting emerged as one of the most fiercely debated policy questions among scholars, judges, and politicians during the 1990s. While the battle has raged along multiple fronts—normative, constitutional, methodological—the central empirical contention revolves around the policy’s partisan impact. Critics of racial redistricting claim, and Republicans hope, that packing black voters into majority-minority districts cripples the Democratic party outside of the safe seats it creates for black representatives (e.g., Bullock 1995; Lublin 1997; Lublin and Voss 1998; Swain 1995a, 1995b; Thernstrom and Thernstrom 1997). Friendlier analysts, by contrast, downplay the damage nearby Democrats typically will suffer (e.g., Engstrom 1995; Grofman and Handley 1998; LDF 1994; McDonald and Lucas 1998; Petrocik and Desposato 1998). The true electoral effect of racial redistricting remains unclear.\(^1\)

Virtually all studies of racial redistricting’s partisan impact have focused solely on one or two congressional elections.\(^2\) Whatever their practical significance, these high-profile contests provide few actual cases to test how electoral borders shape Democratic fortunes, especially in the critical range where African Americans fall just short of a majority. Restricting attention to congressional elections unnecessarily limits the scope of analysis, since the hypothesized behavioral regularities that undergird this empirical debate are not unique to national politics.
This article therefore switches the spotlight to state House elections in ten southern states—all of the former Confederacy save Arkansas. These states are worth particular attention because each created new majority-minority districts after the 1990 census, responding to pressure from black legislators and the U.S. Justice Department. Turning to state legislative contests greatly increases the number of cases. The South’s smallest state House has more than three times as many districts as the region’s largest congressional delegation. We examine every election for a decade (i.e., from the last election held under the 1980s plan through 1998), as many as five elections in some states.

Our assessment of racial redistricting’s partisan implications should provide some comfort to both sides of the debate. The findings suggest that racial redistricting systematically harms the party chosen by most black voters, as critics contend. The new black districts cost the Democratic party legislative seats in all ten southern states and likely account for the Democrats losing control of state Houses in both South Carolina and Virginia for the first time since Reconstruction. Nevertheless, the main force driving Republican growth in southern state legislatures is a strong shift toward the Republicans among white voters, a trend that dwarfs the consequences of moving people around. In most states, Democratic losses were modest, hardly sufficient to deter activists seeking to maximize black descriptive representation.

Our expansive data set not only allows greater empirical leverage for estimating how Democrats fare after the introduction of a new electoral map, it also permits us to probe the social forces driving those partisan effects. In particular, we find that white southerners show no significant systematic tendency to become more Republican as electoral units gain in African-American population, contrary to the popular “white backlash” hypothesis. It is precisely the absence of this backlash pattern that explains why redistricting costs so many Democratic seats. The initial wedge of the 1990s Republican realignment struck most heavily among constituencies with a modest black population, of the sort created by “bleaching” Democratic districts to construct adjacent majority-minority strongholds, not in the dwindling number of potential backlash districts where Democrats must construct a biracial coalition to win.

Toward a Theoretical Understanding of Partisan Effects?

African-American voters strongly support the Democratic party. White southerners, by contrast, display a strain of political conservatism that has been funnelling them toward the GOP. Since racial redistricting pulls black voters into majority-minority enclaves, and must do so within the bounds of similarly sized legislative districts, it naturally strips an overwhelmingly loyal Democratic voting base out of surrounding constituencies and replaces them with whites who usually exhibit no such fidelity. Common sense would seem to dictate that redistricting must hurt the South’s Democrats.

The reality is not so obvious. Any number of features, unique to a given state or a given electoral map, could attenuate the actual costs Democrats face. For example, Democratic incumbents may be able to prevent raids on their own constituency or push unsupportive white voters from their district. Whites stuffed as “filler people” into majority-minority districts might be disproportionately Republican, leaving more Democrats among the whites who dominate elsewhere. Similarly, those drawing the electoral map may take as many minority voters as possible from diehard Republican districts, where they tend to be wasted anyway.

It would be improper, however, to conclude that redistricting does not typically hurt Democrats just because the costs are probabilistic. A generalized theory arguing for neutral partisan effects would require something more than the ability to identify exceptions. It would require a social process strong enough to overcome any central tendency toward Democratic losses, one that over time would regularly compensate for bleaching loyal minorities out of surrounding districts. Is there any theoretical

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3 We exclude Arkansas because racial data for the court-ordered 1990 districts are unavailable. District racial composition presumably matters less there than anywhere else in the South, since the percentage of Democrats in the state House was higher than any other Southern state’s throughout most of the period—above 85 percent until the arrival of term limits in 1998 (Barone, Lilley, and DeFranco 1998; Barth and Blair 1997).

4See the state-level case studies in Grofman 1998.

5 The Texas congressional delegation includes thirty members. The Tennessee lower chamber consists of ninety-nine members.

6 Mississippi actually used its 1980s redistricting plan for the 1991 elections. After the adoption of a new plan based on 1990 Census data, the Court ordered a special election for the entire state legislature in 1992. Accordingly, we utilize 1991 as the last plan for the 1980s and include the 1992 special election as the first under the new plan. We ignore special elections caused by redistricting in other states because only a few seats were up at any one time.

