Ohio 2004 Election: Turnout, Residual Votes and Votes in Precincts and Wards Walter R. Mebane, Jr., and Michael C. Herron June 9, 2005

During the first five months of 2005, the DNC Ohio 2004 Investigative Project collected extensive data from precincts throughout Ohio. Eric Greenwald spearheaded the data collection effort. The effort produced a combination of electronic spreadsheet files and many PDF files containing images from faxes of scanned documents. The most important spreadsheet was a file produced by the Ohio Secretary of State office that reported registered voter counts, counts of votes cast and voting returns for precincts from all Ohio counties. The image documents needed to be converted into spreadsheet format in order to be merged with the other data. Matthew Rado performed this work. Michael Herron was responsible for merging all the files in a comprehensive precinct-level database. That task was made difficult especially by a proliferation of naming conventions Boards of Elections (BoEs) used to refer to precincts. Herron hired an assistant to help with that name reconciliation task. Along the way there were also numerous ambiguities, errors and inconsistencies in the files provided by the county BoEs that especially Greenwald and Herron worked to resolve.

This report reviews the most important patterns we have uncovered in the precinct data as of this writing. We begin by summarizing the principal findings. Then we present explanations for the series of figures and tables that are computed from the data and presented in the latter part of this report. The figures and tables are intended to be viewed in order, and the discussion of them builds a story from beginning to end. The discussion there is organized in three phases: first, getting to the polls (voter turnout); second, getting one's vote to count (residual votes); third, getting one's preferences for a candidate accurately recorded (vote choices). Appendices included at the end of this report briefly describe the data and the statistical tools used to perform and report the analysis.

Summary of Principal Findings

- 1. Problems with election administration seriously affected the 2004 election. Not providing a sufficient number of voting machines in each precinct was associated with roughly a two to three percent reduction in voter turnout presumably due to delays that deterred many people from voting. The inferior voting machine technology used in most places throughout the state (punchcard machines instead of precinct-tabulated optical scan machines) was associated with an additional one percent of votes that were cast not being counted.
- 2. Increases in voter turnout above the rates expected based on the 2002 general election were strongly associated with the proportion voting Yes on Issue 1 (opposing gay marriage). Typical increases associated with support for Issue 1 range from a low of about one-half percent among precincts in Cuyahoga County and other counties using punchcard voting machine technology (except Hamilton County), to more than one percent in precincts in Hamilton County and in counties using centrally tabulated optical scan voting machine technology or direct record electronic (DRE) machines (except Franklin county), up to two percent or more in Allen, Franklin and Lucas counties. Support for Issue 1 mobilized many people to vote who may not have done so otherwise.

- 3. Strong similarities at the precinct level between the vote for Kerry (instead of Bush) in 2004 and the vote for the Democratic candidate for governor in 2002 (Hagan) present strong evidence against the claim that widespread fraud systematically misallocated votes from Kerry to Bush. In most counties we also observe the pattern we expect in the relationship between Kerry's support and other precinct-level factors: Kerry's support across precincts increases with the support for the Democratic candidate for Senator in 2004 (Fingerhut), decreases with the support for Issue 1 and increases with the proportion African American. Only in Cuyahoga County is the relationship between Kerry's vote and the support for Issue 1 significantly unusual.
- 4. If increases in registration reflect voter mobilization efforts, then mobilization tended to help Kerry in all the places included in this analysis except in precincts using precinct-tabulated optical scan machines (which are all in Allen County). But if increases in voter turnout are the standard for measuring mobilization efforts, then Kerry does not come off so well. Over all precincts and wards in the analysis, the proportion voting for Kerry decreases as turnout in 2004 increases, even when turnout in the 2002 election is taken into account. This suggests that voter mobilization efforts focused on turnout on balance hurt Kerry, at least if one takes 2002 as the baseline.
- 5. Changes in registration in a precinct are for the most part positively but weakly related to changes in turnout: for the most part, a proportional increase in registration means an increase in voter turnout. One interpretation is that in these precincts new registrants tend to be somewhat more likely to vote than previous registrants were. The exception occurs among precincts using precinct-tabulated optical scan machines, where a proportional increase in registration means a decrease in voter turnout.
- 6. The presidential residual vote rate (here defined as the fraction of ballots without a vote for either Bush, Kerry, Bedarnik or Peroutka) is inversely related to the number of voting machines per registered voter in both DRE precincts and precincts using precinct-tabulated optical scan machines: more machines meant a lower residual vote rate. The mechanism that most likely produces this effect is easy to understand: with fewer machines per voter, polling places become more crowded and voters are less likely to take the time to check or correct their ballots.

Explanation and Interpretation of Each Figure and Table

Table 1: This shows the Ohio counties that used each of four kinds of voting machine technology in the 2004 general election. Four machine technologies were used in Ohio in 2004: direct record electronic (DRE) or touchscreen machines; centrally tabulated optical scan machines; precinct-tabulated optical scan machines (used in only Allen County); and punchcards. The distinction between centrally tabulated and precinct-tabulated optical scan machines is that the latter allow what is known as "second chance voting," i.e., the opportunity for a voter to review the ballot if, after inserting it in a counting machine, the voter is made aware of problems in it.

Figure 1: This shows the distribution of voter turnout (number of votes cast divided by number of registered voters) across Ohio precincts by voting machine technology. Each boxplot shows the distribution for one of the technologies. As in all the figures in this report in which the

"Punchcard" category appears along with "Punchcard Cuyahoga" and "Punchcard Hamilton" categories, the set of "Punchcard" precincts excludes the precincts in Cuyahoga and Hamilton counties, which are reported separately. Turnout tends to be lowest in Cuyahoga and DRE precincts and highest in Hamilton and Optical Central precincts. Turnout in Punchcard precincts is typically about as high as in Optical Central precincts, but numerous Punchcard precincts have unusually low turnout. Optical Precinct precincts typically have turnout slightly higher than DRE precincts. *It is unlikely that the type of voting machine technology is in itself a reason for the median level of turnout in a county.* For instance, contrast Cuyahoga and Hamilton counties.

Table 2: This shows the Ohio counties (79 of them) for which we have specific information about the number of voting machines used in each precinct in the 2004 general election.

Table 3: This reports robust estimates of an overdispersed binomial regression model that has voter turnout depending on both the type of voting technology and the number of voting machines per registered voter in each precinct. The model is estimated separately for the precincts in each voting machine technology category, hence the interecept parameter measures the overall mean level of turnout among precincts in each category. The model also includes a parameter to measure the effect the ratio of voting machines to the number of registered voters has on turnout. Using MV to denote the voting machines per registered voter ratio MV = (voting machines)/(registered voters), a linear predictor for precinct *i* may be written as

$$Z_i = b_0 + b_1 \mathbf{M} \mathbf{V}_i$$

follows:

The fact that the estimate for b_1 is $\hat{b}_1 = 113$ for DRE precincts and is $\hat{b}_1 = 149$ for Hamilton precincts indicates a substantial dependence between the machine/voter ratio and voter turnout in those precincts: where the number of voting machines per person is higher, voter turnout tends to be higher. For Optical Central and Punchcard precincts there is also a significant albeit smaller positive relationship between the machine/voter ratio and voter turnout. For Cuyahoga and Optical Precinct precincts the relationship is small and negative, although the estimate is not statistically significant in the latter case. The display at the bottom of Table 3 illustrates the magnitude of these effects by computing expected turnout rates for precincts at the first quartile, the median and the third quartile of the MV values for precincts using each type of technology. Moving from the first to the third quartile of the voting machines per registered voter ratio is associated with an increase of about 3.6 percent in voter turnout among DRE precincts, 2.5 percent among Hamilton precincts, two perceent among Punchcard precincts and 0.7 percent among Optical Central precincts. Among Optical Precinct and Cuyahoga precincts the expected turnout rate declines by small amounts when moving in this simulated way from the first to the third quartile. The key result here supports the claim that a scarcity of voting machines caused delays (i.e., long lines) that deterred many people from voting. The effect of the number of voting machines per registered voter is especially pronounced in precincts that used DRE technology (e.g., in Franklin County) and in Hamilton County. The results are also compatible with an alternative explanation, however, which is that BoEs allocated machines to precincts in relationship to their expectations regarding voter turnout and those expectations tended to be accurate at least in terms of the differences in turnout between precincts. We try to assess this alternative explanation below. It is well known, however, that long lines and long waits characterized voters' experiences at many polling places in Ohio in 2004, and that BoEs did not do a uniformly good job anticipating voter turnout. Even though we lack data to be able to

measure the time it took to vote in each precinct, it is unreasonable to believe that all of the relationships shown here reflect the success of prior administrative plans. Instead the estimated relationships between the number of voting machines per registered voter and voter turnout reflect widespread administrative failures on election day in 2004.

Table 4: This lists the outlier precincts identified in the analysis reported in Table 3. Listed are the county name, the state precinct code and the studentized residual for each precinct that ultimately received zero weight in that analysis. The table groups the outlier precincts by the kind of voting machine technology used in each one. All the outliers have negative residuals, meaning that they all have observered voter turnout much lower than expected based on the technology and the number of voting machines per registered voter. A substantial number of precincts in Butler County (11 of 288 precincts) have observed voter turnout much lower than expected.

Table 5: This shows the Ohio counties that contained precincts that had the same boundaries in both the 2002 and 2004 elections. Overall, 5,423 precincts had constant boundaries between the two elections. The determination that a precinct's boundaries did not change is not perfectly reliable. In most cases we relied on reports from BoE officials about which precincts had changed, supplemented by plausibility checks conducted using voter registration data. We found that the reports from BoE officials were often mistaken, sometimes revised in response to our queries. Surely the data still include errors. For Cuyahoga County the constant-boundary determination was based not on official reports but on direct comparisons between the shapefiles for the precincts used in the 2002 and 2004 elections.

Table 6: This shows the Ohio counties containing precincts with constant boundaries between 2002 and 2004 for which we were able to obtain specific information about the number of voting machines used in each precinct in the 2004 general election.

Table 7: This shows results from a Poisson regression analysis of the number of voting machines in each precinct. The purpose is to address the argument that a relationship exists between voter turnout and the number of voting machines per registered voter because BoEs allocate more voter machines to precincts where they expect turnout to be higher. In this Poisson regression the number of voting machines in each precinct is specified to depend on two variables: the number of voters registered in the precinct in 2004; and the rate of voter turnout in the precinct in the 2002 general election. The Poisson regression specifies that the expected number of machines is an exponential function of a linear function of the regressors. Let RV2004 denote the number of registered voters in 2004 and let NV2002 denote the number of votes cast in 2002 (this model fits the data better than one that uses the 2002 voter turnout rate for the second regressor). The Poisson regression specifies

Expected number of machines_i = $\exp(a_0 + a_1 \log(\text{RV2004}_i) + a_2 \log(\text{NV2002}_i))$,

where a_0 , a_1 and a_2 are unknown coefficients to be estimated. If the number of machines in a precinct tends to be proportional to the number of registered voters, then $a_0 < 0$, $a_1 = 1$ and $a_2 = 0$. If the expected number of machines in a precinct is higher given that turnout in 2002 was higher, then $a_2 > 0$. The analysis is restricted to precincts that had the same boundaries in both the 2002 and 2004 elections. No results appear in Table 7 for the Optical Precinct precincts, even though Allen County precinct boundaries were constant, because every precinct in Allen County had three machines. In no case does the estimate for a_1 equal 1.0, but the estimate is large and positive for Punchcard, Cuyahoga and Hamilton precincts. The estimate for a_1 is positive but

small and statistically insignificant for DRE precincts (note that these are only Mahoning County precincts). In all these punchcard and DRE cases, the results indicate that the expected number of voting machines in a precinct tended to increase with the number of voters registered for the 2004 election, although the increase was less than proportional. Oddly, for Optical Central precincts the number of voting machines tends to decrease as the number of registered voters increases. For DRE, Punchcard and Hamilton precincts the results also show that the expected number of voting machines in a precinct tended to increase with the number of votes cast in the 2002 general election. Oddly, among Cuyahoga precincts the expected number of voting machines tends to decrease as the number of votes cast in 2002 increases. There is clear evidence that the allocation of machines among DRE, Punchcard and Hamilton precincts depends on the number of votes cast in the previous general election: more votes in a precinct in the previous election means more machines. In Cuyahoga, weirdly, the relationship is reversed: more votes in a precinct in the previous election means fewer machines. A weakness in this analysis is that we lack data about the previous election results in Franklin County, where most of the DRE precincts in Table 3's analysis are located. Precincts with constant boundaries were lacking there. The fact that the number of machines increased with the votes cast in the previous election in Mahoning County tells us nothing about the situation in Franklin County.

Figures 2 and 3: These show that voter turnout is higher in precincts in which a lower proportion of the population is African American. It makes sense to take the relationship between race and voter turnout into account.

Table 8: This reports robust estimates of an overdispersed binomial regression model that has voter turnout depending on the type of voting technology, the number of voting machines per registered voter in each precinct and the proportion of the population in each precinct that is African American. The negative estimated coefficient shows that turnout is typically lower when the proportion African American is higher. But the results regarding voting machine technology and the number of voting machines per registered voter remain largely unchanged. *Even with the proportion African American taken into account, the results support the claim that a scarcity of voting machines caused delays that deterred many people from voting.* Using the estimated parameters to compute expected voter turnout when the proportion African American is fixed equal to the median value for that proportion among precincts that use the referent voting machines per registered voter ratio is associated with changes comparable to those reported in Table 3.

Table 9: This lists the outlier precincts identified in the analysis reported in Table 8. The list overlaps considerably with the list in Table 4.

Figure 4: This shows the distribution of voter turnout by voting machine technology across Ohio precincts that did not change boundaries between the 2002 general election and the 2004 general election. The picture is not all that different from Figure 1. This similarity is important because we will be looking at changes in turnout from 2002 to 2004, and it is reassuring that the subset of precincts that had constant boundaries is not grossly different from the set of all precincts.

Figure 5: This shows the distribution of voter turnout by voting machine technology across Ohio wards in four large counties. These wards did not change boundaries between the 2002 general election and the 2004 general election. As is the case with the precinct data, Hamilton wards are more similar to the Punchcard precincts with unchanged boundaries (which include Hamilton's precincts) than Cuyahoga wards are. Cuyahoga wards have substantially lower turnout rates. Franklin wards have slightly lower turnout than the DRE precincts that have unchanged boundaries (all of which are in Mahoning County). Lucas wards have somewhat lower turnout than the Optical Central precincts that have unchanged boundaries.

Figure 6: This shows a scatterplot relating turnout in 2004 to turnout in the 2002 general election in precincts that had the same boundaries in both elections. The plot also shows the slope of the line produced by ordinary least squares regression of the 2004 turnout rate on the 2002 turnout rate. The positive slope of the line is not surprising, as we would expect the same precincts to have typically high or typically low turnout in different elections. *Turnout did not increase in every precinct throughout Ohio from 2002 to 2004. Several precincts show substantial drops in turnout.* In some cases these precincts include very small numbers of registered voters.

Figure 7: This shows a scatterplot relating turnout in 2004 to turnout in the 2002 general election in the selected wards that had the same boundaries in both elections, along with the ordinary least squares regression line. Unsurprisingly the slope of the line is positive. Turnout in 2004 is never lower than turnout in 2002.

Figure 8: This shows scatterplots relating turnout in 2004 to turnout in the 2002 general election in precincts that had the same boundaries in both elections, separating the precincts by the type of voting machine technology. In every case, turnout in 2004 is positively related to turnout in 2002. Among Optical Precinct, Punchcard and Cuyahoga precincts are several precincts that had higher turnout in 2002 than in 2004.

Figure 9: This shows scatterplots relating turnout in 2004 to turnout in the 2002 general election in the selected wards that had the same boundaries in both elections, separating the precincts by county. In every case, turnout in 2004 is positively related to turnout in 2002. Every ward has higher turnout in 2004 than in 2002. *The plots show clearly that at every level of 2002 turnout, wards in Hamilton and Lucas counties had higher 2004 turnout than did wards in Cuyahoga and Franklin counties.*

Table 10: This reports robust estimates of an overdispersed binomial regression model that has 2004 voter turnout depending on 2002 voter turnout. Estimates appear separately for technology groupings of the precincts that had the same boundaries in the two elections and for county groupings of the wards that had constant boundaries. Using V2002 to represent the rate of voter turnout in 2002, the linear predictor in the model may be written as follows:

 $Z_i = c_0 + c_1 \text{logit}(V2002_i)$

(see the Appendix for an explanation of the logit function). If turnout in 2004 were the same as in 2002 except uniformly higher, then we would have $c_0 > 0$ and $c_1 = 1$ (the Appendix explains this). We already know from the scatterplots that that is not the pattern in these data. Indeed, the estimates for c_1 in Table 10 are positive but smaller than 1.0. Several precincts but no wards are outliers. *Turnout in 2002 is a good predictor but far from a perfect predictor of turnout in 2004*.

Table 11: This lists the outlier precincts identified in the analysis reported in Table 10. *Precinct outliers occur sporadically when turnout in 2002 is used to predict turnout in 2004. There are no ward outliers.*

Table 12: This reports robust estimates of an overdispersed binomial regression model that has 2004 voter turnout depending on 2002 voter turnout and the number of voting machines per registered voter. Estimates appear separately for technology groupings of the precincts that had the same boundaries in the two elections and for county groupings of the wards that had constant

boundaries. Using V2002 to represent the rate of voter turnout in 2002 and using MV to denote the voting machines per registered voter ratio MV = (voting machines)/(registered voters), the linear predictor in the model may be written as follows:

$$Z_i = c_0 + c_1 \operatorname{logit}(V2002_i) + c_2 \operatorname{MV}_i$$

(see the Appendix for an explanation of the logit function). The estimator already adjusts turnout in each precinct for the number of voters registered to vote there in 2004, so this model represents one way to check whether the number of voting machines per registered voter has an effect on voter tunout independent of the efforts BoEs may undertake to allocated more voting machines to places where they expect voter turnout to be higher. This approach is far from perfect. For instance, the analysis produces the correct answer only if the relationship between turnout in 2002 and the allocation of voting machines in 2004 follows a particularly simple functional form (moreoever, not exactly the form used in the analysis reported in Table 7). Caveats notwithstanding, the fact that the estimate for c_2 is statistically significant and positive for DRE, Punchcard and Hamilton precincts may further support a conclusion that a scarcity of voting machines caused delays in those places that deterred many people from voting. Net of the level of 2004 voter turnout expected based on voter turnout in 2002, there is no significant relationship between the number of voting machines per registered voter and 2004 voter turnout among Optical Precinct or Cuyahoga precincts. Weirdly, the net relationship between the number of voting machines per registered voter and 2004 voter turnout is negative among the Optical Central precincts in the analysis.

Table 13: This lists the outlier precincts identified in the analysis reported in Table 12. The list of outliers is virtually the same as in the model that includes only the past voter turnout regressor. The turnout anomalies in these places seem to have little to do with the number of voting machines per registered voter.

Figure 10: This shows scatterplots relating the number of registered voters in 2004 to the number of registered voters in the 2002 general election in precincts that had the same boundaries in both elections, separating the precincts by the type of voting machine technology. The lines in this case are 45 degree lines, not regression lines. *Weirdness, defined as large reductions in the number of registered voters, occurs often among Optical Precinct (Allen County), Punchcard, Cuyahoga and Hamilton precincts.*

Figure 11: This shows scatterplots relating the number of registered voters in 2004 to the number of registered voters in the 2002 general election in the selected wards that had the same boundaries in both elections, separating the wards by county. The lines in this case are 45 degree lines, not regression lines. Only one ward in Franklin County shows a large reduction in the number of registered voters.

Figure 12: This shows scatterplots relating the change in turnout from 2002 to 2004 to the proportional change in voter registration from 2002 to 2004 in precincts that had the same boundaries in both elections, separating the precincts by the type of voting machine technology. The proportional change in registration is (RV2004 - RV2002)/RV2002. The lines are the regression lines. *Changes in registration are for the most part positively but weakly related to changes in turnout: for the most part, a proportional increase in registration means an increase in voter turnout. One interpretation is that in these precincts new registrants tend to be somewhat more likely to vote than previous registrants were. The exception occurs among Optical Precinct precincts, where a proportional increase in registration means an decrease in voter turnout.*

Figure 13: This shows scatterplots relating the change in turnout from 2002 to 2004 to the proportional change in voter registration from 2002 to 2004 in the selected wards that had the same boundaries in both elections, separating the wards by county. The lines are the regression lines. *Among wards in Cuyahoga, Franklin, Hamilton and Lucas counties, a proportional increase in registration is associated with an increase in turnout, which suggests that in these wards new registrants tend to be more likely to vote than previous registrants were.*

Figure 14: This shows a scatterplot relating the proportion voting Yes on Issue 1 (opposing gay marriage) to 2004 voter turnout across all Ohio precincts. The line is the regression line. *Where a higher proportion of voters support Issue 1, turnout is higher.*

Figures 15 and 16: These show scatterplots relating the proportion voting Yes on Issue 1 (opposing gay marriage) to the change in voter turnout rates from 2002 to 2004 across all precincts that had the same boundaries in both elections, where both variables have been residualized by regressing each on 2002 turnout (each is regressed on 2002 turnout and the residuals from that regression are retained; these residuals appear in the scatterplots). This is one way to assess whether a higher proportion voting yes on Issue 1 in a precinct is associated with higher turnout in that precinct even when turnout in the previous election is taken into account. The line is the regression line. *Turnout in 2004 increases as support for Issue 1 increases, even when turnout in the 2002 election is taken into account. These results support the claim that support for Issue 1 mobilized some people to vote who may not have done so otherwise.*

Figures 17 and 18: These show scatterplots relating the proportion voting Yes on Issue 1 (opposing gay marriage) to the change in voter turnout rates from 2002 to 2004 across all precincts and selected wards that had the same boundaries in both elections, where both variables have been residualized by regressing each on 2002 turnout. Precincts are separated by the type of voting machine technology and the wards are separated by county. The lines are the regression lines. *For each subset of precincts grouped by voting machine technology, turnout in 2004 increases as support for Issue 1 increases, even when turnout in the 2002 election is taken into account. The relationship is extremely weak among wards in Cuyahoga County, but the analysis by precinct shows a relationship not much different from the one found in other places. It appears that Cuyahoga wards are internally heterogenoeous with respect to voter mobilization and support for Issue 1. These results support the claim that support for Issue 1 mobilized some people to vote who may not have done so otherwise.*

Table 14: This reports robust estimates of an overdispersed binomial regression model that has 2004 voter turnout depending on 2002 voter turnout and the support for Issue 1. Estimates appear separately for technology groupings of the precincts that had the same boundaries in the two elections and for county groupings of the wards that had constant boundaries. Using V2002 to represent the rate of voter turnout in 2002 and using I1 to denote the proportion voting Yes on Issue 1, the linear predictor in the model may be written as follows:

$$Z_i = c_0 + c_1 \operatorname{logit}(V2002_i) + c_2 \operatorname{logit}(I1_i)$$

(see the Appendix for an explanation of the logit function). The estimator already adjusts turnout in each precinct for the number of voters registered to vote there in 2004, so this model represents one way to check whether support for Issue 1 has an effect on voter tunout independent of the relationship between previous voter turnout and support for Issue 1. This approach is far from perfect. For instance, it omits consideration of the previously considered effects of the number of voting machines per registered voter. Caveats notwithstanding, the fact that the estimate for c_2 is statistically significant and positive for every collection of precincts and for the wards in Franklin and Lucas counties supports a conclusion that support for Issue 1 mobilized some people to vote who may not have done so otherwise. The estimates for c_2 among wards in Cuyahoga and Hamilton counties are not statistically significant, but the fact that the estimates among precincts in those counties are significant suggests that the insignificant ward-level effects reflect the fact that those wards are internally heterogenoeous with respect to voter mobilization and support for Issue 1. A ward-level analysis simply misses the important politics relating to Issue 1 in Cuyahoga and Hamilton counties.

Table 15: This illustrates the magnitude of the Issue 1 effects estimated in Table 14, by computing expected turnout rates for precincts at the first quartile, the median and the third quartile of the proportion voting Yes on Issue 1 for precincts using each type of technology and for the wards in each county. *Moving from the first to the third quartile of the proportion voting Yes on Issue 1 is associated with an increase of about 1.9 percent in voter turnout among Optical Precinct precincts, 1.7 percent among DRE and Hamilton precincts, 1.2 percent among Optical Central precincts, and about one-half perceent among Punchcard and Cuyahoga precincts. Among wards in Franklin and Lucas counties moving from the first to the third quartile of the proportion voting Yes on Issue 1 is associated with an increase of slightly more than two percent in voter turnout. Support for Issue 1 mobilized many people to vote who may not have done so otherwise.*

Table 16: This lists the outlier precincts identified in the analysis reported in Table 14. The list of outliers is virtually the same as in the model that includes only the past voter turnout regressor. The turnout anomalies in these places seem to have little to do with the support for Issue 1.

Figures 19 and 20: These show scatterplots relating the proportion of votes for Kerry to the proportional change in voter registration from 2002 to 2004 in precincts and wards in selected counties that had the same boundaries in both elections, separating the precincts by the type of voting machine technology and the wards by county. The lines are the regression lines. A larger increase in registration is associated with a higher proportion of votes for Kerry everywhere except among the Optical Precinct precincts. Among Optical Precinct precincts, a larger increase in registration is associated with a lower proportion of votes for Kerry. *If increases in registration reflect voter mobilization efforts, then mobilization tended to help Kerry in all the places included in this analysis except the Optical Precinct precincts.*

Figure 21: This shows a scatterplot relating the proportion voting for Kerry to 2004 voter turnout across all Ohio precincts. The line is the regression line. *Where a higher proportion of voters vote for Kerry, turnout is lower.* Of course it is well known that core Democratic constituencies have lower turnout rates than core Republican constituencies. So this display says nothing about the efficacy of voter mobilization efforts in the state.

Figures 22, 23, 24 and 25: These show scatterplots relating the proportion voting for Kerry to the change in voter turnout rates from 2002 to 2004 across all precincts and selected wards that had the same boundaries in both elections, where both variables have been residualized by regressing each on 2002 turnout. Precincts are separated by the type of voting machine technology and the wards are separated by county. The lines are the regression lines. *Over all precincts and wards and for each subset of precincts grouped by voting machine technology and wards grouped by county, the proportion voting for Kerry decreases as turnout in 2004 increases, even when turnout in the 2002 election is taken into account. This suggests that voter mobilization*

efforts focused on turnout on balance hurt Kerry, at least if one takes 2002 as the baseline. The exception to this pattern occurs among Optical Central precincts where, with 2002 turnout taken into account, the proportion voting for Kerry increases as turnout in 2004 increases.

Figure 26: This shows the distribution of the residual vote rate across Ohio precincts by voting machine technology. A residual vote is conventionally measured as a ballot that does not have a valid vote for president. The residual vote rate is the proportion of such ballots out of all ballots cast. In the current data we have information about the number of votes cast and the number of ballots that have a vote for either Bush, Kerry, Bedarnik or Peroutka. We measure the residual vote rate as the proportion of votes cast that do not have a vote for one of those candidates. The difference in the median residual vote rate among precincts using each of the four voting machine technologies is not easy to see in the figure, so I report that here.

Technology	Median
DRE	0.0097
Optical Central	0.0086
Optical Precinct	0.0076
Punchcard	0.0164
Cuyahoga	0.0147
Hamilton	0.0174

The median is smallest for the Optical Precinct (Allen County) precincts and largest for the Punchcard precincts. *The median residual vote rate among the Optical Precinct precincts is about the same as the proportion of people some have estimated voluntarily choose not to vote for president (based on survey data, Knack and Kropf 2003 estimate that 0.75 percent of voters voluntarily abstain from voting in the presidential race). The median rate among Punchcard precincts is more than twice as large and clearly unacceptable. Using all four technologies there are a number of precincts that have substantially higher residual vote rates. Both the number of such precincts and the magnitude of the residual vote rate in each one are especially high for DRE, Optical Central, Punchcard, Cuyahoga and Hamilton precincts.*

Table 17: This reports robust estimates of a separate overdispersed binomial regression model for the precincts using each type of voting technology, with the residual vote depending on the number of voting machines per registered voter in each precinct. The analysis here includes Cuyahoga and Hamilton precincts with the other precincts using punchcard voting machine technology. Using MV to denote the voting machines per registered voter ratio MV = (voting machines)/(registered voters), for the set of precincts using each type of voting machine technology the linear predictor for precinct *i* is

$$Z_i = b_0 + b_1 \mathbf{M} \mathbf{V}_i \; .$$

The differences between the intercepts b_0 for the different models capture baseline differences between the precincts using the different voting machine technologies. The coefficients b_1 measure the effect the ratio of voting machines to the number of registered voters has on residual the vote for each set of precincts. The fact that the estimate for b_1 is $\hat{b}_1 = -30.9$ for DRE precincts and $\hat{b}_1 = -69.0$ for Optical Precinct precincts indicates a substantial dependence between the machine/voter ratio and the residual vote rate in those precincts. The separate estimates show that the residual vote rate is related to the number of voting machines per registered voter in both DRE and Optical Precinct precincts: more machines meant a lower residual vote rate. The mechanism that most likely produces this effect is easy to understand: with fewer machines per voter, polling places become more crowded and voters are less likely to take the time to check or correct their ballots. The display at the bottom of Table 17 illustrates the magnitude of these effects by computing expected residual vote rates for precincts at the first quartile, the median and the third quartile of the MV values for precincts using each type of technology. Notwithstanding the statistically significant relationship between the machine ratio and the residual vote ratio, moving from the first to the third quartile of the voting machines per registered voter ratio is associated with small differences for both DRE and Optical Precinct precincts. Differences across voting technologies are large, however. At the third quartiles of the voting machines per registered voter ratio observed for each of the voting machine technologies in 2004, the expected residual vote rate is more than 50 percent larger in DRE or Optical Central precincts than in Optical Precinct precincts, and the rate is more than 165 percent larger in Punchcard precincts than in Optical Precinct precincts. Nearly one percent of the votes cast for president in Ohio were lost because they were cast using punchcard technology instead of precinct-tabulated optical scan technology. Many precincts are flagged as outliers. All the outliers have positive studentized residuals, which means that the observed residual vote rate in those precincts is substantially larger than the expected according to the model.

Table 18, Table 19, Table 20, Table 21 and Table 22: These list the outliers for each type of machine technology from the analysis reported in Table 17. *All of the outliers in the analysis of the residual vote are positive: many precincts have substantially more residual votes than expected according to the residual vote rate that prevails among precincts that used the same kind of voting machine technology.* The outliers for DRE precincts are predominantly precincts in Franklin County, and the outliers for Optical Central precincts are predominantly precincts in.Ashland County. Among Punchcard precincts, Hamilton has the most outliers, then Cuyahoga, Summit, Montgomery, Trumbull, Stark, Richland, Lorain and Holmes. A few other counties also have multiple outlier precincts.

Table 23: This reports robust estimates of a separate overdispersed binomial regression model for the precincts using each type of voting technology, with the residual vote depending on the number of voting machines per registered voter in each precinct and the proportion of the population in each precinct that is African American. Using MV to denote the voting machines per registered voter ratio MV = (voting machines)/(registered voters) and AA to denote the proportion of the population that is African American, for the set of precincts using each type of voting machine technology the linear predictor for precinct *i* is

$$Z_i = b_0 + b_1 \mathbf{M} \mathbf{V}_i + b_2 \mathbf{A} \mathbf{A}_i \,.$$

If African Americans are more likely to cast a residual vote (see Herron and Sekhon 2005 for a literature review and discussion), then $b_2 > 0$. This is what we find, everywhere except among Optical Central precincts. There, unusually, a higher proportion of African Americans in a precinct is associated with a lower residual vote rate. Results regarding the effect the ratio of voting machines to the number of registered voters has on residual the vote are much the same as in the analysis reported in Table 17. The display at the bottom of Table 23 illustrates the magnitude of these effects by computing expected residual vote rates for precincts at the first quartile, the median and the third quartile of the MV values for precincts using each type of technology, setting the proportion African American equal to the median value observed among

precincts of the referent type. Moving from the first to the third quartile of the voting machines per registered voter ratio is associated with small differences for both DRE and Optical Precinct precincts. Differences across voting technologies are again large, however. *The expected residual vote rate at the third quartile of the machines per registered voter ratio falls to 0.54 percent for Optical Precinct machines. At the third quartiles of the voting machines per registered voter ratio observed for each of the voting machine technologies in 2004, the expected residual vote rate is more than 50 percent larger in DRE or Optical Central precincts than in Optical Precinct precincts, and the rate is more than 165 percent larger in Punchcard precincts than in Optical Precinct precincts. Nearly one percent of the votes cast for president in Ohio were lost because they were cast using punchcard technology instead of precinct-tabulated optical scan technology.* Many precincts are flagged as outliers, although fewer than when the proportion African American is not included as a regressor.

Table 24 Table 25 Table 26 Table 27: These list the outliers for each type of machine technology from the analysis reported in Table 23. *All of the outliers in the analysis of the residual vote are positive: many precincts have substantially more residual votes than expected according to the residual vote rate that prevails among precincts that used the same kind of voting machine technology.*

Table 28: This shows the median residual vote rates among the outliers identified in the analysis reported in Tables 23 through 27, along with the median residual vote rates among precincts that are not outliers. The medians among non-outlier precincts match the results computed at the bottom of Table 23. *The outliers have substantially higher residual vote rates, with median rates nearly four times those of the nonoutlier precincts.*

Table 29: This shows estimates of binary logit regression models for the probability that a precinct is an outlier in the analysis reported in Table 23, given the proportion reported voting for Kerry instead of Bush in the precinct. Statistically significant relationships occur for Optical Central and Punchcard precincts. Among Optical Central precincts, the higher the proportion of votes recorded for Bush in a precinct, the higher the probability that the precinct is an outlier that has an extraordinarily high residual vote rate. *Among Punchcard precincts, the higher the proportion of votes recorded for Kerry in a precinct, the higher the probability that the precinct is an outlier that has an extraordinarily high residual vote rate. The number of votes potentially affected by these extreme political biases in the distribution of the outliers is relatively small, however.* The following table reports the total number of residual votes among the outliers for each type of voting machine technology.

Technology	Total
DRE	1,218
Optical Central	719
Optical Precinct	89
Punchcard	6,644

Even if every one of those residual votes represents an intended vote that was not counted due to mechanical or other problems, the total number of them is not enough to change the outcome of the election. Indeed, even if we consider all precincts that have residual vote rates that are unexpectedly high given the model of Table 23, the total number of votes potentially affected by apparently anomalous events remains relatively small. The following table reports the total

number of residual votes among precincts that have a studentized residual greater than 2.0 for each type of voting machine technology.

Technology	Total
DRE	3,264
Optical Central	1,349
Optical Precinct	164
Punchcard	17,901

That is surely enough potentially lost votes to be a serious concern, but not enough to change the election outcome in Ohio in 2004. Residual vote anomalies were not enough, on their own, to change the election outcome.

Figure 27: This shows a scatterplot relating residual vote rate to the proportion voting for Kerry across all precincts. The line is the regression line. *The residual vote rate is slightly higher in precincts where the proportion voting for Kerry was higher. This suggests that losing those votes on balance hurt Kerry.*

Figure 28: This shows a scatterplot relating residual vote rate to the proportion voting Yes on Issue 1 (opposing gay marriage) across all precincts. The line is the regression line. The variability of the residual vote rate is smaller among precincts that heavily opposed Issue 1, but there is no linear relationship between votes on the issue and the residual vote rate.