7 The partisan effects of redistricting are important when assessing the policy’s impact on black representation, since even Democrats elected by a white majority are much more likely to vote with minority state legislators than are Republicans (Epstein and O’Halloran 1999, 388).
reason to think that the "common sense" would be wrong over the long term.

Two systematic patterns would counterbalance the effect of removing a district’s strongly Democratic minority population. Either whites in mixed-race precincts must be the South’s most heavily Republican voters or whites would need to change their voting habits dramatically depending upon the racial makeup of an electoral arena. These two hypothesized behavioral regularities operate at different geographical levels, but both presume that whites react negatively to the presence of a large local minority population and therefore fall under the same theoretical rubric: the “white backlash” hypothesis popular in the southern politics literature.8

First, consider the precinct-level version. White voters in mixed-race communities exist in an integrated social and economic world that other whites do not share. Proximity may spur competition between races and expand the opportunity for negative interracial contact—spawning an antipathy ripe for political exploitation.9 Integrated whites inclined to react against this “power threat” in their neighborhood would cohere behind the racially conservative Republican party, hoping for policies that would give them the upper hand in any intergroup conflict (Huckfeldt and Kohfeld 1989, 80–83). As a result, creating majority-minority districts would not harm the Democrats much, because the white voters carried into these safe Democratic seats usually would be the region’s most (racially) conservative. Whites shunted to the surrounding bleached districts, by contrast, would be those least sympathetic to the GOP.

An electorally based “white backlash” pattern also would mitigate the costs of redistricting. Creating majority-minority districts usually requires disassembling one or more “minority influence” districts, places with sizeable black minorities. If whites in these racially mixed districts are particularly likely to cohere behind the racially conservative party, as a means of maintaining supremacy (Blalock 1967; Key 1984, chapter 15), then breaking those apart presumably would undermine the motive for “white backlash.” Democrats would not suffer after losing minority voters because the whites left behind would become correspondingly more likely to support them. Every safe vote lost would be compensated by increasing the odds of attracting the remainder.

The most direct way to determine whether a “white backlash” phenomenon mitigates the partisan effects of racial redistricting would be to test whether southern voting behavior actually follows backlash patterns. Contemporary efforts in this direction often return negative results (Corbello 1998; Gaddie and Bullock 1997; Voss 1996, 2000; Voss and Lublin 2001). However, the direct approach limits analysis to cases with particularly good registration and voting data.

An alternate method is to probe for backlash indirectly, by observing the relationship between a district’s racial makeup and its political orientation. Researchers have already found the indirect approach useful for studying redistricting (Cameron, Epstein, and O’Halloran 1996; Lublin 1997; McDonald and Lucas 1998), despite a limited number of congressional districts in the critical range (Lublin 1999, 184). Carrying a similar methodology over to state legislative elections would seem particularly valuable (Epstein and O’Halloran 1999, 372), even if devolution had not made representation in state legislatures more important. The indirect approach is imperfect, because it cannot break apart the multiple political influences represented by district racial composition, but any backlash pattern strong enough to be worth disciplinary interest would show up in the partisan distribution of legislative seats.

8Other names include the “racial threat” or “group threat” hypothesis and the “Black Belt” hypothesis. The idea was popularized by V.O. Key, Jr. (1949) 1984, but enjoys wide application; see Voss (2000, chapters 2–4) for a comprehensive literature review. All are consistent with Epstein and O’Halloran’s (1999, 370) admonition that the level of racial polarization is not constant across locales or contexts.

9Note that this geographically bounded “backlash” reasoning is different from the more colloquial use of the term, which simply refers to generic white resentment of minorities. The hypothesis stresses reaction against proximity to minorities. Of course, proximity also expands the opportunity for positive interaction, including the sort of intimate exposure that breaks down stereotypes. Social psychologists who believe that familiarity breeds tolerance rather than contempt, however, recognize that the “contact hypothesis” is highly contingent (Brewer and Miller 1984, 291–295). One requirement, that blacks and whites meet in a position of status equality, seems rare in the southern arena.

Methodology

The logit model offers one simple means for capturing the impact of a district’s racial composition on Democratic fortunes.10 It seems appropriate because the probability of Democratic victory roughly follows the logistic

10Cameron, Epstein, and O’Halloran (1996, 801–802) use locally weighted regression (or “loess”) techniques for an analysis of the relationship between district racial composition and a representative’s liberalism, the latter of which is a continuous scale. However, they switch to parametric models in subsequent categorical analysis (Cameron Epstein, and O’Halloran 1996, 803–804; Epstein and O’Halloran 1999, 378–382), a decision we embrace here. The parametric models are better able to borrow strength from every district in a state, whereas loess runs the risk of pure “data fitting.”
model’s cumulative density function, an S-shaped curve that climbs rapidly as the black proportion increases but levels off once blacks are so populous that Democratic victory becomes almost assured.

However, the standard logit specifies a monotonic relationship between racial composition and probability of electing a Democrat. Since Democratic fortunes shoot up as African Americans become more numerous in the electorate, the model must predict that Republicans will perform best in all-white districts. This assumption may be appropriate where white voters are almost uniformly conservative, but completely contradicts expected behavior in most Southern states.11 The standard logit cannot capture a backlash pattern, for example, in which white cohesion cancels out or even reverses the partisan effect of growing black density.