Figure 29: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for governor (Tim Hagan) in the 2002 election, across all precincts that had the same boundaries in both elections. The line is the regression line. *Votes for Kerry and for Hagan are strongly and positively related: in precincts where Hagan did better, Kerry tended to do better. In most precincts Kerry received a higher proportion of the vote than Hagan did.*

Figure 30: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for governor (Tim Hagan) in the 2002 election, across all precincts that had the same boundaries in both elections, separating the precincts by the type of voting machine technology. The lines are the regression lines. *For each subset of precincts grouped by voting machine technology, votes for Kerry and for Hagan are strongly and positively related: in precincts where Hagan did better, Kerry tended to do better.*

Figure 31: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for governor (Tim Hagan) in the 2002 election, across the selected wards that had the same boundaries in both elections, separating the wards by county. The line is the regression line. *Votes for Kerry and for Hagan are strongly and positively related: in wards where Hagan did better, Kerry tended to do better. In most wards Kerry received a higher proportion of the vote than Hagan did.*

Figure 32: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for governor (Tim Hagan) in the 2002 election, across the selected wards that had the same boundaries in both elections, separated respectively by voting machine technology and by county. The lines are the regression lines. *For the wards viewed separately by county, votes for Kerry and for Hagan are strongly and positively related: in wards where Hagan did better, Kerry tended to do better.*

Table 30: This reports robust estimates of an overdispersed binomial regression model that has the proportion voting for Kerry depending on the proportion voting for the Democratic

candidate for governor (Tim Hagan) in the 2002 election. Estimates appear separately for the precincts that had the same boundaries in the two elections and for the wards that had constant boundaries. Using D2002 to represent the proportion voting for Hagan, the linear predictor in the model may be written as follows:

$$Z_i = d_0 + d_1 \text{logit}(\text{D2002}_i)$$

(see the Appendix for an explanation of the logit function). If the vote for Kerry were the same as the vote for Hagan except uniformly higher, then we would have $d_0 > 0$ and $d_1 = 1$ (the Appendix explains this). Indeed, the estimate for d_1 is not substantially different from 1.0 in either the precinct analysis or the ward analysis, and in both cases the estimate for d_0 is greater than zero. The tendency to vote for Kerry in 2004 is the same as the tendency to vote for Hagan in 2002, except it is uniformly higher. The fact that the pattern of voting for Kerry is so similar to the pattern of voting for the Democratic candidate for governor in 2002 in these precincts and wards is strong evidence against the claim that widespread fraud systematically misallocated votes from Kerry to Bush (unless someone wants to go further and make the unsupported claim that the 2002 election for governor was stolen in exactly the same way, precinct by precinct and ward by ward). Relatively few precincts or wards are outliers in this analysis.

Table 31: This lists the outlier precincts identified in the analysis reported in Table 30. A few precincts but no wards from Hamilton County are outliers.

Table 32: This reports robust estimates of an overdispersed binomial regression model that has the proportion voting for Kerry depending on the proportion voting for the Democratic candidate for governor (Tim Hagan) in the 2002 election and on the proportion voting Yes on Issue 1 (opposing gay marriage). Estimates appear separately for the precincts that had the same boundaries in the two elections and for the wards that had constant boundaries. Kerry did well in precincts and wards where Hagan did well, and he did poorly where Hagan did poorly, and in addition support for Kerry was lower where support for Issue 1 was higher. No surprises here.

Table 33: This lists the outlier precincts identified in the analysis reported in Table 32. By and large the outliers are the same as when the Issue 1 vote is not included in the model.

Figure 33: This shows the distribution of the proportion voting for Kerry across Ohio precincts by voting machine technology.

Figure 34: This shows the distribution of the proportion voting for the 2004 Democratic candidate for Senator (Eric Fingerhut) across Ohio precincts by voting machine technology.

Figure 35: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for Senator (Eric Fingerhut) across all precincts. The line is the regression line. *Votes for Kerry and for Fingerhut are strongly and positively related: in precincts where Fingerhut did better, Kerry tended to do better. In most precincts where Fingerhut received more than 40 percentof the vote, Kerry received a higher proportion of the vote than Fingerhut did.*

Figure 36: This shows scatterplots relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for Senator (Eric Fingerhut) across all precincts, separating the precincts by the type of voting machine technology. The lines are the regression lines. *For each subset of precincts grouped by voting machine technology, votes for Kerry and for Fingerhut are strongly and positively related: in precincts where Fingerhut did better, Kerry tended to do better.*

Figures 37 and 38: These show the distribution of the proportion voting for Kerry across Ohio precincts by voting machine technology, separately for precincts that have fewer than ten percent African American population and precincts that have greater than ten percent African American population. *Kerry's support is substantially higher in the precincts that have the higher proportion African American*.

Figure 39 and 40: These show scatterplots relating the proportion voting for Kerry to the proportion voting for the Democratic candidate for Senator (Eric Fingerhut) across all precincts, separately for precincts that have fewer than ten percent African American population and precincts that have greater than ten percent African American population, separating the precincts by the type of voting machine technology. The lines are the regression lines. *For each subset of precincts grouped by voting machine technology, votes for Kerry and for Fingerhut are strongly and positively related: in precincts where Fingerhut did better, Kerry tended to do better. Kerry's support and Fingerhut's support are both substantially higher in precincts that have the higher proportion African American.*

Figure 41: This shows the distribution of the proportion voting Yes on Issue 1 (opposing gay marriage) across Ohio precincts by voting machine technology. In most precincts there was a majority in favor of Issue 1, but there were many precincts where Issue 1 was heavily rejected.

Figure 42: This shows a scatterplot relating the proportion voting for Kerry to the proportion voting Yes on Issue 1 (opposing gay marriage) across all precincts. The line is the regression line. *Votes for Kerry and for Issue 1 are strongly and negatively related: in precincts where Issue 1 did better, Kerry tended to do worse. The variation among precincts in the vote for Issue 1 is greater among the precincts where support for Kerry was the highest than it is among the precincts where Kerry's support was lowest.*

Figure 43: This shows scatterplots relating the proportion voting for Kerry to the proportion voting Yes on Issue 1 (opposing gay marriage) across all precincts, separating the precincts by the type of voting machine technology. The lines are the regression lines. For each subset of precincts grouped by voting machine technology, votes for Kerry and for Issue 1 are strongly and negatively related: in precincts where Issue 1 did better, Kerry tended to do worse. There is a telling separation in the plot for DRE precincts, among the precincts where support for Kerry was the highest. *Evidently there are precincts where voters strongly oppose Issue 1 and strongly support Kerry, and there are precincts where a majority of voters support Issue 1 and strongly support Kerry.* Both kinds of precincts are included in the DRE and Punchcard sets of precincts. Precincts that strongly opposed Issue 1 do not appear among the Optical Central and Optical Precinct precincts, even though in both of those sets there are precincts that strongly support Kerry.

Figure 44 and 45: This shows scatterplots relating the proportion voting for Kerry to the proportion voting Yes on Issue 1 (opposing gay marriage) across all precincts, separately for precincts that have fewer than ten percent African American population and precincts that have greater than ten percent African American population, separating the precincts by the type of voting machine technology. The lines are the regression lines. *Kerry's support is substantially higher and support for Issue 1 is lower in precincts that have the higher proportion African American*.

Table 34: This reports robust estimates of overdispersed binomial regression models that have the proportion voting for Kerry depending on the proportion voting the proportion voting for the 2004 Democratic candidate for Senator (Eric Fingerhut), the proportion voting Yes on Issue 1 (opposing gay marriage) and the proportion of the population in each precinct that is African American. A separate model is estimated for each Ohio county. Motivated by evidence that, on the whole, the support for Kerry was strongly related to each of these three variables, the idea is to use the coefficients estimated for each county's precincts to help identify places where the relationship between the three variables and Kerry's support is anomalous. Anomalous values for a county's coefficients may be evidence that the election returns were manipulated in that county. Specifically, let DS denote the proportion voting for the Democratic candidate for Senator, let I1 denote the proportion voting Yes on Issue 1, and let AA denote the proportion of the population that is African American. The linear predictor in the model for each precinct i may be written as follows:

$$Z_i = b_0 + b_1 \text{logit}(\text{DS}_i) + b_2 \text{logit}(\text{I1}_i) + b_3 \text{AA}_i$$

(see the Appendix for an explanation of the logit function). We expect Kerry's support to increase with the support for Fingerhut, decrease with the support for Issue 1 and increase with the proportion African American. Hence we expect to see $b_1 > 0$, $b_2 < 0$ and $b_3 > 0$. At the very least we do not expect to see statistically significant estimates having the opposite signs for these parameters. For the most part we observe the pattern we expect: Kerry's support increases with the support for Fingerhut, decreases with the support for Issue 1 and increases with the proportion African American. The results for Hamilton County in Table 34 are typical. All the coefficient estimates for Hamilton are statistically different from zero, and $\hat{b}_1 > 0$, $\hat{b}_2 < 0$ and $\hat{b}_3 > 0$. Only seven of Ohio's 88 counties deviate significantly from that pattern. One of the deviations occurs for Cuyahoga County, where there is a significant estimate for b_2 that has the wrong sign. Cuyahoga is the only county in Ohio for which the estimate for b_2 is positive and statistically significant. Harrison County is the only other county for which the point estimate for b_2 is positive, but that estimate is not statistically significant ($\hat{b}_2 = 0.126$, SE = 0.242). Among all Ohio's counties, only in Cuyahoga is there a tendency for Kerry's support to be higher in precincts where the support for Issue 1 is higher, given the support for Fingerhut and the proportion African American. Six other counties have anomalous coefficients following the pattern shown in Table 34 for Crawford County: there is a statistically significant estimate for b_3 that has the wrong sign. The estimate suggests that Kerry's support is higher in precincts where the proportion of African Americans is lower. The other five counties for which this pattern occurs are Jackson, Vinton, Washington, Williams and Wyandot. Crawford and these other five counties have respectively 46, 38, 19, 36, 44 and 24 precincts in the analysis. Because the proportion African American in these counties is so small, and the counties are so small they do not have many precincts, it is possible that this result does not reflect problems in the election. It may be that the African American voters in these counties tend to vote Democratic but are surrounded by especially Republican neighbors. Or the African American voters who live in these counties may themselves be especially Republican. Close inspection by someone who is familiar with the voters in these counties is warranted.

Table 35: This lists the outlier precincts identified for all Ohio counties in the analysis for which the illustrative results are reported in Table 34. *Most of the outliers are located in Cuyahoga county, and all of the residuals for those Cuyahoga outliers are negative. That warrants investigation. On the whole the number of outliers is too small to support a belief that the tallied votes were subject to widespread misallocation from Kerry to Bush.*

Table 1: Voting Machine Technologies Used in Ohio Counties in 2004

Direct record electronic (DRE): Auglaize, Franklin, Knox, Lake, Mahoning, Pickaway, Ross.

Centrally tabulated optical scan (Optical Central): Ashland, Clermont, Coshocton, Erie, Geauga, Hancock, Hardin, Lucas, Miami, Ottawa, Sandusky, Washington.

Precinct-tabulated optical scan (Optical Precinct): Allen.

Punchcard: Adams, Ashtabula, Athens, Belmont, Brown, Butler, Carroll, Champaign, Clark, Clinton, Columbiana, Crawford, Cuyahoga, Darke, Defiance, Delaware, Fairfield, Fayette, Fulton, Gallia, Greene, Guernsey, Hamilton, Harrison, Henry, Highland, Hocking, Holmes, Huron, Jackson, Jefferson, Lawrence, Licking, Logan, Lorain, Madison, Marion, Medina, Meigs, Mercer, Monroe, Montgomery, Morgan, Morrow, Muskingum, Noble, Paulding, Perry, Pike, Portage, Preble, Putnam, Richland, Scioto, Seneca, Shelby, Stark, Summit, Trumbull, Tuscarawas, Union, Van Wert, Vinton, Warren, Wayne, Williams, Wood, Wyandot.

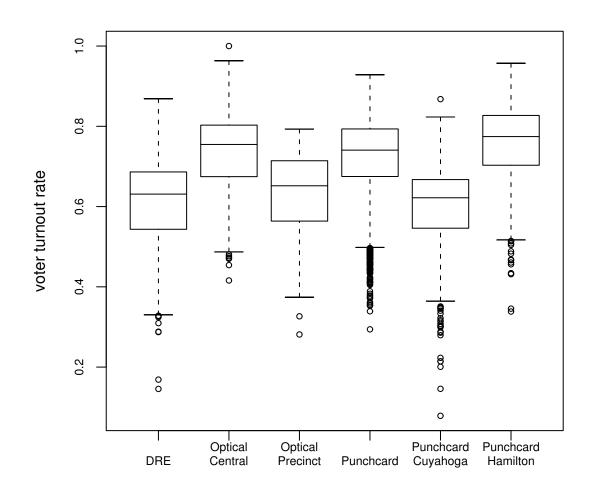


Figure 1: Turnout in Ohio 2004 Precincts by Machine Type

Table 2: Ohio Counties with Information on Number of Voting Machines Used in Each Precinct in2004

Direct record electronic (DRE): Auglaize, Franklin, Knox, Lake, Mahoning, Pickaway, Ross.

Centrally tabulated optical scan (Optical Central): Ashland, Erie, Hardin, Lucas, Ottawa, Sandusky.

Precinct-tabulated optical scan (Optical Precinct): Allen.

Punchcard: Adams, Ashtabula, Athens, Belmont, Brown, Butler, Carroll, Champaign, Clark, Clinton, Columbiana, Crawford, Cuyahoga, Darke, Defiance, Delaware, Fairfield, Fayette, Fulton, Gallia, Greene, Guernsey, Hamilton, Harrison, Henry, Highland, Hocking, Holmes, Huron, Jackson, Jefferson, Lawrence, Licking, Logan, Lorain, Madison, Marion, Meigs, Mercer, Monroe, Montgomery, Morgan, Morrow, Muskingum, Noble, Paulding, Perry, Pike, Portage, Preble, Putnam, Richland, Scioto, Shelby, Stark, Summit, Trumbull, Tuscarawas, Union, Van Wert, Vinton, Wayne, Williams, Wood, Wyandot.

Table 3: Voter Turnout:	Machines per	Voter Regressor
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		DRE			Punchcard		
Variable	Coef.	SE	t-ratio	С	oef.	SE	t-ratio
(Intercept)	-0.0143	0.0352	-0.406	0).739	0.0226	32.6
Machines per Registered Voter	113.0000	8.1800	13.900	35	5.000	2.7400	12.8
	Opt	ical Centr	al		(Cuyahoga	
Variable	Coef.	SE	t-ratio	Со	oef.	SE	t-ratio
(Intercept)	0.859	0.0445	19.30	0	0.502	0.0271	18.50
Machines per Registered Voter	29.800	6.6100	4.51	-8	8.200	2.9900	-2.74
	Opti	ical Precin	nct			Hamilton	
Variable	Coef.	SE	t-ratio	Co	oef.	SE	t-ratio
(Intercept)	0.614	0.138	4.460	-0).137	0.179	-0.763
Machines per Registered Voter	-10.700	20.400	-0.524	140	0.000	19.000	7.390

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of registered voters voting versus the number of registered voters not voting. DRE precincts: LQD $\sigma = 5.61$; tanh $\sigma = 5.56$; n = 1, 535; 2 outliers. Optical Central precincts: LQD $\sigma = 4.22$; tanh $\sigma = 4.26$; n = 807; 4 outliers. Optical Precinct precincts: LQD $\sigma = 4.45$; tanh $\sigma = 4.31$; n = 139; 1 outlier. Punchcard precincts: LQD $\sigma = 4.68$; tanh $\sigma = 4.43$; n = 5, 478; 35 outliers. Cuyahoga precincts: LQD $\sigma = 4.41$; tanh $\sigma = 4.07$; n = 1, 411; 7 outliers. Hamilton precincts: LQD $\sigma = 4.45$; tanh $\sigma = 4.41$; n = 979; 6 outliers. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

Expected Voter Turnout at Machine Ratio Quartiles

	Quartile				
Precinct Technology	25%	50%	75%		
DRE	0.584	0.598	0.622		
Centrally Tabulated Optical Scan	0.734	0.738	0.741		
Precinct Tabulated Optical Scan	0.636	0.633	0.630		
Punchcard	0.726	0.735	0.744		
Cuyahoga	0.607	0.607	0.606		
Hamilton	0.753	0.765	0.778		

	DRE			l Central	l	Optic	al Preci	nct
County	Code	SRes	County	Code	SRes	County	Code	SRes
Franklin	ABY	-4.10	Erie	AED	-4.75	Allen	ABB	-4.19
Franklin	AZB	-4.43	Erie	AEE	-4.49			
			Lucas	AHJ	-5.73			
			Lucas	ADQ	-4.09			
			Punch	ncard				
County	Code	SRes	County	Code	SRes	County	Code	SRes
Butler	AAK	-4.18	Delaware	ABV	4.05	Richland	ABN	-4.21
Butler	AAF	-5.47	Fairfield	AEP	-4.55	Richland	ABO	-5.02
Butler	AAO	-4.38	Greene	AGJ	-4.20	Stark	AAT	-4.02
Butler	ACQ	-4.79	Greene	AIN	-4.94	Stark	ABB	-4.33
Butler	ACU	-4.12	Holmes	AAC	-4.87	Stark	ABC	-4.30
Butler	ADQ	-4.34	Holmes	AAM	-4.19	Stark	ABU	-4.64
Butler	AEY	-4.73	Holmes	AAW	-4.05	Summit	ABE	-4.80
Butler	AFA	-4.06	Montgomery	ABC	-7.93	Summit	ADU	-4.49
Butler	AFD	-5.92	Montgomery	ABP	-4.09	Wood	AAC	-5.75
Butler	AFE	-5.76	Montgomery	API	-6.52	Wood	AAH	-4.28
Butler	AJR	-5.57	Montgomery	AQS	-4.25	Wood	AAI	-4.18
Darke	ABD	-4.88	Portage	AGL	-4.15			
Cu	iyahoga		Han	nilton				
County	Code	SRes	County	Code	SRes			
Cuyahoga	ANR	-4.24	Hamilton	AFQ	-5.31			
Cuyahoga	APF	-6.70	Hamilton	AHD	-6.21			
Cuyahoga	AYP	-10.08	Hamilton	AKL	-4.34			
Cuyahoga	AYT	-5.84	Hamilton	ALW	-4.70			
Cuyahoga	AZO	-4.03	Hamilton	BDP	-0.04			
Cuyahoga	CXC	-5.59	Hamilton	BQD	-2.32			
Cuyahoga	DDR	-4.72		-				

 Table 4: Outliers: Voter Turnout: Machines per Voter Regressor

Table 5: Ohio Counties including Precincts with Constant Boundaries from 2002 to 2004

Direct record electronic (DRE): Mahoning.

Centrally tabulated optical scan (Optical Central): Ashland, Clermont, Coshocton, Geauga, Hardin, Miami, Ottawa.

Precinct-tabulated optical scan (Optical Precinct): Allen.

Punchcard: Adams, Athens, Belmont, Butler, Carroll, Clinton, Columbiana, Cuyahoga, Darke, Greene, Hamilton, Harrison, Hocking, Lawrence, Licking, Logan, Lorain, Madison, Marion, Meigs, Monroe, Morgan, Morrow, Noble, Paulding, Perry, Pike, Portage, Preble, Shelby, Trumbull, Tuscarawas, Van Wert, Vinton, Wayne, Williams.

Table 6: Ohio Counties with Information on Number of Voting Machines Used in Each Precinct in 2004 and including Precincts with Constant Boundaries from 2002 to 2004

Direct record electronic (DRE): Mahoning.

Centrally tabulated optical scan (Optical Central): Ashland, Hardin, Ottawa.

Precinct-tabulated optical scan (Optical Precinct): Allen.

Punchcard: Adams, Athens, Belmont, Butler, Carroll, Clinton, Columbiana, Cuyahoga, Darke, Greene, Hamilton, Harrison, Hocking, Lawrence, Licking, Logan, Lorain, Madison, Marion, Meigs, Monroe, Morgan, Morrow, Noble, Paulding, Perry, Pike, Portage, Preble, Shelby, Trumbull, Tuscarawas, Van Wert, Vinton, Wayne, Williams.

Table 7: Number of Machines:	2004 Registered	Voters and 2002 Vote	s Cast Regressors

		DRE		
Variable	Coef.	SE	t-ratio	
(Intercept)	-1.42	0.78	-1.8	
Log(Registered Voters in 2004)	0.12	0.14	0.8	
Log(Votes Cast in 2002)	0.36	0.11	3.3	
	Opti	ical Ce	ntral	
Variable	Coef.	SE	t-ratio	
(Intercept)	2.18	0.48	4.5	
Log(Registered Voters in 2004)	-0.45	0.20	-2.2	
Log(Votes Cast in 2002)	0.32	0.22	1.4	
	Punchcard			
Variable	Coef.	SE	t-ratio	
(Intercept)	-2.55	0.16	-16.3	
Log(Registered Voters in 2004)	0.58	0.03	17.9	
Log(Votes Cast in 2002)	0.08	0.03	2.6	
	С	uyahog	ga	
Variable	Coef.	SE	t-ratio	
(Intercept)	-3.13	0.31	-10.1	
Log(Registered Voters in 2004)	0.80	0.05	15.6	
Log(Votes Cast in 2002)	-0.06	0.03	-1.7	
	Hamilton			
Variable	Coef.	SE	t-ratio	

Variable	Coef.	SE	t-ratio
(Intercept)	-3.29	0.34	-9.8
Log(Registered Voters in 2004)	0.72	0.06	11.9
Log(Votes Cast in 2002)	0.07	0.04	1.8

Notes: Poisson regression estimates. For each precinct, the dependent variable is the number of voting machines. DRE n = 312 precincts. Optical Central n = 181 precincts. Punchcard n = 2,400 precincts. Cuyahoga n = 927 precincts. Hamilton n = 1,013 precincts. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

African American proportion less than .10

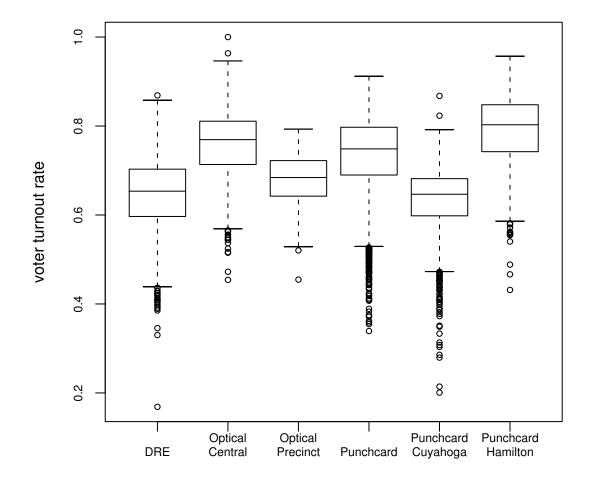
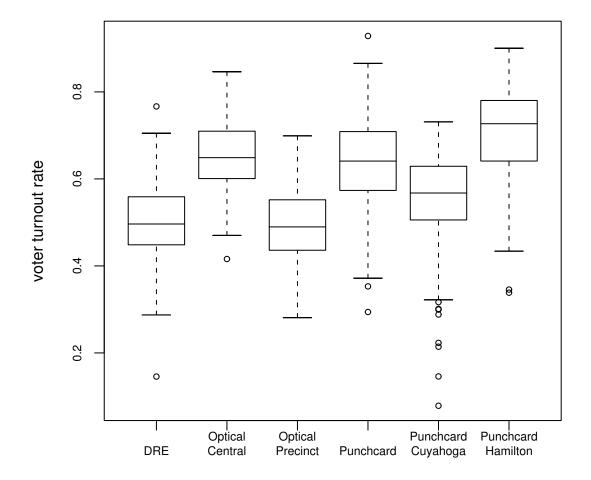


Figure 2: Turnout in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Less Than 10 Percent



African American proportion greater than .10

Figure 3: Turnout in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Greater Than 10 Percent

Table 8: Voter Turnout: Machine Technology, Machines per Voter and Precinct Racial Composition Regressors

		DRE			Punchcard		
Variable	Coef.	SE	t-ratio	Co	oef.	SE	t-ratio
(Intercept)	0.26	0.0318	8.17	0	.754	0.0221	34.1
Machines per Registered Voter	74.60	7.0100	10.60	38	.600	2.6900	14.3
Proportion African American	-0.98	0.0438	-22.40	-0	.851	0.0380	-22.4
	Optical Central			Cuyahoga			
Variable	Coef.	SE	t-ratio	Co	oef.	SE	t-ratio
(Intercept)	0.976	0.0432	22.60	0	.630	0.0289	21.80
Machines per Registered Voter	23.500	6.3300	3.71	-10	.100	3.2100	-3.13
Proportion African American	-0.689	0.0545	-12.70	-0	.371	0.0201	-18.50
	Op	tical Preci	nct]	Hamilton	
Variable	Coef.	SE	t-ratio	Co	oef.	SE	t-ratio
(Intercept)	0.783	0.0976	8.020	0	.212	0.167	1.27
Machines per Registered Voter	-5.770	14.3000	-0.402	117	.000	17.500	6.67
Proportion African American	-2.360	0.2630	-8.940	-0	.610	0.044	-13.90

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of registered voters voting versus the number of registered voters not voting. DRE precincts: LQD $\sigma = 4.82$; tanh $\sigma = 4.66$; n = 1, 535; 7 outliers. Optical Central precincts: LQD $\sigma = 3.91$; tanh $\sigma = 3.92$; n = 807; 6 outliers. Optical Precinct precincts: LQD $\sigma = 3.08$; tanh $\sigma = 3.11$; n = 139; 1 outlier. Punchcard precincts: LQD $\sigma = 4.51$; tanh $\sigma = 4.26$; n = 5, 478; 28 outliers. Cuyahoga precincts: LQD $\sigma = 3.67$; tanh $\sigma = 3.53$; n = 1, 411; 15 outliers. Hamilton precincts: LQD $\sigma = 4.14$; tanh $\sigma = 4.10$; n = 979; 4 outliers. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

Expected Voter Turnout at Machine Ratio Quartiles with Median African American Proportions

	Quartile				
Precinct Technology	25%	50%	75%		
DRE	0.616	0.625	0.640		
Centrally Tabulated Optical Scan	0.749	0.751	0.754		
Precinct Tabulated Optical Scan	0.662	0.660	0.658		
Punchcard	0.732	0.742	0.752		
Cuyahoga	0.630	0.629	0.628		
Hamilton	0.773	0.783	0.794		

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	DRE			Optic	al Centra	1	Optical Precinct			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	County	Code	SRes	County	Code	SRes	County	Code	SRes	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Franklin	AAO	-4.01	Erie	ABV	-4.06	Allen	ABZ	4.47	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Franklin	ABT	-4.04	Erie	AED	-4.93				
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Franklin	ABY	-4.86	Erie	AEE	-4.65				
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Franklin	AIF	-4.23	Erie	AEH	-4.06				
$\begin{tabular}{ c c c c c c } \hline Lake & AEG -4.66 \\ \hline \hline Punchcard \\ \hline \hline \hline County & Code & SRes & County & Code & SRes \\ \hline Athens & AAL & -4.07 & Butler & AFE & -5.90 & Holmes & AAW & -4.37 \\ \hline Butler & AAK & -4.21 & Butler & AJR & -5.84 & Montgomery & ABC & -8.31 \\ \hline Butler & AAF & -5.48 & Columbiana & AAL & -4.13 & Montgomery & ANP & -4.09 \\ \hline Butler & AAO & -4.45 & Columbiana & AAM & -4.03 & Montgomery & API & -6.29 \\ \hline Butler & ACQ & -5.02 & Darke & ABD & -5.20 & Montgomery & AYV & -4.10 \\ \hline Butler & ADQ & -4.22 & Delaware & ABV & 4.14 & Portage & AGL & -4.28 \\ \hline Butler & AEY & -4.93 & Fairfield & AEP & -4.34 & Summit & ABE & -4.60 \\ \hline Butler & AFA & -4.26 & Holmes & AAC & -5.18 & Wood & AAC & -5.84 \\ \hline Butler & AFD & -6.18 & Holmes & AAM & -4.50 & Wood & AAH & -4.44 \\ \hline \hline \hline \hline County & Code & SRes & \hline \hline County & Code & SRes \\ \hline Hamilton & AFQ & -4.00 & Cuyahoga & ABM & -4.00 \\ \hline Hamilton & AFQ & -4.00 & Cuyahoga & ABM & -4.00 \\ \hline Hamilton & BDP & -0.06 & Cuyahoga & APF & -6.75 \\ \hline Cuyahoga & AYP & -11.27 \\ \hline Cuyahoga & AYP & -11.27 \\ \hline Cuyahoga & AZO & -4.63 \\ \hline Cuyahoga & BAC & -4.51 \\ \hline Cuyahoga & BAC & -4.51 \\ \hline Cuyahoga & BAQ & -4.02 \\ \hline \hline \end{array}$	Franklin	AMZ	-4.01	Lucas	AOG	-4.39				
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Franklin	AZB	-5.24	Lucas	AHJ	-5.11				
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	Lake	AEG	-4.66							
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				Р	unchcard	l				
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	County	Code	SRes	County	Code	SRes	County	Code	SRes	
$ \begin{array}{c cccc} Butler & AAF & -5.48 \\ Butler & AAO & -4.45 \\ Butler & ACQ & -5.02 \\ Butler & ADQ & -4.22 \\ Butler & ADQ & -4.22 \\ Butler & AEY & -4.93 \\ Butler & AFA & -4.26 \\ Butler & AFD & -6.18 \\ \end{array} \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Athens	AAL	-4.07	Butler	AFE	-5.90	Holmes	AAW	-4.37	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Butler	AAK	-4.21	Butler	AJR	-5.84	Montgomery	ABC	-8.31	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Butler	AAF	-5.48	Columbiana	AAL	-4.13	Montgomery	ANP	-4.09	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Butler	AAO	-4.45	Columbiana	AAM	-4.03	Montgomery	API	-6.29	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Butler	ACQ	-5.02	Darke	ABD	-5.20	Montgomery	AYV	-4.10	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Butler	ADQ	-4.22	Delaware	ABV	4.14	Portage	AGL	-4.28	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Butler	AEY	-4.93	Fairfield	AEP	-4.34	Summit	ABE	-4.60	
HamiltonCuyahogaCountyCodeSResHamiltonAFQ-4.00HamiltonAHD-5.10HamiltonBDP-0.06HamiltonBNY-4.55CuyahogaABPAmiltonBNY-4.55CuyahogaCuyahogaAPF-6.75CuyahogaAYPCuyahogaAYR-4.03CuyahogaAYR-4.03CuyahogaAZO-4.63CuyahogaBAC-4.51CuyahogaBAQ-4.66CuyahogaBAQ-4.02CuyahogaCGB-4.51	Butler	AFA	-4.26	Holmes	AAC	-5.18	Wood	AAC	-5.84	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Butler	AFD	-6.18	Holmes	AAM	-4.50	Wood	AAH	-4.44	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Ha	amilton		Cu	yahoga					
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	County	Code	SRes	County	Code	SRes				
$\begin{array}{ccccccc} Hamilton & BDP & -0.06 \\ Hamilton & BNY & -4.55 \\ \end{array} \begin{array}{ccccccccccccccccccccccccccccccccccc$	Hamilton	AFQ	-4.00	Cuyahoga	ABM	-4.00				
$\begin{array}{ccccccc} \mbox{Hamilton BNY} & -4.55 & \mbox{Cuyahoga} & \mbox{APF} & -6.75 \\ \mbox{Cuyahoga} & \mbox{AYP} & -11.27 \\ \mbox{Cuyahoga} & \mbox{AYR} & -4.03 \\ \mbox{Cuyahoga} & \mbox{AYT} & -7.12 \\ \mbox{Cuyahoga} & \mbox{AZO} & -4.63 \\ \mbox{Cuyahoga} & \mbox{BAC} & -4.51 \\ \mbox{Cuyahoga} & \mbox{BAQ} & -4.66 \\ \mbox{Cuyahoga} & \mbox{BAT} & -4.18 \\ \mbox{Cuyahoga} & \mbox{BDQ} & -4.02 \\ \mbox{Cuyahoga} & \mbox{CGB} & -4.51 \end{array}$	Hamilton	AHD	-5.10	Cuyahoga	ABP	-4.21				
$\begin{array}{cccc} Cuyahoga & AYP & -11.27\\ Cuyahoga & AYR & -4.03\\ Cuyahoga & AYT & -7.12\\ Cuyahoga & AZO & -4.63\\ Cuyahoga & BAC & -4.51\\ Cuyahoga & BAQ & -4.66\\ Cuyahoga & BAT & -4.18\\ Cuyahoga & BDQ & -4.02\\ Cuyahoga & CGB & -4.51\\ \end{array}$	Hamilton	BDP	-0.06	Cuyahoga	ANR	-4.73				
$\begin{array}{cccc} Cuyahoga & AYR & -4.03 \\ Cuyahoga & AYT & -7.12 \\ Cuyahoga & AZO & -4.63 \\ Cuyahoga & BAC & -4.51 \\ Cuyahoga & BAQ & -4.66 \\ Cuyahoga & BAT & -4.18 \\ Cuyahoga & BDQ & -4.02 \\ Cuyahoga & CGB & -4.51 \end{array}$	Hamilton	BNY	-4.55	Cuyahoga	APF	-6.75				
$\begin{array}{cccc} Cuyahoga & AYT & -7.12 \\ Cuyahoga & AZO & -4.63 \\ Cuyahoga & BAC & -4.51 \\ Cuyahoga & BAQ & -4.66 \\ Cuyahoga & BAT & -4.18 \\ Cuyahoga & BDQ & -4.02 \\ Cuyahoga & CGB & -4.51 \end{array}$				Cuyahoga	AYP	-11.27				
$\begin{array}{cccc} Cuyahoga & AZO & -4.63 \\ Cuyahoga & BAC & -4.51 \\ Cuyahoga & BAQ & -4.66 \\ Cuyahoga & BAT & -4.18 \\ Cuyahoga & BDQ & -4.02 \\ Cuyahoga & CGB & -4.51 \end{array}$				Cuyahoga	AYR	-4.03				
Cuyahoga BAC -4.51 Cuyahoga BAQ -4.66 Cuyahoga BAT -4.18 Cuyahoga BDQ -4.02 Cuyahoga CGB -4.51				Cuyahoga	AYT	-7.12				
Cuyahoga BAQ -4.66 Cuyahoga BAT -4.18 Cuyahoga BDQ -4.02 Cuyahoga CGB -4.51				Cuyahoga	AZO	-4.63				
Cuyahoga BAT -4.18 Cuyahoga BDQ -4.02 Cuyahoga CGB -4.51				Cuyahoga	BAC	-4.51				
Cuyahoga BDQ -4.02 Cuyahoga CGB -4.51				Cuyahoga	BAQ	-4.66				
Cuyahoga CGB -4.51				Cuyahoga	BAT	-4.18				
				Cuyahoga	BDQ	-4.02				
Cuvahoga $CXC = -6.78$				Cuyahoga	CGB	-4.51				
Cuyanoga CAC -0.10				Cuyahoga	CXC	-6.78				
Cuyahoga DDR -5.04				Cuyahoga	DDR	-5.04				

Table 9: Outliers: Voter Turnout: Machine Technology, Machines per Voter and Precinct Racial Composition Regressors

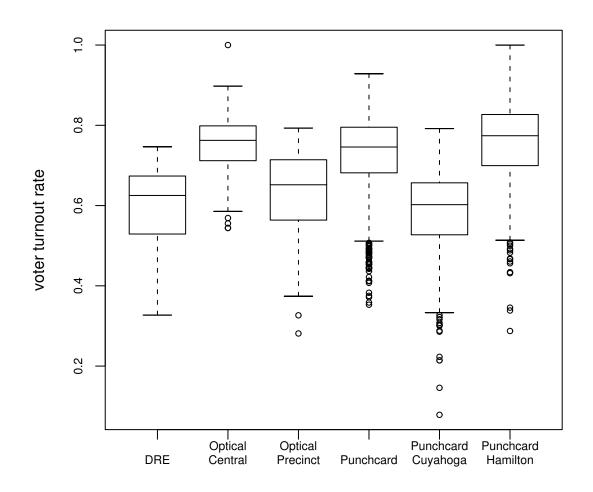


Figure 4: Turnout in Ohio 2004 in Precincts with Constant Boundaries Since 2002 by Machine Type

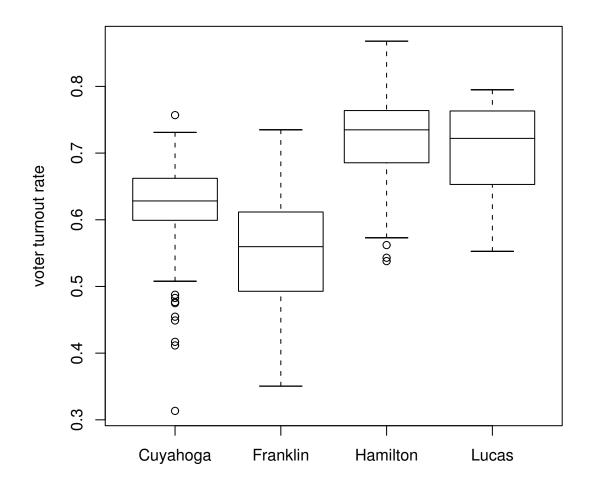


Figure 5: Turnout in Ohio 2004 in Wards with Constant Boundaries Since 2002 by County