It also cannot capture the relative Democratic sympathies of districts with a negligible black population—not just those in Texas, where Mexican Americans tend to support Democrats even when they reside in mostly nonblack districts, but also Southern highland regions that feature a vibrant tradition of white populism (Hair 1969, 209; Hyman 1990). Historically, upland counties have not supported the Democratic party; they were the locus of “mountain republicanism” discussed by numerous authorities on southern politics (e.g., Heard 1952, 40–41; Key [1949] 1984, chapter 13; Seagull 1975, chapter 6). But these “100 to 200 counties strung along the Appalachian highlands” have never displayed any interest in racial or economic conservatism (Key 1984, 283–285). There is no reason to expect themes embodied by the Republican Contract with America to hold any particular resonance there (Lamis 1990, 173). No model could capture the partisan effects of redistricting without allowing some kind of kink in the function at low levels of black density, such that all-white highland areas are allowed to be more Democratic than slightly more diverse suburbs.

It may, at first, appear difficult to imagine what kind of changes one might make to the logistic probability curve to test alternative theories of the relation between party and district racial composition. However, the logit’s S-shaped function is actually just the adjusted form of a linear model, in which the log-odds of Democratic victory are regressed on black density.12 Conceiving our model as a linear regression, we can test alternative theories of the relationship between race and party by utilizing the same nonlinear variations that researchers commonly use with Ordinary Least Squares (i.e., exponential and log transformations). The resulting logit functions are not particularly intuitive, even if the “tricks” for nonlinearity are familiar, but they can be converted into probability models using the standard logistic transformation and presented graphically in a manner easy for the reader to grasp.

Modeling the Relationship Between District Racial Composition and Party

We tested four different functional forms for each state legislative election: first a standard logit predicting how the racial composition of a state House district influences the party of its representative, the other three testing for the behavioral and historical patterns that might compromise this simple model.

The conventional logit, a linear log-odds model, contains only one term: proportion black of the district population. Since the model’s systematic component requires Democratic chances to rise sharply, until leveling off as contests become a sure bet, it implies that white backlash plays little role in elections. Adding blacks never produces a backlash sufficient to counteract or exceed the gains; removing blacks never softens white cohesion sufficient to eliminate the costs.

The parabolic and cubic log-odds models represent two different variations of the white-backlash theory. If the whites in a racially mixed district cohere politically, either because they wish to maintain supremacy in the district or because they resent black neighbors, then these models should find a critical range where removing black voters from a district actually helps the Democrats. Heavier mobilization among the district’s whites, another form of backlash, also would curtail the effects of racial composition. Absence of these patterns would not invalidate the “white backlash” hypothesis entirely, since changes in the white probability of voting Democratic could be so minuscule that they never match the effect of altering racial composition, but it would result in such a watered-down version of the theory that it would provide no consolation to Democrats fearing racial redistricting.

The parabolic model adds black percentage squared, allowing one bend toward the center of the log-odds.

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11 We do not take issue with Epstein and O’Halloran’s (1999) use of the standard logit, for two reasons. First, their analysis is limited to South Carolina, which contains few predominantly white Democratic areas. Second, much of their analysis uses a binary dependent variable intended to represent whether the black candidate of choice won. Since they rule out any white politician being the black candidate of choice except in majority-minority districts (1999, 371), this measurement rule almost guarantees a monotonic relationship.

12 The logit curve takes on the S-shaped form 1/(1 + e⁻z), where z = b₀ + b₁X₁ + b₂X₂ + ... + bₙXₙ (or z = XB) in the traditional regression notation.
function (see Fording 1997). This model would be most useful if both predominantly white and majority black districts had greater odds of electing Democrats than districts with a sizable black minority, where whites could cohere behind the racially conservative party to maintain supremacy. The cubic model also adds black percentage cubed, permitting a second bend. It allows Democratic fortunes to rise as black density increases, taper off, or even reverse as whites feel threatened, and then surge again as black voters approach a majority.

The natural log model allows for the continuing role of highland exceptionalism in southern politics. It allows a sharp kink in the log-odds function at low levels of black density, letting Democratic odds shift upwards in all-white districts if necessary. Rural upland regions with almost no black residents may vote more heavily Democratic than white suburbs with small black populations, especially after the 1990’s Republican realignment, so this model permits such a pattern. Creating majority-minority strongholds can and does create much whiter legislative districts elsewhere, but it never replicates the historical forces that drive voting in Appalachia. Any model of the partisan effects of racial redistricting that does not accommodate systematic divergence among heavily white districts will fail to estimate accurately the damage Democrats face from the policy.

In all models, the dependent variable was binary, coded 1 for Democrats and 0 for all others. After running the simple logit for each election in each state, we tried each of the more complex functional forms. They only required adding transformations of black density, so conventional hypothesis tests were sufficient to determine whether each bend in the standard logit picked up a statistically significant pattern. We used two tests available for Maximum Likelihood Estimation (MLE) models (King 1989, section 4.6). Wald’s test is a generalized form of the familiar two-tailed t-test. Likelihood ratio tests similarly reveal if the improvement of complex models over simpler models likely was due to random chance.

The only complication came in when both natural-log and parabolic models picked up statistically significant deviations from the standard logit. These two are not nested in each other, and therefore do not permit the standard MLE model comparisons (King 1989, 84–86).