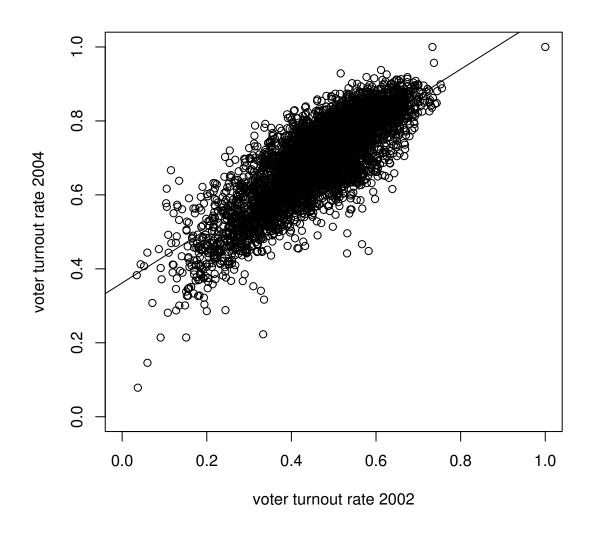


Figure 6: Turnout in Ohio 2004 by Turnout in 2002 in Precincts with Constant Boundaries Since 2002

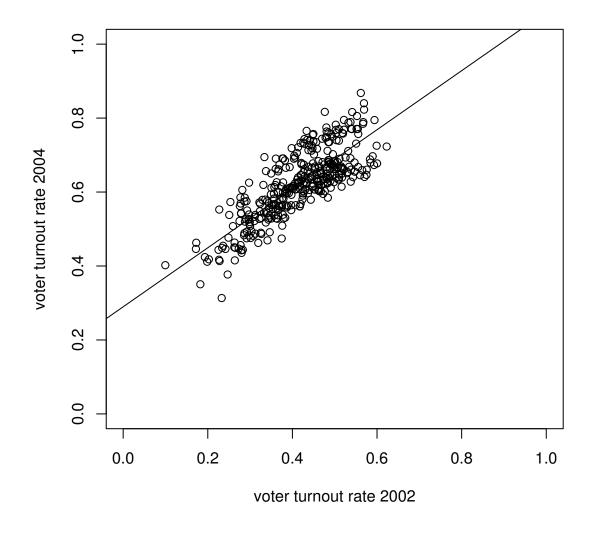


Figure 7: Turnout in Ohio 2004 by Turnout in 2002 in Wards with Constant Boundaries Since 2002

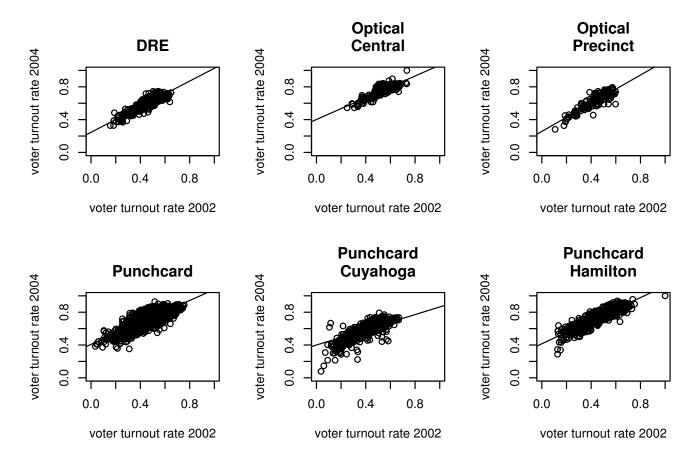


Figure 8: Turnout in Ohio 2004 by Turnout in 2002 in Precincts with Constant Boundaries Since 2002 by Machine Type

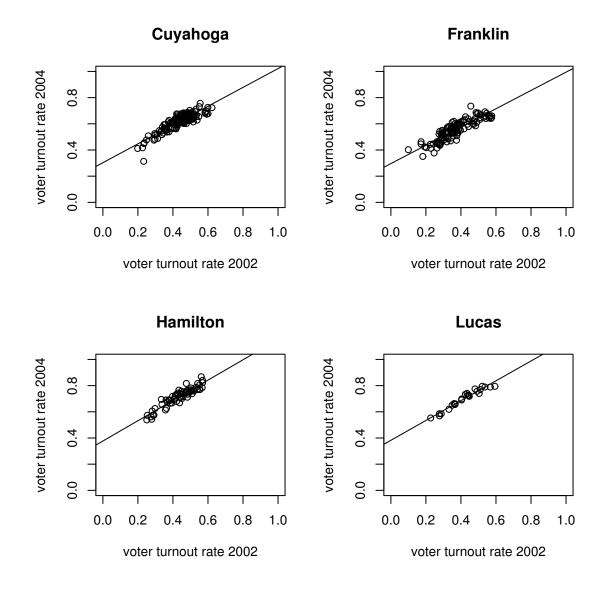


Figure 9: Turnout in Ohio 2004 by Turnout in 2002 in Wards with Constant Boundaries Since 2002 by County

	DRE				Cuyahoga Wards		
Variable	Coef.	SE	t-ratio		Coef.	SE	t-ratio
(Intercept)	0.566	0.00993	57.0		0.671	0.0120	55.7
Logit(Voter Turnout in 2002)	0.770	0.01720	44.7		0.711	0.0229	31.1
	0	ptical Cent	tral		Franklin Wards		
Variable	Coef.	SE	t-ratio		Coef.	SE	t-ratio
(Intercept)	1.150	0.00885	130.0		0.584	0.0235	24.9
Logit(Voter Turnout in 2002)	0.665	0.01710	39.0		0.613	0.0379	16.2
	Optical Precinct				Hamilton Wards		
Variable	Coef.	SE	t-ratio		Coef.	SE	t-ratio
(Intercept)	0.799	0.0187	42.7		1.140	0.0198	57.8
Logit(Voter Turnout in 2002)	0.848	0.0224	37.8		0.867	0.0389	22.3
	Punchcard				Lucas Wards		
Variable	Coef.	SE	t-ratio	_	Coef.	SE	t-ratio
(Intercept)	1.100	0.0053	207.0		1.160	0.0221	52.5
Logit(Voter Turnout in 2002)	0.777	0.0125	62.3		0.846	0.0387	21.9
	Cuyahoga				Hamilton		
Variable	Coef.	SE	t-ratio	_	Coef.	SE	t-ratio
(Intercept)	0.665	0.0074	90.0		1.250	0.0067	187.0
Logit(Voter Turnout in 2002)	0.671	0.0114	58.7		0.883	0.0136	64.7

Table 10: 2004 Voter Turnout: 2002 Voter Turnout Regressor

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of registered voters voting versus the number of registered voters not voting. DRE precincts: LQD $\sigma = 1.94$; tanh $\sigma = 1.81$; n = 312; no outliers. Optical Central precincts: LQD $\sigma = 2.41$; tanh $\sigma = 2.21$; n = 591; 4 outliers. Optical Precinct precincts: LQD $\sigma = 1.96$; tanh $\sigma = 1.74$; n = 139; 1 outlier. Punchcard precincts: LQD $\sigma = 2.92$; tanh $\sigma = 2.72$; n = 2,402; 10 outliers. Cuyahoga precincts: LQD $\sigma = 2.16$; tanh $\sigma = 1.95$; n = 929; 12 outliers. Hamilton precincts: LQD $\sigma = 2.10$; tanh $\sigma = 2.00$; n = 1,013; 3 outliers. Cuyahoga wards: LQD $\sigma = 3.73$; tanh $\sigma = 3.44$; n = 151; no outliers. Franklin wards: LQD $\sigma = 5.90$; tanh $\sigma = 5.54$; n = 117; no outliers. Hamilton wards: LQD $\sigma = 3.17$; tanh $\sigma = 3.01$; n = 65; no outliers. LQD $\sigma = 2.48$; tanh $\sigma = 2.81$; n = 24; no outliers. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

					U					
Optical Central			Optic	Optical Precinct			Hamilton			
County	Code	SRes	County	Code	SRes	С	ounty	Code	SRes	
Geauga	ACA	-5.08	Allen	AFJ	-4.24	Н	amilton	AAN	-6.90	
Miami	ABX	-6.83				Н	amilton	ANZ	4.66	
Miami	ABY	4.87				Н	amilton	AOD	4.01	
Miami	ABZ	5.64								
P	Inchcard		Cu	iyahoga						
					CD					
County	Code	SRes	County	Code	SRes					
Athens	AAE	5.54	Cuyahoga	AMO	-6.25					
Athens	AAG	6.22	Cuyahoga	APD	-6.08					
Athens	AAW	4.78	Cuyahoga	APJ	0.71					
Butler	AEY	4.77	Cuyahoga	APV	-4.64					
Butler	AFD	5.27	Cuyahoga	AYP	-4.28					
Butler	AFE	5.94	Cuyahoga	AYT	10.99					
Greene	AIN	5.23	Cuyahoga	CQY	-5.42					
Licking	ACY	-5.62	Cuyahoga	CRU	-6.23					
Wayne	ACP	-4.90	Cuyahoga	CSB	4.40					
Williams	AAJ	-4.41	Cuyahoga	CZZ	6.54					
			Cuyahoga	DAB	-5.90					
			Cuyahoga	DAF	-2.69					

Table 11: Outliers: 2004 Voter Turnout: 2002 Voter Turnout Regressor

	DRE			Punchcard			
Variable	Coef.	SE	t-ratio	Coef.	SE	t-ratio	
(Intercept)	0.409	0.0555	7.36	0.941	0.0209	45.10	
Logit(Voter Turnout in 2002)	0.731	0.0227	32.20	0.771	0.0125	61.60	
Machines per Registered Voter	25.000	8.6100	2.90	19.900	2.5300	7.85	
	Opt	ical Centı	ral		Cuyahoga		
Variable	Coef.	SE	t-ratio	Coef.	SE	t-ratio	
(Intercept)	1.120	0.0275	40.90	0.670	0.0195	34.300	
Logit(Voter Turnout in 2002)	0.859	0.0310	27.70	0.671	0.0114	58.800	
Machines per Registered Voter	-12.900	3.3500	-3.86	-0.496	2.1400	-0.232	
	Opti	cal Precin	nct		Hamilton		
Variable	Coef.	SE	t-ratio	Coef.	SE	t-ratio	
(Intercept)	0.778	0.0458	17.000	1.180	0.0484	24.4	
Logit(Voter Turnout in 2002)	0.848	0.0226	37.600	0.882	0.0136	64.8	
Machines per Registered Voter	3.330	6.4900	0.514	7.090	5.0500	1.4	

Table 12: 2004 Voter Turnout: 2002 Voter Turnout and Machines per Voter Regressors

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of registered voters voting versus the number of registered voters not voting. DRE precincts: LQD $\sigma = 1.96$; tanh $\sigma = 1.81$; n = 312; no outliers. Optical Central precincts: LQD $\sigma = 1.64$; tanh $\sigma = 1.59$; n = 181; 1 outlier. Optical Precinct precincts: LQD $\sigma = 1.94$; tanh $\sigma = 1.74$; n = 139; 1 outlier. Punchcard precincts: LQD $\sigma = 2.91$; tanh $\sigma = 2.70$; n = 2,400; 11 outliers. Cuyahoga precincts: LQD $\sigma = 2.15$; tanh $\sigma = 1.95$; n = 929; 12 outliers. Hamilton precincts: LQD $\sigma = 2.09$; tanh $\sigma = 1.99$; n = 1,013; 3 outliers. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

							1		U
Opti	cal Centi	ral	Opt	Optical Precinct			Hamilton		
County	Code	SRes	County	Code	SRes		County	Code	SRes
Ottawa	ACN	0.18	Allen	AFJ	-4.28		Hamilton	AAN	-6.81
							Hamilton	ANZ	4.70
							Hamilton	AOD	4.03
Pu	inchcard		(Cuyahoga					
County	Code	SRes	County	Code	SRes				
Athens	AAE	6.12	Cuyahog	a AMO	-6.28				
Athens	AAG	7.04	Cuyahog		-6.10				
Athens	AAW	5.59	Cuyahog	a APJ	0.63				
Belmont	AAO	-4.10	Cuyahog	a APV	-4.66				
Butler	AEY	4.52	Cuyahog	a AYP	-4.30				
Butler	AFD	5.35	Cuyahog	a AYT	9.42				
Butler	AFE	5.85	Cuyahog	a CQY	-5.46				
Greene	AIN	5.29	Cuyahog	a CRU	-6.25				
Licking	ACY	-5.05	Cuyahog	a CSB	4.41				
Wayne	ACP	-4.73	Cuyahog	a CZZ	6.55				
Williams	AAJ	-4.32	Cuyahog	a DAB	-5.92				
			Cuyahog	a DAF	-2.35				

Table 13: Outliers: 2004 Voter Turnout: 2002 Voter Turnout and Machines per Voter Regressors

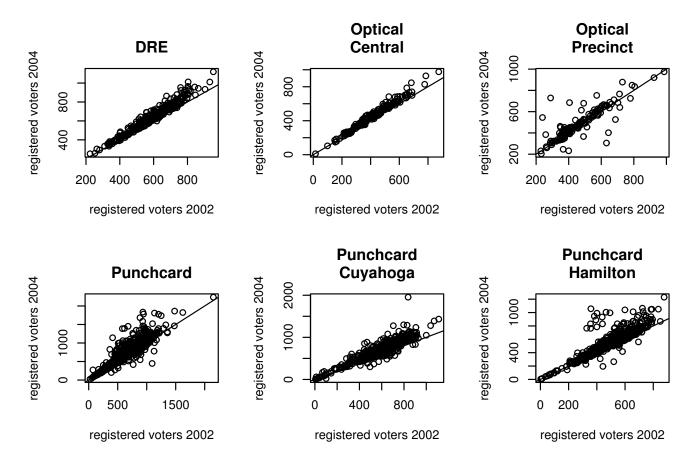


Figure 10: 2004 Registered Voters by 2002 Registered Voters in Precincts with Constant Boundaries Since 2002 by Machine Type

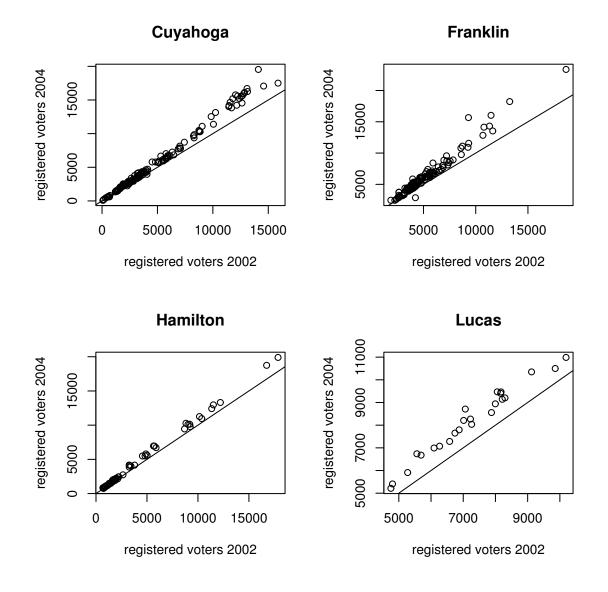


Figure 11: 2004 Registered Voters by 2002 Registered Voters in Wards with Constant Boundaries Since 2002 by County

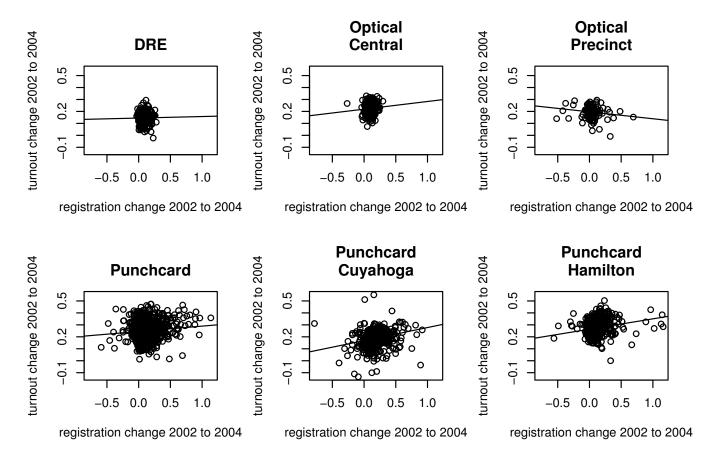


Figure 12: Change in Turnout by Change in Registration in Ohio from 2002 to 2004 in Precincts with Constant Boundaries Since 2002 by Machine Type

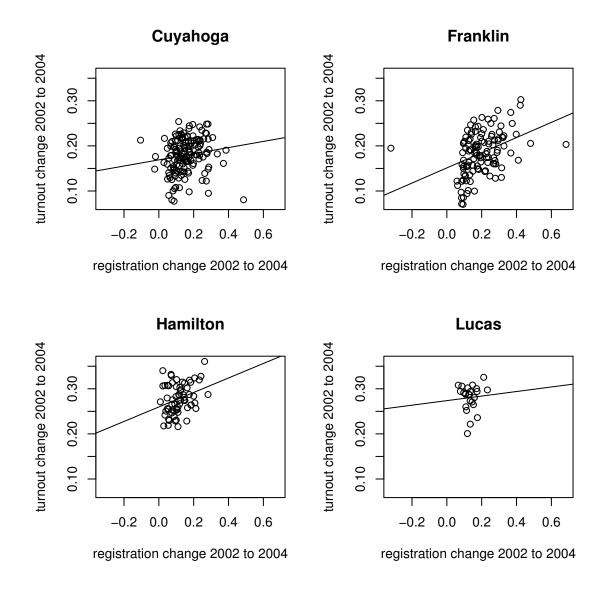
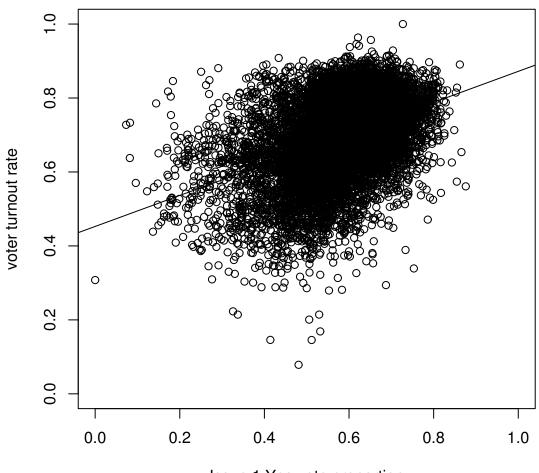