Consequently, we also tested the fit of each model, examining which most accurately predicted the number of Democrats elected over different ranges of proportion black. Usually the fit clearly favored one of the two nonlinear transformations. If it did not, we simply picked whichever nonlinear transformation was most successful for other election years in the same state. The appendix presents these statistics for each model and identifies the particular models chosen in each case.

Our expectations for this stage of the analysis are straightforward. The basic linear model should best fit the data in states without Appalachian regions: Florida, Louisiana, Mississippi, and South Carolina. In contrast, Alabama, Georgia, North Carolina, Tennessee, and Virginia all contain portions of the Appalachian mountains or foothills, so the natural-log model should best fit these states. The large Hispanic population in Texas also should fit that model, since they usually reside near few blacks and yet exhibit long-standing Democratic loyalties. We do not expect any state to follow a white-backlash pattern in the modern South.

Predicting the Impact of Redistricting and Realignment

Once we select the best probability model for each election in each state, we can evaluate the partisan effect of redistricting actually conveyed in the 1990s through the exploration of counterfactuals. Following Grofman and Handley (1998), we decompose shifts in the number of Democrats across elections into three categories: a redistricting effect, a realignment effect, and an interaction (of redistricting and realignment) effect. Expressed mathematically:

\[ \text{Expected number of Democrats} = \text{Redistricting} + \text{Realignment} + \text{Redistricting x Realignment} \]

\[ \text{Redistricting} = \text{Model} - \text{Baseline} \]

\[ \text{Realignment} = \text{Baseline} - \text{Baseline control} \]

\[ \text{Redistricting x Realignment} = \text{Redistricting} - \text{Realignment} \]

13Our goal is to track the decline of Democratic dominance, so the small number of nonmajority party representatives were coded as 0. One alternative to this method would be to model Democratic vote as the dependent variable and use OLS to estimate the parameters. So many state legislative candidates were unopposed that this seemed unwise. Moreover, we want to explain changes in the probability of winning seats, not votes, which logit is better equipped to predict.

14This error test was simple to carry out and provided a good gauge of the strength of various models. First, we calculated each district's predicted probability of electing a Democrat. Second, we divided observations into one of four groups based on the district black percentage (0–5, 5–15, 15–25, 35–100 percent) and summed the probabilities within each category to compute the number of expected Democrats. Finally, this estimate was subtracted from the actual number of Democrats elected in each group to calculate the prediction error. This error test is more useful than simply examining "percent predicted correctly." For example, one would expect one of five districts with a .8 chance of electing a Democrat to elect a non-Democrat, whereas this stray district conventionally would be counted as an error.

15In any case, when the difference in the error for two models was small, the graphs for each model of the probability of electing a Democrat at varying percentages of blacks in the district indicated that the actual substantive difference between the two models is negligible (i.e., the graphs are very similar for both models).

16Grofman and Handley (1998, 54–55) use slightly different terminology even though their essential meaning is left unchanged. In-
$Y'_1 - Y'_0 = D + A + I$

where $Y'_0$ is the number of seats held by the Democrats in 1990, and $Y'_1$ is the number of seats won by the Democrats in a later election. $D$ equals the redistricting effect; $A$ equals the realignment effect; $I$ equals the interaction effect.

The redistricting effect represents what would have happened to Democratic fortunes under the new districts, presuming that preferences had remained constant after the process. The realignment effect represents what would have happened to Democratic fortunes under the old districts, had the country witnessed an identical pro-Republican swing. The interaction effect is what reconciles these two counterfactuals with the actual results of the post-redistricting election, necessary in part because other demographic traits shift with electoral lines and also influence voting. The redistricting term, after all, ignores that realignment probably would have changed the effect of racial composition. The realignment term, similarly, ignores that redistricting probably caused some of the realignment by shaping candidate and voter decisions (Lubin and Voss 1998). The interaction term combines these two effects.

Our specific formula for the computation is as follows:

$$D = \sum_{i=1}^{n} \frac{1}{1 + e^{-(X_i \beta)}} - Y'_0$$
$$A = \sum_{i=1}^{n} \frac{1}{1 + e^{-(X_i \beta)}} - Y'_0$$
$$I = (Y'_1 - Y'_0) - (D + A)$$

where $i$ is an index for the district number and $n$ the total number of districts. $B_0$ is a $k \times 1$ vector of $k$ coefficients from the 1990 model, $B_1$ from the post-1990 model. $X_{0i}$ is a $1 \times k$ vector containing 1990 values of the explanatory variables (i.e., the proportion black plus any necessary transformations); $X_{1i}$ is a vector containing the parallel information for the post-1990 plan. Computing the redistricting counterfactual therefore simply requires plugging the 1990s racial compositions into the 1980s coefficients. The realignment counterfactual requires plugging the 1980s racial composition data into the 1990s coefficients.

Instead of “composition effect,” we use “redistricting effect” to reflect both the focus of our paper and the major cause of compositional changes. Similarly, we use “realignment effect” in place of “behavioral effect” to indicate that the behavioral changes are part of a major growth in Republican strength during the 1990s.

### Findings

This section first presents the models that fit each state and election best. Regional partisan differences and the presence of Hispanics explain most departures from the linear model. It then estimates Democratic losses due to redistricting.

#### State Models: Little Support for the White-Backlash Theory

Figure 1 presents scatterplots with the proportion black on the x-axis and the predicted probability of electing a Democrat on the y-axis for selected elections in each state.

**Florida, Louisiana, Mississippi, and South Carolina.** As predicted, the linear model best fit the data for most elections held in states with no Appalachian districts. The basic linear model worked well in Florida and Louisiana for all elections (1990–98 in Florida, 1987–95 in Louisiana). The linear model additionally fits most elections in Mississippi (1991–2) and South Carolina (1990–92, 1996). For these states, the probability of electing a Democrat always rises as the proportion of blacks increases until the probability approaches 1. Examining the elections from these states provides little to no evidence to support the white-backlash theory, but substantial evidence to support the contrasting claim that removing blacks from a district always harms the Democrats. Table 1 reports the specific probability of Democratic victory estimated for each state in each election, with standard errors computed using the Tomz, Wittenberg, and King (1999) CLARIFY code (see King, Tomz, and Wittenberg 2000).

**Alabama, Georgia, North Carolina, and Virginia.** As expected, the natural-log model best represents all elections in North Carolina (1990–98) and Virginia (1989–97), as well as elections held during the first part of the period in Alabama (1990–4) and Georgia (1990–2). According to all of these models, the probability of electing a Democrat declines, sometimes dramatically, as the share of blacks increases.

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17 The parabolic and cubic models, respectively, best fit the 1994 and 1998 South Carolina elections. These models merely allow the curve to track the data more precisely; they never indicate a backlash pattern. The parabolic curve never has a negative slope, so the probability of electing a Democrat always increases with the proportion of blacks. The parabolic model simply allows for a flatter curve for both low and high values of proportion black, with a steeper slope in the middle. The cubic model for 1998 is practically a step model. The relationship is still monotonic.

18 The parabolic curve best fit the remaining Alabama (1998) election.
blacks in the population rises from 0, but reverses at some point below 10 percent black. White backlash cannot explain the successful fit of these curves, as it is inexplicable that whites would feel threatened politically by a tiny minority population but not by a much more sizeable concentration of black population strength.

The log model succeeds instead because of unusually high levels of support for the Democratic party in Appalachian highlands. Although they were historically Union-ist and Republican in the nineteenth century, these poor, rural, and overwhelmingly white areas are more likely to support Democrats than the growing number of suburban and small-town districts with only slightly more diverse demographics. The all-white Democratic districts consistently appear within the Appalachian region. All of the Alabama districts less than 4 percent black that elected Democrats in 1990 were located in northern Alabama. In 1992, North Carolina Democrats held seven of the eight
seats from districts less than 3.5 percent black. All of the Democrats were elected from mountain districts adjoining Tennessee. Seven of the nine least-black districts in Virginia elected Democrats in 1991. Six of those formed a compact rural region in southwestern Virginia wedged between Kentucky, North Carolina, and West Virginia; the seventh was also located in southwest Virginia. This

North Carolina has multimember districts. Only three of the five districts less than 3.5 percent black were single-member districts; one district elected two representatives and another elected three.

20 The Appalachian regional effect does not explain why the log curve most successfully models the 1995 Mississippi election. Two of the four least-black districts that elected Democrats were located in the northeastern corner of the state, about as close as Mississippi comes to populist hill country. More likely, the success of the log model there simply results from coincidence; 5 percent of the non-linear transformations should appear significant by chance alone.
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Note: The value in each cell equals the probability of a Democratic victory in that state in the year indicated by the column label for the proportion black indicated by the row label. Looking down any column reveals how the estimated probability of a Democratic victory for the year indicated by the column label varies as the proportion black in a district increases. Looking across any row shows how the estimated probability of a Democratic victory at the proportion black indicated by the row label varies across time. Estimated from models described in the text; standard errors in parentheses were computed using the Tomz, Wittenberg, and King (1999) CLARIFY code. CLARIFY did not work for the cubic models so we have reported the original probability estimates from the logit models without standard errors for all cubic models (all TN models and SC 98). Proportion Hispanic equals .1 for Texas.
political geography is familiar to any student of Southern politics, although the relatively pro-Democratic pattern certainly is not.21

Interestingly, once the Republican party took control of Congress and gained stature within Southern institutions, their influence expanded in Appalachia as well. Democrats lost many of the these districts late in the decade, greatly reducing the temporary Democratic tendencies of these all-white locales. This continuing transformation explains why the basic linear model better fits the data for Georgia in the latter period (1994–8), for example. Despite stalling nationally, Republican realignment continued at the state legislative level into the late 1990s.

**Tennessee.** Tennessee diverges from the two patterns predominant in other Southern states. The cubic model fits best for all years, although the transformation itself usually falls short of statistical significance. Particularly for 1990, the curves have the potential to support the white- backlash theory, as the probability of electing a Democrat declines between 15 and 25 percent black. The effect mostly results from the paucity of districts between 20 and 25 percent black, however, because two suburban Memphis districts drive the pattern. Even Tennessee provides a thin reed upon which to rest claims of white backlash.

**Texas.** Since Texas contains a large and overwhelmingly Democratic Latino population,22 we control for the district share of Hispanics in all of the models for that state, not just the black percentage.23 We modeled the effect of both black density and Hispanic density using the same four functional forms. As expected, the log model best fits the data for black density for 1990–94. The linear model worked well for 1996–8, however. On the Hispanic side, a natural- log term consistently improved the logit model throughout the period.