Figure 13: Change in Turnout by Change in Registration in Ohio from 2002 to 2004 in Wards with Constant Boundaries Since 2002 by County



Issue 1 Yes vote proportion

Figure 14: Turnout in Ohio 2004 Precincts by Issue 1 Proportion Yes

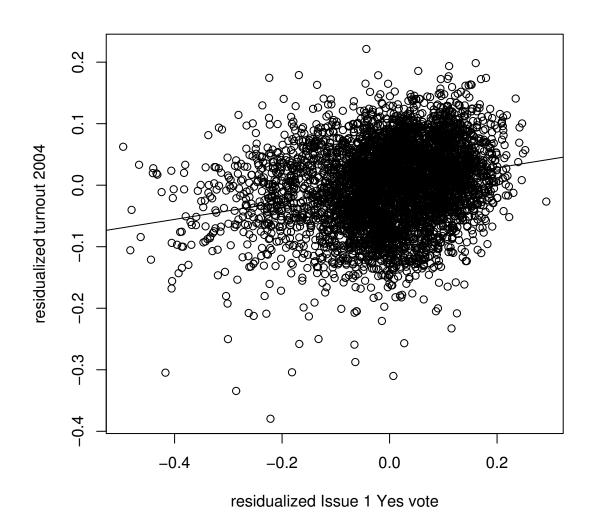


Figure 15: 2004 Turnout by Issue 1 Proportion Yes (Residualized) in Precincts with Constant Boundaries Since 2002

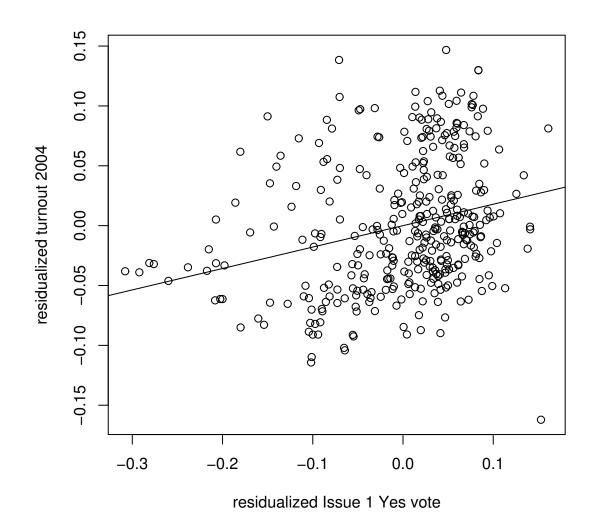


Figure 16: 2004 Turnout by Issue 1 Proportion Yes (Residualized) in Wards with Constant Boundaries Since 2002

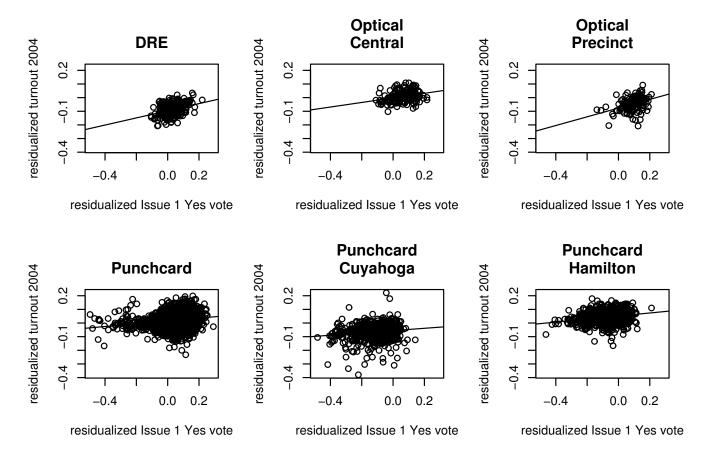


Figure 17: 2004 Turnout by Issue 1 Proportion Yes (Residualized) in Precincts with Constant Boundaries Since 2002, by Machine Type

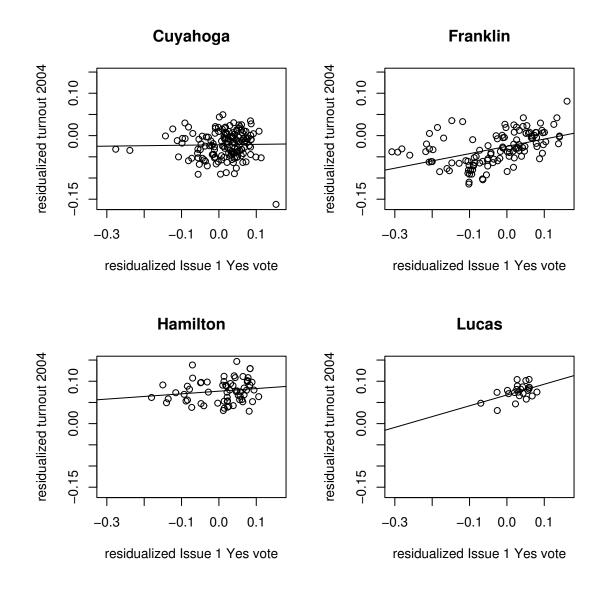


Figure 18: 2004 Turnout by Issue 1 Proportion Yes (Residualized) in Wards with Constant Boundaries Since 2002, by County

	DRE				Cuyahoga Wards		
Variable	Coef.	SE	t-ratio	Co	ef.	SE	t-ratio
(Intercept)	0.455	0.0200	22.80	0.6	700	0.0120	55.800
Logit(Voter Turnout in 2002)	0.712	0.0182	39.20	0.7	090	0.0228	31.200
Logit(Yes on Issue 1)	0.236	0.0392	6.03	0.0	107	0.0281	0.381
	Optical Central			Fr	anklin Waı	ds	
Variable	Coef.	SE	t-ratio	Co	ef.	SE	t-ratio
(Intercept)	1.040	0.0178	58.60	0.	614	0.0217	28.30
Logit(Voter Turnout in 2002)	0.670	0.0155	43.20	0.	611	0.0348	17.60
Logit(Yes on Issue 1)	0.191	0.0302	6.32	0.	149	0.0312	4.78
	Op	Optical Precinct			Hamilton Wards		rds
Variable	Coef.	SE	t-ratio	Co	ef.	SE	t-ratio
(Intercept)	0.628	0.0599	10.50	1.1	500	0.0197	58.200
Logit(Voter Turnout in 2002)	0.749	0.0426	17.60	0.8	560	0.0410	20.900
Logit(Yes on Issue 1)	0.199	0.0651	3.06	0.0	374	0.0432	0.865
		Punchcard			Luca		ls
Variable	Coef.	SE	t-ratio	Co	ef.	SE	t-ratio
(Intercept)	1.0600	0.00854	124.00	1.	120	0.0171	65.70
Logit(Voter Turnout in 2002)	0.7680	0.01240	61.70	0.	796	0.0358	22.20
Logit(Yes on Issue 1)	0.0626	0.01240	5.03	0.	336	0.0805	4.18
	Cuyahoga				Hamilton		
Variable	Coef.	SE	t-ratio	Co	ef.	SE	t-ratio
(Intercept)	0.6710	0.00742	90.40	1.1	230	0.00639	193.0
Logit(Voter Turnout in 2002)	0.6690	0.01130	59.20	0.	833	0.01400	59.5
Logit(Yes on Issue 1)	0.0561	0.01400	4.01	0.	169	0.01550	10.9

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of registered voters voting versus the number of registered voters not voting. DRE precincts: LQD $\sigma = 1.89$; tanh $\sigma = 1.76$; n = 312; no outliers. Optical Central precincts: LQD $\sigma = 2.34$; tanh $\sigma = 2.13$; n = 591; 4 outliers. Optical Precinct precincts: LQD $\sigma = 1.93$; tanh $\sigma = 1.72$; n = 139; no outliers. Punchcard precincts: LQD $\sigma = 2.92$; tanh $\sigma = 2.71$; n = 2,402; 10 outliers. Cuyahoga precincts: LQD $\sigma = 2.14$; tanh $\sigma = 1.94$; n = 929; 12 outliers. Hamilton precincts: LQD $\sigma = 2.02$; tanh $\sigma = 1.91$; n = 1,013; 2 outliers. Cuyahoga wards: LQD $\sigma = 3.72$; tanh $\sigma = 3.45$; n = 151; no outliers. Franklin wards: LQD $\sigma = 4.98$; tanh $\sigma = 4.89$; n = 117; 1 outlier. Hamilton wards: LQD $\sigma = 3.20$; tanh $\sigma = 3.01$; n = 65; no outliers. Lucas wards: LQD $\sigma = 2.64$; tanh $\sigma = 2.64$; n = 24; no outliers. Punchcard precincts exclude Cuyahoga and Hamilton precincts.

Table 15: Expected 2004 Voter Turnout: 2002 Voter Turnout and Issue 1 Vote Regressor

Expected Voter Turnout at Issue 1 Vote Quartiles with Median 2002 Voter Turnout

		Quartile	
Precinct Technology	25%	50%	75%
DRE	0.611	0.619	0.628
Centrally Tabulated Optical Scan	0.746	0.752	0.758
Precinct Tabulated Optical Scan	0.639	0.650	0.658
Punchcard	0.742	0.745	0.748
Cuyahoga	0.601	0.604	0.606
Hamilton	0.766	0.776	0.783
		Quartile	;
Wards	25%	50%	75%
Cuyahoga	0.628	0.628	0.629
Franklin	0.548	0.561	0.570
Hamilton	0.723	0.725	0.727
Lucas	0.710	0.717	0.721

Franklin	Columb	ous City 41	4.28				
Opti	cal Centr	ral	Hamilton				
County	Code	SRes	County	Code	SRes		
Geauga	ACA	-5.16	Hamilton	AAN	-6.66		
Miami	ABX	-6.97	Hamilton	ANZ	4.39		
Miami	ABY	5.03					
Miami	ABZ	5.84					
Opti	cal Centi	ral	Cu	yahoga			
County	Code	SRes	County	Code	SRes		
Athens	AAE	6.02	Cuyahoga	AMO	-5.77		
Athens	AAG	6.88	Cuyahoga	APD	-5.96		
Athens	AAW	5.47	Cuyahoga	APJ	0.59		
Butler	AEY	5.15	Cuyahoga	APV	-4.55		
Butler	AFD	5.63	Cuyahoga	AYP	-4.24		
Butler	AFE	6.28	Cuyahoga	AYT	8.97		
Greene	AIN	5.17	Cuyahoga	CQY	-5.14		
Licking	ACY	-4.83	Cuyahoga	CRU	-6.05		
Wayne	ACP	-4.91	Cuyahoga	CSB	4.79		
Williams	AAJ	-4.39	Cuyahoga	CZZ	6.56		
			Cuyahoga	DAB	-5.85		
			Cuyahoga	DAF	-2.22		

SRes

County

Ward

Table 16: Outliers: 2004 Voter Turnout: 2002 Voter Turnout and Issue 1 Vote Regressor

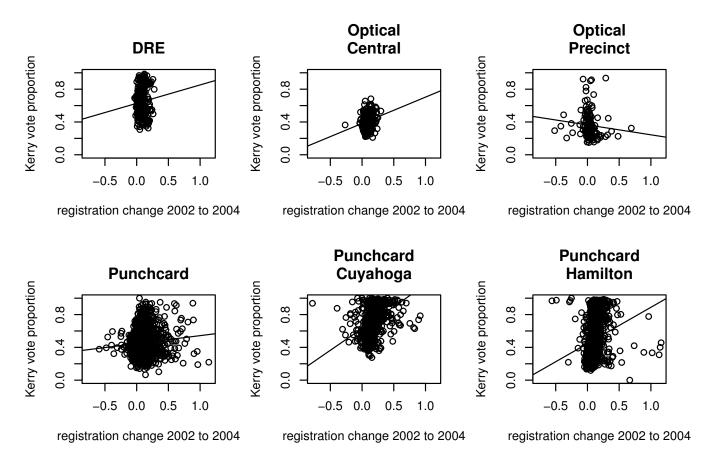


Figure 19: Democratic President Proportion by Change in Proportional Change Registration in Ohio from 2002 to 2004 in Precincts with Constant Boundaries Since 2002 by Machine Type

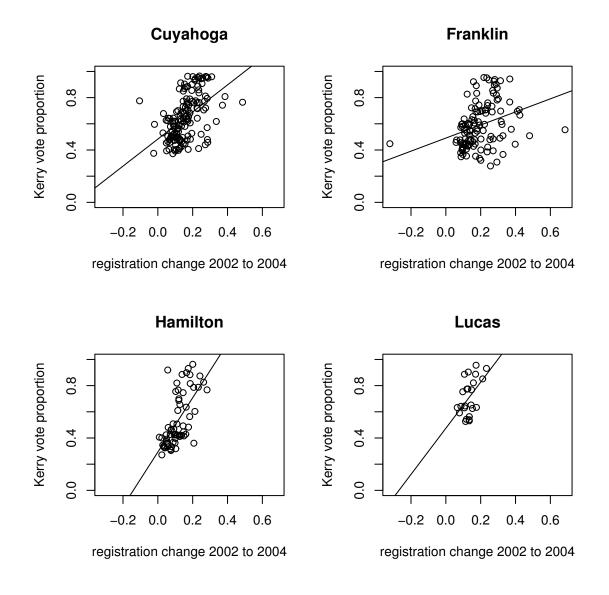


Figure 20: Democratic President Proportion by Change in Proportional Change Registration in Ohio from 2002 to 2004 in Wards with Constant Boundaries Since 2002 by County

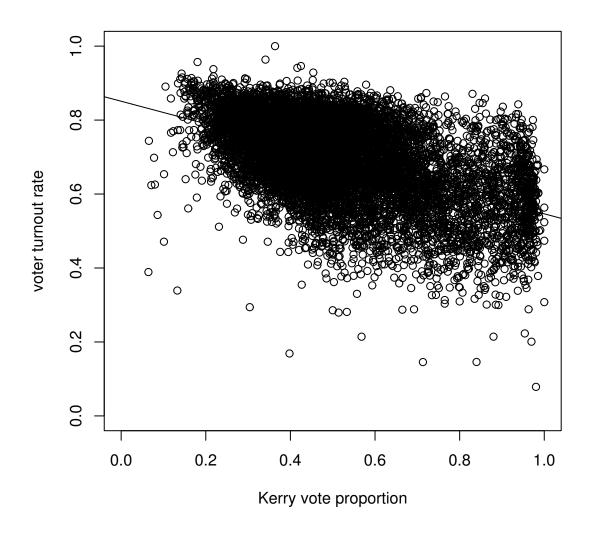


Figure 21: Turnout in Ohio 2004 Precincts by Democratic President Proportion

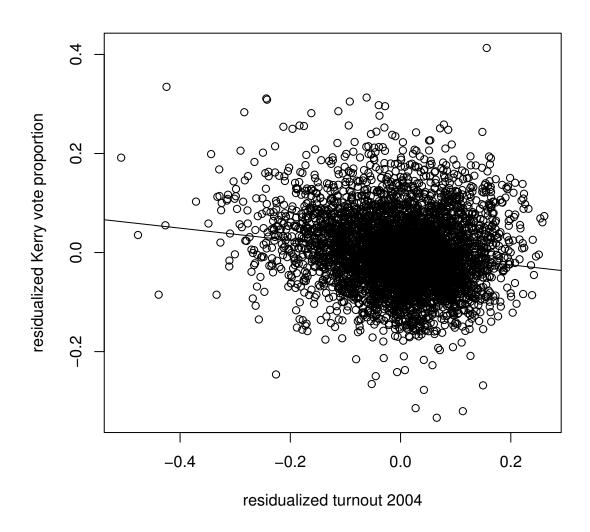


Figure 22: Democratic President Proportion by 2004 Turnout (Residualized) in Precincts with Constant Boundaries Since 2002

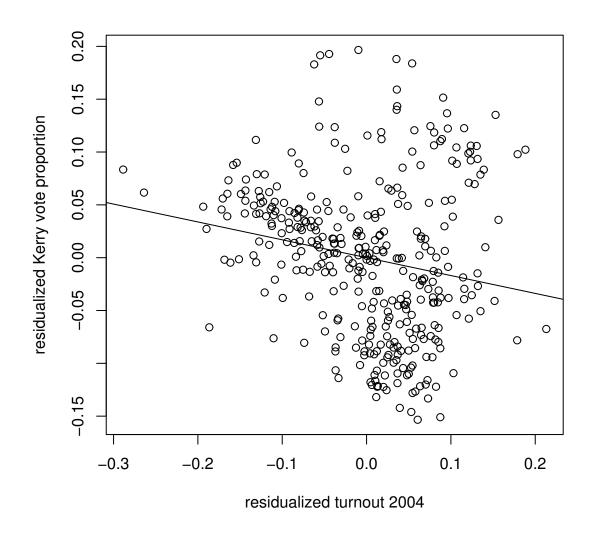


Figure 23: Democratic President Proportion by 2004 Turnout (Residualized) in Wards with Constant Boundaries Since 2002