Once again, regional effects explain the success of the natural-log models. Blacks and Hispanics tend to concentrate in different districts, so Democratic success is often quite high in places where one or the other ethnic group appears in negligible numbers. Blacks concentrate in east Texas and almost uniformly back Democrats. Latino Texans also support the Democrats, but are highly concentrated in districts with few blacks located in south Texas. The natural-log terms capture the phenomenon. The natural-log term for blacks does give out after 1994, however, when rising levels of Hispanic turnout strengthen those controls.

East Texas districts elected Democrats at a high rate compared to other districts with very few Hispanics. Culturally part of the South, East Texas nevertheless has retained an attachment to the Democratic party. This mostly rural region also contains far fewer Northern immigrants, who are unlikely to share the southern historical attachment to the Democrats, than Texas's large metropolitan areas, and more natives with relatively low incomes (Barone, Lilley, and DeFranco 1998). As a result, conservative Democratic candidates have been able to hold out, indicating that what drives the natural-log model may not be Appalachian geography so much as a history of populism.

### Racial Redistricting Cost the Democrats, But Realignment Had a Greater Impact

Table 2 breaks down changes in the number of Democratic seats from the last election held under the 1980s districting plan to each election held in the 1990s. Table 2a and 2b reveal the number of seats that the Democrats lost, judging from our probability models, due to the independent effects of redistricting and realignment. Redistricting and realignment also interacted to change election outcomes; the impact of the interaction effect is shown in Table 2c. Some argue that changes due to the interaction should not be counted when calculating the impact of redistricting, because they stem in part from changes in voting behavior (e.g., Grofman and Handley 1998). We prefer to think of those figures as the unanticipated effect of redistricting, or the effect of districting based on nonracial variables. Combining the effects presented in Table 2a and 2c produces the change that cannot be attributed directly to realignment.24

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21These heavily white districts in Appalachia are often not particularly Democratic. Indeed, as their history would suggest, they often lean to the Republicans. However, they are nevertheless more willing to support Democrats than other heavily white areas, which are often overwhelmingly Republican suburbs.

22Failure to distinguish Latinos from other nonblacks can misleadingly lead to the conclusion that Democrats fare better in heavily "white" districts (Lublin 1999).

23Florida also contains a sizeable Latino population. However, the proportion of Latinos in Florida is only around one-half of that in Texas. Moreover, Florida Latinos are much more heterogeneous in their politics. Consequently, we did not control separately for the presence of Latinos in Florida.

24The D, A, and I aggregates summarized here fall into a hazy terrain between description and inference. Since we have a census of
TABLE 2 Change in Seats Held by Democrats Since 1990 Due to Redistricting and Realignment

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Number of Black Majority Districts

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Number of Seats

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Note: Louisiana and Virginia held elections in odd-numbered years. Mississippi held elections in 1992 and 1995. All other states held elections in even-numbered years. The estimated effect of Redistricting represents how many seats the Democrats lost, assuming the counterfactual that people responded to district racial density in the same way that they did in the last election held under a state’s 1980s-era electoral map. The estimated effect of Realignment represents how many seats Democrats lost, assuming the counterfactual that district racial demographics remained unchanged from their 1980s-era distribution. The Interaction effect reconciles these two seat changes with the actual change in each state legislature’s partisan composition. A negative sign represents Democratic loss, such as the 20-seat realignment loss estimated for Georgia in 1994.

The results for part (a) are presented only for the first election held in each state under each new redistricting plan, since the independent effect of redistricting must be invariant within a given electoral map. When a state has multiple entries for the 1990s, such as Texas, that indicates frequent changes in electoral districts. Realignment effects can vary from election to election, however, so the remaining portions of the table present results for each election held in the state. See the text for precise details on how the two counterfactuals were computed.

We estimate that racial redistricting independently cost the Democrats at least one seat in each state. In two states, the independent effect of redistricting apparently

... southern elections, our logit coefficients are population summaries; the only source of noise is our decision to use a parametric model. Yet projecting from observed partisan change to what would happen over repeated redistricting cycles does involve error; the observed changes that we observe here would not be identical with a different set of districts or a different sort of realignment. We therefore used simulations from CLARIFY, based on the covariances among our logit coefficients, to compute 500 sets of aggregate statistics for each model and used their variation to represent the uncertainty. Results indicated that, while the redistricting effect for any one state-year model was within two standard deviations of zero, the chance of finding consistently partisan redistricting effects over the entire region was well below conventional confidence levels. Thus we can state with confidence that redistricting generally would lose the Democrats a large number of Southern state legislative seats, although how these would be distributed across states might vary with each sample.

... took control of the chamber away from the Democrats for the first time since the end of Reconstruction. The loss of six seats by South Carolina Democrats cost them control of the House chamber in 1994 and 1996. If one includes the interaction effect, around eight seats for 1994–98, South Carolina Democrats likely would have unified control of state government in 1999. Virginia Democrats similarly would not have had to share control after 1997 if redistricting had not independently cost them more than two seats (nearly five seats if one includes the interaction effect).25 North Carolina Demo-

25Democrats won 52 percent (64 of 124) of South Carolina House seats in 1994, down from 59 percent (73 of 124) in 1992, but defections allowed the Republicans to organize the House in 1995. After the 1996 elections, Democrats held 48 percent (59 of 124) of House seats. South Carolina Democrats continue to hold the state
crats, who lost control of the House in 1994, might have won back control in 1996, instead of 1998, if redistricting had not cost them several seats (two independent of realignment, around five including in the interaction effect).