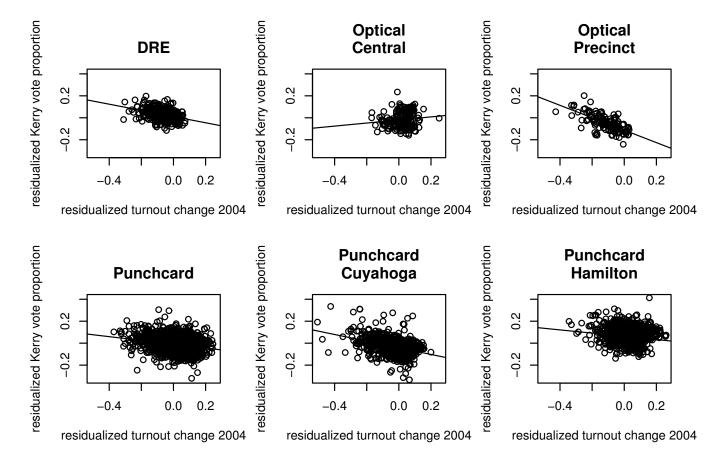


Figure 24: Democratic President Proportion by 2004 Turnout (Residualized) in Precincts with Constant Boundaries Since 2002, by Machine Type

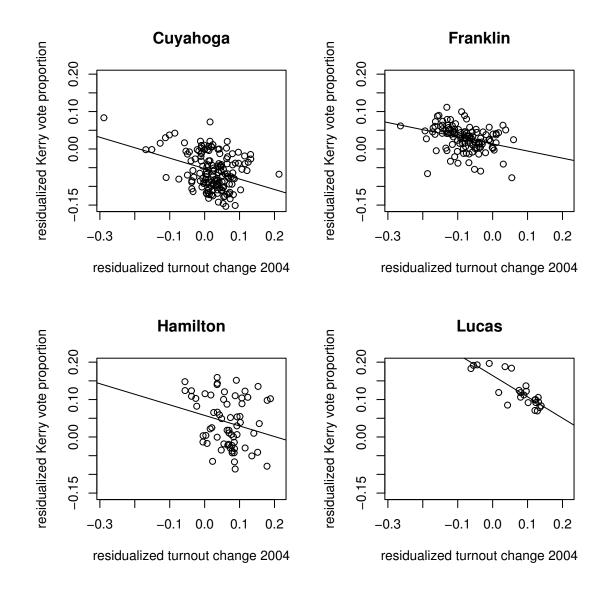


Figure 25: Democratic President Proportion by 2004 Turnout (Residualized) in Wards with Constant Boundaries Since 2002, by County

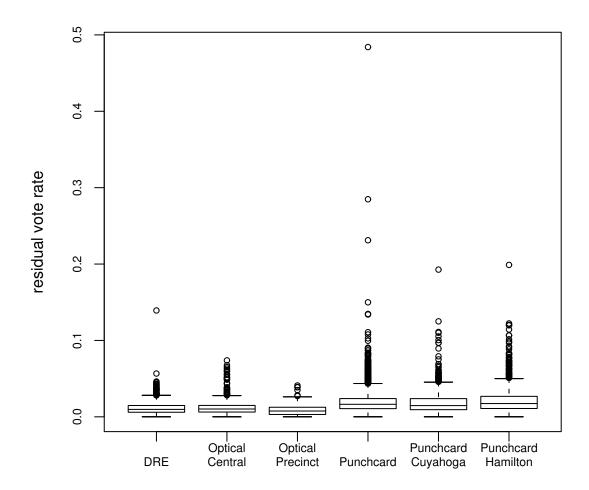


Figure 26: Residual Vote Rate in Ohio 2004 Precincts by Machine Type

		DRE			
Variable	Coef.	SE	t-ratio		
(Intercept)	-4.53	0.0428	-106.00		
Machines per Registered Voter	-30.90	10.4000	-2.97		
	С	ptical Cer	tral		
Variable	Coef.	SE	t-ratio		
(Intercept)	-4.58	0.0477	-95.900		
Machines per Registered Voter	-4.48	7.3100	-0.613		
	Optical Precinct				
	0	ptical Prec	inct		
Variable	O Coef.	ptical Prec SE	t-ratio		
Variable (Intercept)		-			
	Coef.	SE	t-ratio		
(Intercept)	Coef. -4.59	SE 0.22	<i>t</i> -ratio -20.90 -1.98		
(Intercept)	Coef. -4.59	SE 0.22 34.90	<i>t</i> -ratio -20.90 -1.98		
(Intercept) Machines per Registered Voter	Coef. -4.59 -69.00	SE 0.22 34.90 Punchcar	<i>t</i> -ratio -20.90 -1.98 d		

Table 17: Residual Vote: Machines per Voter Regressor

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct, the dependent variable counts the number of residual votes versus the number of votes for one of four presidential candidates (Bush, Kerry, Bedarnik or Peroutka). The residual vote is the number of ballots cast that did not include a vote for one of those four candidates. DRE: LQD $\sigma = 0.96$; tanh $\sigma = 1.08$; n = 1,535 precincts; 77 precincts are outliers. Optical Central: LQD $\sigma = 0.86$; tanh $\sigma = 0.98$; n = 807 precincts; 41 precincts are outliers. Optical Precinct: LQD $\sigma = 0.76$; tanh $\sigma = 0.94$; n = 139 precincts; 9 precincts are outliers. Punchcard: LQD $\sigma = 1.28$; tanh $\sigma = 1.35$; n = 7,865 precincts; 266 precincts are outliers. Punchcard precincts include Cuyahoga and Hamilton precincts.

Expected Residual Vote Rate at Machine Ratio Quartiles

		Quartile	
Technology	25%	50%	75%
DRE	0.0097	0.0096	0.0093
Centrally Tabulated Optical Scan	0.0100	0.0099	0.0099
Precinct Tabulated Optical Scan	0.0071	0.0064	0.0060
Punchcard	0.0160	0.0160	0.0160

				DRE				
County	Code	SRes	County	Code	SRes	County	Code	SRes
Franklin	AAQ	4.66	Franklin	AFS	4.01	Franklin	ATF	4.58
Franklin	ABF	6.48	Franklin	AFW	4.08	Franklin	ATN	5.94
Franklin	ABK	9.22	Franklin	AGG	5.24	Franklin	AUK	5.08
Franklin	ABL	4.64	Franklin	AGM	4.83	Franklin	AWA	4.98
Franklin	ABN	4.06	Franklin	AGQ	6.03	Franklin	AXK	6.40
Franklin	ABP	6.05	Franklin	AHF	5.48	Franklin	AXM	4.18
Franklin	ABR	4.70	Franklin	AHJ	5.28	Franklin	AXP	4.70
Franklin	ABS	5.09	Franklin	AHK	6.15	Franklin	AXZ	4.97
Franklin	ABU	9.64	Franklin	AHW	4.16	Franklin	AYQ	5.33
Franklin	ACB	4.10	Franklin	AHX	4.09	Franklin	AYU	9.19
Franklin	ACQ	7.94	Franklin	AIK	6.22	Franklin	AYZ	5.21
Franklin	ACX	5.25	Franklin	AIQ	4.15	Franklin	AZD	4.51
Franklin	ADF	4.49	Franklin	AIW	4.27	Franklin	AZH	7.79
Franklin	ADL	4.14	Franklin	AJJ	5.85	Franklin	BAB	4.60
Franklin	ADO	4.56	Franklin	AJY	4.59	Franklin	BAG	4.65
Franklin	ADP	5.48	Franklin	AKD	4.47	Franklin	BAJ	5.47
Franklin	AEJ	7.29	Franklin	AKG	8.71	Franklin	BAK	6.00
Franklin	AES	4.27	Franklin	AKP	5.33	Franklin	BBE	4.98
Franklin	AEU	5.39	Franklin	AKT	5.72	Franklin	BBK	4.76
Franklin	AEY	5.09	Franklin	AKU	5.52	Knox	AAR	4.20
Franklin	AFD	4.16	Franklin	AKY	7.02	Lake	ADN	5.73
Franklin	AFI	9.59	Franklin	ALR	4.46	Mahoning	ARC	24.93
Franklin	AFJ	4.81	Franklin	ALW	4.65	Mahoning	ARZ	4.24
Franklin	AFL	4.08	Franklin	AML	7.56	Mahoning	ASC	6.48
Franklin	AFN	6.53	Franklin	AOW	13.15	Ross	AAH	5.13
Franklin	AFO	5.88	Franklin	ATE	5.13			

Table 18: Outliers, DRE Machine Technology: Residual Vote: Machines per Voter Regressor

Optical Central									
County	Code	SRes	County	Code	SRes	County	Code	SRes	
Ashland	AAB	4.05	Ashland	ABQ	11.88	Erie	ADN	10.70	
Ashland	AAC	12.47	Ashland	ABT	12.82	Erie	AEG	4.09	
Ashland	AAD	10.41	Ashland	ABY	8.45	Hardin	ABE	4.83	
Ashland	AAH	4.99	Ashland	ABZ	6.98	Lucas	ASN	4.63	
Ashland	AAK	4.15	Ashland	ACC	12.77	Lucas	ABV	4.86	
Ashland	AAQ	5.32	Ashland	ACD	5.90	Lucas	AAB	4.34	
Ashland	AAR	10.01	Ashland	ACG	12.01	Lucas	ANQ	7.24	
Ashland	AAU	11.13	Ashland	ACH	5.56	Lucas	AHJ	5.03	
Ashland	AAV	9.93	Ashland	ACJ	4.04	Ottawa	ACE	4.25	
Ashland	ABA	10.69	Ashland	ACK	6.96	Sandusky	AAM	4.23	
Ashland	ABB	8.59	Ashland	ACL	6.69	Sandusky	ABE	6.07	
Ashland	ABI	12.04	Ashland	ACO	11.11	Sandusky	ABK	6.51	
Ashland	ABK	8.50	Ashland	ACP	8.01	Sandusky	ACS	4.22	
Ashland	ABN	5.96	Ashland	ACS	13.08				
			Optio	cal Prec	inct				
County	Code	SRes	County	Code	SRes	County	Code	SRes	
Allen	ABF	4.64	Allen	ACG	8.48	Allen	AFJ	4.20	
Allen	ABW	4.61	Allen	ACZ	4.51	Allen	AGI	9.13	
Allen	ABX	8.41	Allen	AEK	7.61	Allen	AGK	5.57	

Table 19: Outliers, Optical Scan Machine Technologies: Residual Vote: Machines per Voter Regressor

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County	Code	SRes	County	Code	SRes	County	Code	SRes
Adams	AAM	7.35	Cuyahoga	BAC	4.77	Hamilton	AIV	5.94
Adams	ABC	4.31	Cuyahoga	BAJ	4.47	Hamilton	AJF	6.73
Ashtabula	AAQ	7.65	Cuyahoga	BBQ	6.86	Hamilton	AJN	7.95
Ashtabula	AAS	4.30	Cuyahoga	BEF	4.25	Hamilton	AJQ	4.21
Athens	ABC	4.87	Cuyahoga	BMT	4.01	Hamilton	AKC	6.85
Belmont	AAC	6.59	Cuyahoga	BMV	4.02	Hamilton	AKK	15.13
Belmont	ACH	5.05	Cuyahoga	BNY	4.47	Hamilton	AKP	6.47
Butler	ADJ	7.98	Cuyahoga	BOB	4.54	Hamilton	AKT	5.82
Butler	AKV	6.10	Cuyahoga	BQB	11.15	Hamilton	AKU	5.10
Carroll	AAJ	4.20	Cuyahoga	BQW	8.05	Hamilton	ALE	4.10
Carroll	AAS	5.27	Cuyahoga	CFQ	6.98	Hamilton	ALO	5.33
Clark	AAO	4.19	Cuyahoga	CGD	5.30	Hamilton	ALU	11.09
Clark	AAQ	4.13	Cuyahoga	CTG	4.17	Hamilton	ALV	5.20
Clark	ACI	7.25	Cuyahoga	DDT	6.35	Hamilton	ALZ	6.51
Clark	ACM	6.32	Darke	AAG	63.32	Hamilton	AMD	12.27
Clark	ACV	5.29	Fairfield	ADY	5.73	Hamilton	AMI	4.83
Crawford	AAB	4.05	Greene	ADP	4.46	Hamilton	AMS	6.84
Cuyahoga	ABM	10.31	Hamilton	AAF	7.15	Hamilton	ANU	9.79
Cuyahoga	AHY	7.73	Hamilton	AAQ	4.65	Hamilton	ANZ	13.63
Cuyahoga	AJZ	4.60	Hamilton	ACB	4.83	Hamilton	AOE	6.51
Cuyahoga	AKV	4.44	Hamilton	ACG	5.31	Hamilton	AOK	6.12
Cuyahoga	AMM	5.26	Hamilton	ACV	7.52	Hamilton	APA	6.00
Cuyahoga	ANB	5.18	Hamilton	ADC	8.79	Hamilton	APQ	11.84
Cuyahoga	ANN	5.48	Hamilton	ADH	7.35	Hamilton	AQK	6.03
Cuyahoga	ANX	10.88	Hamilton	ADW	4.58	Hamilton	AQM	4.46
Cuyahoga	AOH	4.36	Hamilton	AEI	4.49	Hamilton	AQW	9.06
Cuyahoga	APT	8.11	Hamilton	AFF	5.20	Hamilton	ARW	5.37
Cuyahoga	APY	23.81	Hamilton	AFG	6.54	Hamilton	AUJ	4.84
Cuyahoga	AQG	4.42	Hamilton	AFK	10.04	Hamilton	AVK	6.71
Cuyahoga	AQM	6.02	Hamilton	AFP	7.42	Hamilton	AVV	4.09
Cuyahoga	ARP	5.59	Hamilton	AFU	6.61	Hamilton	AWP	4.00
Cuyahoga	ASL	12.31	Hamilton	AGE	10.72	Hamilton	AXI	4.94
Cuyahoga	ASV	4.22	Hamilton	AGP	11.14	Hamilton	BBQ	6.06
Cuyahoga	AUD	6.38	Hamilton	AGR	5.03	Hamilton	BDJ	5.15
Cuyahoga	AUI	5.45	Hamilton	AGS	5.54	Hamilton	BFK	5.48
Cuyahoga	AWA	4.13	Hamilton	AGU	8.77	Hamilton	BKZ	6.21
Cuyahoga	AWW	5.50	Hamilton	AHA	8.82	Hamilton	BLJ	8.10
Cuyahoga	AXU	5.13	Hamilton	AHC	4.19	Hamilton	BLK	7.10
Cuyahoga	AYJ	5.29	Hamilton	AID	9.00	Hamilton	BON	10.89
Cuyahoga	AYX	5.43	Hamilton	AIE	12.56	Hamilton	BOP	5.88

Table 20: Outliers, Punchcard Machine Technology I: Residual Vote: Machines per Voter Regressor