The estimated independent effect of realignment was actually positive in Florida, Louisiana, North Carolina, Tennessee, Texas, and Virginia in 1991–2, indicating that the Democrats would have gained seats absent redistricting. Although several of these states enjoyed pro-Democratic gerrymanders (Lublin 1997, 110), this finding also likely resulted from southerner Bill Clinton’s presidential candidacy buffering his party in the region—a temporary delay of what has proved to be a steady, gradual realignment away from the Democrats in eight of the ten states. Moreover, disappointment with Clinton undoubtedly played a role in the massive losses, particularly in Georgia and North Carolina, in 1994.

North Carolina and Tennessee form the only exceptions to the pattern of steady erosion in Democratic support over the 1990s. North Carolina Democrats suffered a crushing loss of more than twenty-five seats due to realignment in 1994, but they made up over one-half of those losses over the next two elections. In 1992–98, Tennessee Democrats always won at least three more seats than in 1990. In every state other than North Carolina and Tennessee, realignment cost the Democrats an increasing number of seats with each election. By 1998, the realignment effect far outweighed even the total effect of redistricting in all states except Tennessee.

It is worth noting that institutional factors may influence the magnitude of the negative effect of redistricting on Democratic prospects. In particular, anecdotal evidence suggests that Democratic efforts to gerrymander may minimize the negative effect of redistricting. Despite drawing seven new black majority districts apiece, Democrats in Louisiana and North Carolina, for example, both managed to limit their losses to under three seats. A systematic analysis of the relationship of partisan control to redistricting losses, however, is beyond the scope of this study—since the state-level sample size is too small to permit rigorous exploration of the question. In any case, the estimated effect of racial redistricting on Democratic prospects was negative in all ten states.

### Analysis: Why Did Racial Redistricting Hurt the Democrats?

Racial polarization in voting is quite high, and getting higher, as more whites, but not blacks, choose to vote Republican. Racial redistricting would aid the Democrats if racial polarization ever became so extreme that Democrats could carry only black majority districts. For now, though, the situation is not so dire; many whites continue to support Democratic state legislative candidates. As Table 1 shows, the probability of a Democratic victory in 30 percent black districts remained very high in most states throughout the 1990s. Increasing the share of African Americans to 40 percent pumped up the chances of a Democratic victory to a near certainty in many states, including Alabama, North Carolina, and Texas, and to around .9 or higher in most others. Raising the black population share to 50 percent, or 65 percent as often advocated by proponents of racial redistricting (e.g., Parker 1990), boosts the probability of a Democratic victory only marginally.

Nothing in southern voting patterns compensates Democrats in white-majority districts that lose black voters. The probability of a Republican victory noticeably jumps as the proportion of blacks falls below 30 percent. For example, hiking the share of blacks from 30 percent to 50 percent increased the probability of a Democratic victory by under 3 percentage points in Alabama in 1998 (CLARIFY estimates a rise of 2.7, with a standard error of 6.7). Reducing the share of blacks of a similar district from 30 percent to 10 percent, meanwhile, drops the likelihood of a Democrat holding the seat by 52.2 percentage points (standard error of 16.1), to only 39 percent (standard error of 7.7). Racial redistricting creates new seats that are much more vulnerable to Republican attack. Table 3 shows that the proportion of districts less than 20 percent black increased substantially in many states due to redistricting, at the expense of minority-influence districts.26

Redistricting exacerbated the harm of partisan realignment to the Democrats, because it created the

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26 Reducing the share of blacks will not aid Democrats even in states where the log model fits the data. Districts that lose substantial black voters due to racial redistricting can never become the sort of heavily white region that sometimes elects Democrats at unusually high rates.
Table 3  Change in Distribution of Seats from 1980s Plan by Racial Composition

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<td>-14 -10 -9</td>
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Note: The row labels indicate a state legislative district population’s racial density. The columns report change in the number of each type of district, compared to the last 1980s-era electoral map. So Mississippi, for example, lost 10 “influence” districts in the 30–40% black range, and 8 more in the 40–50% range. These districts were replaced by 4 black-majority districts, as well as 15 predominantly white districts of the sort (i.e., 10–20% black) that experienced dramatic realignment toward the Republican party during the 1990s.

favorable terrain on which Republicans saw their greatest gains. The realignment almost exclusively affected white voting behavior, so Republican gains were concentrated in heavily white districts. The probability of Republican success in districts below 20 percent black rose dramatically over the course of the decade, exactly the sort of district that racial redistricting tends to create (see Table 3). The remaining Democrats who represented districts with a healthy minority population, by contrast, did not suffer any pro-Republican realignment. The probability of a Democratic victory fell only a little, or not at all, in 40 percent black or greater districts in most states. The synergy between redistricting and realignment caused the Democrats to lose more seats than either effect could cause independently (see Table 1).

Unexpectedly, the probability of electing a Democrat actually rose in some states, at least temporarily, in the critical 25–50 percent black range, the very type of districts that racial redistricting usually depletes. Alabama districts greater than 17 percent black in 1994 and 22 percent black in 1998 actually had a higher probability of electing a Democrat than in 1990. All districts greater than 17 percent black in Florida from 1992 to 1996 and in Georgia in 1992 were less likely to elect Republicans than similar districts in 1990. South Carolina districts greater than 28 percent black in 1992–94 and 40 percent black in 1996–98 were more likely to elect Democrats than the equivalent districts in 1990. Throughout the 1990s, Tennessee and Texas districts greater than 8 percent and 21 percent black, respectively, elected Democrats at a higher rate than the districts with the same racial composition in 1990.27 Racial redistricting sharply curtailed the quantity of this fertile ground available to Democratic candidates.

A white-backlash phenomenon might have mitigated the negative impact of creating many more heavily white districts, by reducing the political threat that whites felt. Had white voters responded in this way to falling minority populations in their legislative districts, Democratic state legislative prospects might have improved, by depleting the districts just short of a black majority where backlash would concentrate. It is precisely the absence of any backlash phenomenon that explains why racial redistricting harms the party selected by most black voters. It packs minority voters into the same districts as many of their white allies, leaving those Democratic fortresses besieged all sides by the Republican South.

27The Texas figure was calculated with the percentage of Hispanics set at 10 percent, only slightly lower than typically found in districts greater than 10 percent black.
Conclusion

The racial redistricting literature remains inconclusive, at least in terms of the policy's partisan effects. The few congressional contests usually studied provide examples of electoral maps that hurt the Democrats, but also of partisan gerrymanders that protected them—and an insufficient number of either to detect the central tendency. State legislative elections greatly expand the sample available. The findings reported in this article suggest that, while the effects of redistricting are probabilistic, the central tendency is precisely what common sense would dictate: packing loyal Democrats into majority-minority enclaves hurts their party, sometimes minimally, sometimes enough to cost control of a legislative chamber. Minority voters once served as an anchor for Southern Democrats, helping them weather the storm of partisan shifts among a center-right white constituency, but redistricting cut those moorings away.

Our large data set included a wide range of districts, expanding the variation in racial density compared to congressional seats. The greater number of "minority influence" districts allowed statistically viable tests for the main behavioral regularity that could counterbalance the effect of "bleaching" southern districts: a white-backlash phenomenon. If whites reacted negatively when in proximity with African Americans, as the backlash hypothesis predicts, then bleaching predominantly white districts could help the Democrats. Such is not the case. When we allowed a probability model to capture the backlash pattern where a white majority might feel threatened, the only place it came close to doing so was Tennessee—where "minority influence" districts were as rare as they are for congressional contests.

One other wrinkle added to our probability model was more successful: an attempt to capture modern Democratic sympathies in the Appalachian region. The South's highland districts initially resisted realigning toward the GOP in the early 1990s, sending a disproportionately high number of Democratic representatives to the statehouse given their minuscule black population. The trend is all the more surprising given a history of "mountain Republicanism" that dates to the Civil War. Taking the political geography of Appalachia into account is important, because otherwise those districts will inflate the estimated probability of Democratic victory in bleached districts. It is one reason our models recognized that racial redistricting hurt the Democrats in all 10 southern states observed here.

That racial redistricting underruts the political party supported by most African-American voters does not necessarily mean that activists should abandon such attempts to increase black representation. African Americans may not wish to abandon a strategy that has resulted in the election of substantial numbers of black state legislators for the first time since Reconstruction (Davidson and Grofman 1994). Gains in the quality of representation easily could outweigh losses in Democratic strength, especially in Southern states where white Democrats are often conservative—a judgment that this research cannot inform.

Nevertheless, in highly competitive arenas, the loss of a few Democratic seats can tip whole legislative chambers to the Republican party. Racial redistricting cost the Democrats control of state legislative chambers in at least two states (South Carolina, Virginia, and possibly North Carolina). Racial redistricting also heightened both polarization and diversity in state legislatures across the South. The rise of black liberal Democrats and white conservative Republicans at the expense of white moderates provides a greater spectrum of views within any chamber, but also assures greater polarization and probably gridlock (McDonald 1999). Highly conservative Republican state representatives have little need to consider, let alone compromise with, black preferences. The analysis reported here therefore should give policy makers a more realistic sense of the costs that accompany this particular policy mechanism, costs that many commentators have tried to ignore or minimize.

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Final manuscript received March 30, 2000.
## Appendix: Model Tests

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Note: For each state and each year, we retained one of four models, either a simple logit or a non-linear transformation of the log-odds equation (choles indicated in boldface). Departures from the conventional logit primarily were based on simple hypothesis tests, which indicate whether the non-linear transformations approach statistical significance. Wald’s test is a generalized form of the familiar two-tailed t-test. Likelihood ratio tests similarly reveal if the improvement of complex models over simpler models likely were due to random chance (see King 1989, section 4.6). The measure of fit becomes necessary only when more than one non-linear transformation improves on the base logit model. To compute it, we first calculated each district’s predicted probability of electing a Democrat. Second, we divided observations into one of four groups based on the district black percentage (0–5, 5–15, 15–25, 25–100), and summed the probabilities within each category to compute the number of expected Democrats. Finally, this estimate was subtracted from the actual number of Democrats elected in each group to calculate the prediction error.

References


McDonald, Michael D., and DeWanye Lucas. 1998. Unpublished manuscript in possession of the authors.