CountyCodeSResCountyCodeSResCountyCodeSResHamiltonBOR7.12MontgomeryADG5.85StarkABF5.55HamiltonBOS4.80MontgomeryADT4.83StarkABF1.08HarrisonAAK6.74MontgomeryAFJ5.22StarkABT6.09HarrisonABF4.34MontgomeryAFV5.30StarkABV6.50HockingABA4.68MontgomeryAFZ4.29StarkAC4.24HolmesAAA6.69MontgomeryAGH5.48StarkAEH5.78HolmesAAA2.17MontgomeryAGS4.43StarkAEH5.78HolmesAAA2.107MontgomeryAGS4.43StarkAAEH5.78HolmesAAR4.23MontgomeryAHW4.56SummitAAI5.01HuronACB4.93MontgomeryAIK7.76SummitABU4.39HuronACB4.93MontgomeryAQW4.99SummitABZ4.78JeffersonAAA5.71MontgomeryAQW4.99SummitABE1.27JacksonAQ6.31MontgomeryAIX4.56SummitABU4.39JeffersonAAA5.71MontgomeryAQW4.99SummitACE7.59LawrenceABP				Punche	ard				
HamiltonBOS4.80MontgomeryADT4.83StarkABQ11.08HarrisonAAX $6.74$ MontgomeryAFJ $7.51$ StarkABR $6.19$ HarrisonABF $4.34$ MontgomeryAFL $5.22$ StarkABT $5.07$ HighlandAAF $4.58$ MontgomeryAFZ $4.29$ StarkACA $4.24$ HolmesAAA $6.69$ MontgomeryAGH $4.14$ StarkACF $7.90$ HolmesAAB $5.71$ MontgomeryAGH $4.43$ StarkAFH $5.78$ HolmesAAC $27.59$ MontgomeryAGS $4.43$ StarkAFH $4.02$ HolmesAAP $18.84$ MontgomeryAHV $5.65$ SummitAAC $5.73$ HolmesAAP $18.84$ MontgomeryAHZ $7.76$ SummitAAE $6.10$ HolmesAAW $19.52$ MontgomeryAHZ $7.76$ SummitABU $4.39$ HuronACB $4.93$ MontgomeryAQS $7.01$ SummitABU $4.78$ JeffersonAAA $5.71$ MontgomeryAQK $4.99$ SummitACC $5.22$ JeffersonAAA $6.31$ MontgomeryAQK $4.99$ SummitACC $5.23$ JeffersonAAM $7.17$ MontgomeryAQK $4.33$ SummitACC $5.22$ LawrenceABP $4.00$ MorrowAAL $5.8$	County	Code	SRes	County	Code	SRes	County	Code	SRes
HarrisonAAX $6.74$ MongomeryAFJ $7.51$ StarkABR $6.19$ HarrisonABF $4.34$ MontgomeryAFL $5.22$ StarkABT $5.07$ HighlandAAF $4.58$ MontgomeryAFZ $4.22$ StarkABC $4.68$ HockingABA $4.66$ MontgomeryAFZ $4.29$ StarkACA $4.24$ HolmesAAA $6.69$ MontgomeryAGH $4.14$ StarkACF $7.90$ HolmesAAB $5.71$ MontgomeryAGB $5.48$ StarkAFU $4.02$ HolmesAAC $27.59$ MontgomeryAHB $5.48$ StarkAFU $4.02$ HolmesAAR $12.07$ MontgomeryAHB $5.65$ SummitAAC $5.73$ HolmesAAR $4.23$ MontgomeryAHF $6.31$ SummitAAB $4.02$ HolmesAAW $19.52$ MontgomeryAHF $6.31$ SummitABU $4.39$ HuronACB $4.93$ MontgomeryAFF $6.31$ SummitABU $4.39$ JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitABZ $4.78$ JeffersonAAA $5.71$ MontgomeryATC $4.40$ SummitACE $7.59$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceABP $4.00$ MorrowAAL $5.81$ <	Hamilton	BOR	7.12	Montgomery	ADG	5.85	Stark	ABF	5.55
HarrisonABF4.34MontgomeryAFL5.22StarkABT5.07HighlandAAF4.58MontgomeryAFV5.30StarkABV6.50HockingABA4.68MontgomeryAFZ4.29StarkACA4.24HolmesAAA6.69MontgomeryAGH4.14StarkACF7.90HolmesAAB5.71MontgomeryAGM5.48StarkAEH5.78HolmesAAC27.59MontgomeryAHJ5.84SummitAAC5.73HolmesAAP18.84MontgomeryAHW5.65SummitAAS6.10HolmesAAW19.52MontgomeryAHZ7.76SummitAAS6.10HolmesAAW19.52MontgomeryAIF6.31SummitABS4.98JeffersonAAA5.71MontgomeryAQK4.99SummitABZ4.78JeffersonAAA5.71MontgomeryAQW4.99SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACE7.79LawrenceABP4.00MorrowAAL5.81SummitACE7.79LawrenceABP4.00MorrowAAL5.81SummitACE6.50LawrenceABP4.0	Hamilton	BOS	4.80	Montgomery	ADT	4.83	Stark	ABQ	11.08
HighlandAAF4.58MongomeryAFV5.30StarkABV6.50HockingABA4.68MontgomeryAFZ4.29StarkACA4.24HolmesAAA6.69MontgomeryAGH4.14StarkACF7.90HolmesAAB5.71MontgomeryAGB4.43StarkAFU4.02HolmesAAC27.59MontgomeryAHU5.84SummitAAC5.73HolmesAAP18.84MontgomeryAHW5.65SummitAAB6.10HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39HuronACB4.93MontgomeryAHZ7.76SummitABU4.39JeffersonAAA5.71MontgomeryAQS7.01SummitABZ4.78JeffersonAAA5.71MontgomeryAQW4.99SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACE6.00LawrenceABP4.00MorrowAAL5.81SummitACE6.59LawrenceABP4.00MorrowAAL5.81SummitACC5.28LawrenceABP4.00MorrowAAL5.81SummitACC5.28LawrenceABW4.29	Harrison	AAX	6.74	Montgomery	AFJ	7.51	Stark	ABR	6.19
HockingABA4.68MongomeryAFZ4.29StarkACA4.24HolmesAAA6.69MontgomeryAGH4.14StarkACF7.90HolmesAAB5.71MontgomeryAGB5.48StarkAEH5.73HolmesAAC27.59MontgomeryAGS4.43StarkAFU4.02HolmesAAM21.07MontgomeryAHU5.65SummitAAC5.73HolmesAAP18.84MontgomeryAHK4.56SummitAAS6.10HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39JacksonAAQ6.31MontgomeryAIF6.31SummitABU4.98JeffersonAAA5.71MontgomeryAUX4.40SummitACC5.24JeffersonAAA5.71MontgomeryAUX4.40SummitACC5.24JeffersonAAA5.71MontgomeryAUX4.40SummitACC5.24JeffersonAAM7.17MontgomeryAUX4.40SummitACC5.24LawrenceADP4.00MorrowAAL5.81SummitACC5.24LawrenceADD5.78NobleAAP6.87SummitACG1.04LorainAEZ5.73NobleAAZ5.19SummitACQ6.69LorainAEX7.28	Harrison	ABF	4.34	Montgomery	AFL	5.22	Stark	ABT	5.07
HolmesAAA $6.69$ MongomeryAGH $4.14$ StarkACF $7.90$ HolmesAAB $5.71$ MontgomeryAGM $5.48$ StarkAEH $5.78$ HolmesAAC $27.59$ MontgomeryAGS $4.43$ StarkAFU $4.02$ HolmesAAM $21.07$ MontgomeryAHU $5.65$ SummitAAC $5.73$ HolmesAAP $18.84$ MontgomeryAHV $5.65$ SummitAAI $5.04$ HolmesAAR $4.23$ MontgomeryAHZ $7.76$ SummitAAI $5.04$ HolmesAAW $19.52$ MontgomeryAHZ $7.76$ SummitABU $4.39$ HuronACB $4.93$ MontgomeryAHF $6.31$ SummitABU $4.39$ JeffersonAAA $5.71$ MontgomeryAQS $7.01$ SummitABZ $4.78$ JeffersonAAM $7.17$ MontgomeryAUX $4.40$ SummitACE $7.59$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACC $5.28$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACE $6.60$ LorainABW $4.29$ PikeAAL $6.23$ SummitACC $6.59$ LorainABW $4.29$ PikeAAQ $5.76$ SummitACQ $6.59$ LorainAEX $7.28$ PikeAAQ $5.76$ Summit <t< td=""><td>Highland</td><td>AAF</td><td>4.58</td><td>Montgomery</td><td>AFV</td><td>5.30</td><td>Stark</td><td>ABV</td><td>6.50</td></t<>	Highland	AAF	4.58	Montgomery	AFV	5.30	Stark	ABV	6.50
HolmesAAB $5.71$ MontgomeryAGM $5.48$ StarkAEH $5.78$ HolmesAAC $27.59$ MontgomeryAGS $4.43$ StarkAFU $4.02$ HolmesAAM $21.07$ MontgomeryAHJ $5.84$ SummitAAC $5.73$ HolmesAAP $18.84$ MongomeryAHU $5.65$ SummitAAI $5.04$ HolmesAAW $19.52$ MontgomeryAHZ $7.76$ SummitAAS $6.10$ HolmesAAW $19.52$ MontgomeryAHZ $7.76$ SummitABU $4.39$ HuronACB $4.93$ MontgomeryAHZ $7.76$ SummitABU $4.39$ JeffersonAAA $5.71$ MontgomeryAQS $7.01$ SummitABZ $4.78$ JeffersonAAN $4.83$ MorgoneryATX $4.40$ SummitACE $7.52$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACE $7.73$ LorainABW $4.29$ PikeAAL $6.23$ SummitACG $7.73$ LorainAEX $7.28$ PikeAAV $7.07$ SummitACT $7.84$ LorainAEX $7.28$ PikeAAV $7.07$ Summit <td< td=""><td>Hocking</td><td>ABA</td><td>4.68</td><td>Montgomery</td><td>AFZ</td><td>4.29</td><td>Stark</td><td>ACA</td><td>4.24</td></td<>	Hocking	ABA	4.68	Montgomery	AFZ	4.29	Stark	ACA	4.24
HolmesAAC27.59MongomeryAGS4.43StarkAFU4.02HolmesAAM21.07MontgomeryAHJ5.84SummitAAC5.73HolmesAAP18.84MontgomeryAHW5.65SummitAAI5.04HolmesAAR4.23MontgomeryAHX4.56SummitAAS6.10HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39HuronACB4.93MontgomeryAQS7.01SummitABY4.98JeffersonAAA5.71MontgomeryAQS7.01SummitABZ4.78JeffersonAAA5.71MontgomeryAQW4.99SummitACB12.74JeffersonAAA7.17MontgomeryATX4.40SummitACB12.74JeffersonAAN4.83MorganAAO4.33SummitACC5.28LawrenceABP4.00MorrowAAL5.81SummitACC7.59LawrenceADD5.78NobleAAI6.72SummitACC7.60LawrenceADD5.78NobleAAZ5.19SummitACG7.73LorainABW4.29PikeAAQ5.76SummitACC7.73LorainAEW6.31PrebleABD4.22SummitACQ7.73LorainAEW6.31P	Holmes	AAA	6.69	Montgomery	AGH	4.14	Stark	ACF	7.90
HolmesAAM21.07MongomeryAHJ $5.84$ SummitAAC $5.73$ HolmesAAP18.84MontgomeryAHW $5.65$ SummitAAI $5.04$ HolmesAAR4.23MontgomeryAHX $4.56$ SummitAAS $6.10$ HolmesAAW19.52MontgomeryAHZ $7.76$ SummitABU $4.39$ HuronACB4.93MontgomeryAHZ $7.76$ SummitABU $4.39$ JeffersonAAA $5.71$ MontgomeryAQS $7.01$ SummitABZ $4.78$ JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitACE $5.28$ JeffersonAAA $7.17$ MontgomeryATX $4.40$ SummitACE $5.28$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceADD $5.78$ NobleAAI $6.72$ SummitACE $7.60$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACG $7.73$ LorainAEW $6.31$ PrebleABD $4.22$ SummitACC $7.73$ LorainAEW $6.31$ PrebleABD $4.22$ SummitACC $7.73$ LorainAEW $6.31$ PrebleABD $4.22$ SummitACV	Holmes	AAB	5.71	Montgomery	AGM	5.48	Stark	AEH	5.78
HolmesAAP18.84MongomeryAHW5.65SummitAAI5.04HolmesAAR4.23MontgomeryAHX4.56SummitAAS6.10HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39HuronACB4.93MontgomeryAIF6.31SummitABU4.39JacksonAAQ6.31MontgomeryAQS7.01SummitABY4.98JeffersonAAA5.71MontgomeryAUX4.40SummitACB12.74JeffersonAAA5.71MontgomeryATX4.40SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACC5.28LawrenceACY6.02NobleAAI6.72SummitACF6.00LawrenceADD5.78NobleAAZ5.19SummitACG10.46LickingAEL5.37NobleAAZ5.19SummitACG7.73LorainABW4.29PikeAAU6.23SummitACQ7.73LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEY4.26RichlandABG5.51SummitADV4.55LorainAEY4.26RichlandABH4.60SummitADV4.55LorainAEY4.26Richland	Holmes	AAC	27.59	Montgomery	AGS	4.43	Stark	AFU	4.02
HolmesAAR4.23MongomeryAHX4.56SummitAAS6.10HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39HuronACB4.93MontgomeryAIF6.31SummitABW10.71JacksonAAQ6.31MontgomeryAQS7.01SummitABY4.98JeffersonAAA5.71MontgomeryAQW4.99SummitABZ4.78JeffersonAAA5.71MontgomeryATX4.40SummitACE12.74JeffersonAAN4.83MorganAAO4.33SummitACE5.28LawrenceABP4.00MorrowAAL5.81SummitACE7.59LawrenceADD5.78NobleAAZ5.19SummitACF6.00LawrenceADD5.78NobleAAZ5.19SummitACG10.46LickingAEL5.37NobleAAZ5.19SummitACC7.73LorainAEW6.31PrekeAAQ5.76SummitACQ6.59LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEZ5.13RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH6.60SummitADD8.37LorainAEZ5.13Richland <td>Holmes</td> <td>AAM</td> <td>21.07</td> <td>Montgomery</td> <td>AHJ</td> <td>5.84</td> <td>Summit</td> <td>AAC</td> <td>5.73</td>	Holmes	AAM	21.07	Montgomery	AHJ	5.84	Summit	AAC	5.73
HolmesAAW19.52MontgomeryAHZ7.76SummitABU4.39HuronACB4.93MontgomeryAIF $6.31$ SummitABW10.71JacksonAAQ $6.31$ MontgomeryAQS $7.01$ SummitABY4.98JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitABZ $4.78$ JeffersonAAM $7.17$ MontgomeryATX $4.40$ SummitABZ $4.78$ JeffersonAAN $4.83$ MorganAAO $4.33$ SummitACE $5.28$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACF $6.00$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACG $7.73$ LorainAEA $7.28$ PikeAAQ $5.76$ SummitACQ $6.59$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACY $4.79$ LorainAEY $4.26$ RichlandABG $5.51$ SummitACY $5.65$ LorainAEZ $5.13$ RichlandABH $6.60$ SummitADN $4.35$ LorainAFG $4.67$ RichlandABL $6.11$ SummitADU $8$	Holmes	AAP	18.84	Montgomery	AHW	5.65	Summit	AAI	5.04
HuronACB $4.93$ MontgomeryAIF $6.31$ SummitABW $10.71$ JacksonAAQ $6.31$ MontgomeryAQS $7.01$ SummitABY $4.98$ JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitABZ $4.78$ JeffersonAAM $7.17$ MontgomeryATX $4.40$ SummitACB $12.74$ JeffersonAAN $4.83$ MorganAAO $4.33$ SummitACE $5.28$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceACY $6.02$ NobleAAI $6.72$ SummitACF $6.00$ LawrenceADD $5.78$ NobleAAP $6.87$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACC $5.59$ LorainABW $4.29$ PikeAAL $6.23$ SummitACC $6.59$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEY $4.26$ RichlandABG $5.51$ SummitACV $4.55$ LorainAEY $4.26$ RichlandABG $5.51$ SummitADV $5.65$ LorainAFG $4.67$ RichlandABL $6.11$ SummitADN	Holmes	AAR	4.23	Montgomery	AHX	4.56	Summit	AAS	6.10
JacksonAAQ $6.31$ MontgomeryAQS $7.01$ SummitABY $4.98$ JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitABZ $4.78$ JeffersonAAM $7.17$ MontgomeryATX $4.40$ SummitACE $12.74$ JeffersonAAN $4.83$ MorganAAO $4.33$ SummitACE $5.28$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceADD $5.78$ NobleAAP $6.87$ SummitACF $6.00$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACF $6.00$ LorainABW $4.29$ PikeAAQ $5.76$ SummitACG $10.46$ LorainAEL $5.37$ NobleAAZ $5.19$ SummitACC $5.59$ LorainAEZ $4.23$ PikeAAQ $5.76$ SummitACQ $6.59$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEY $4.26$ RichlandABG $5.51$ SummitACV $4.98$ LorainAEZ $5.13$ RichlandABH $4.60$ SummitADD $8.37$ LorainAEZ $5.13$ RichlandABH $4.60$ SummitADD $8.37$ LorainAFG $4.67$ RichlandABH $6.60$ SummitADD <td< td=""><td>Holmes</td><td>AAW</td><td>19.52</td><td>Montgomery</td><td>AHZ</td><td>7.76</td><td>Summit</td><td>ABU</td><td>4.39</td></td<>	Holmes	AAW	19.52	Montgomery	AHZ	7.76	Summit	ABU	4.39
JeffersonAAA $5.71$ MontgomeryAQW $4.99$ SummitABZ $4.78$ JeffersonAAM $7.17$ MontgomeryATX $4.40$ SummitACB $12.74$ JeffersonAAN $4.83$ MorganAAO $4.33$ SummitACC $5.28$ LawrenceABP $4.00$ MorrowAAL $5.81$ SummitACE $7.59$ LawrenceACY $6.02$ NobleAAI $6.72$ SummitACF $6.00$ LawrenceADD $5.78$ NobleAAZ $5.19$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACO $7.73$ LorainABW $4.29$ PikeAAL $6.23$ SummitACO $7.73$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEY $4.26$ RichlandABG $5.51$ SummitACV $4.79$ LorainAEY $5.59$ RichlandABH $4.60$ SummitADD $8.37$ LorainAFB $5.59$ RichlandABH $6.60$ SummitADD $8.37$ LorainAFB $5.59$ RichlandABH $6.60$ SummitADD $8.37$ LorainAFG $4.67$ RichlandABH $6.60$ SummitADD	Huron	ACB	4.93	Montgomery	AIF	6.31	Summit	ABW	10.71
JeffersonAAM7.17MontgomeryATX4.40SummitACB12.74JeffersonAAN4.83MorganAAO4.33SummitACC5.28LawrenceABP4.00MorrowAAL5.81SummitACE7.59LawrenceACY6.02NobleAAI6.72SummitACF6.00LawrenceADD5.78NobleAAP6.87SummitACG10.46LickingAEL5.37NobleAAZ5.19SummitACG7.73LorainABW4.29PikeAAL6.23SummitACO7.73LorainAEA7.28PikeAAV7.07SummitACV4.79LorainAEA7.28PikeAAV7.07SummitACV4.79LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABH6.60SummitADX8.42MadisonAAQ8.71RichlandABG5.21SummitADX8.42MadisonAAQ8.71RichlandABU5.	Jackson	AAQ	6.31	Montgomery	AQS	7.01	Summit	ABY	4.98
JeffersonAAN4.83MorganAAO4.33SummitACC5.28LawrenceABP4.00MorrowAAL5.81SummitACE7.59LawrenceACY $6.02$ NobleAAI $6.72$ SummitACF $6.00$ LawrenceADD5.78NobleAAP $6.87$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACG $10.46$ LorainABW $4.29$ PikeAAL $6.23$ SummitACO $7.73$ LorainAEA $7.28$ PikeAAQ $5.76$ SummitACQ $6.59$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACV $4.79$ LorainAEW $6.31$ PrebleABD $4.22$ SummitACV $4.79$ LorainAEZ $5.13$ RichlandABG $5.51$ SummitACY $5.65$ LorainAFB $5.59$ RichlandABJ $6.60$ SummitADN $4.35$ LorainAFG $4.67$ RichlandABL $6.11$ SummitADQ $7.08$ MadisonAAQ $8.71$ RichlandABL $6.11$ SummitADX $8.42$ MadisonAAQ $8.71$ RichlandABR $6.46$ SummitADX $11.49$ MonroeAAI $5.71$ RichlandABU $5.22$ SummitADX $11.49$ <td< td=""><td>Jefferson</td><td>AAA</td><td>5.71</td><td>Montgomery</td><td>AQW</td><td>4.99</td><td>Summit</td><td>ABZ</td><td>4.78</td></td<>	Jefferson	AAA	5.71	Montgomery	AQW	4.99	Summit	ABZ	4.78
LawrenceABP4.00MorrowAAL5.81SummitACE7.59LawrenceACY $6.02$ NobleAAI $6.72$ SummitACF $6.00$ LawrenceADD $5.78$ NobleAAP $6.87$ SummitACG $10.46$ LickingAEL $5.37$ NobleAAZ $5.19$ SummitACG $10.46$ LorainABW $4.29$ PikeAAL $6.23$ SummitACO $7.73$ LorainACZ $4.23$ PikeAAQ $5.76$ SummitACQ $6.59$ LorainAEA $7.28$ PikeAAV $7.07$ SummitACY $4.79$ LorainAEW $6.31$ PrebleABD $4.22$ SummitACY $5.65$ LorainAEY $4.26$ RichlandABG $5.51$ SummitACY $5.65$ LorainAEZ $5.13$ RichlandABH $4.60$ SummitADD $8.37$ LorainAFB $5.59$ RichlandABJ $6.60$ SummitADN $4.35$ LorainAFG $4.67$ RichlandABL $6.11$ SummitADQ $7.08$ MadisonAAQ $8.71$ RichlandABL $6.11$ SummitADX $8.42$ MadisonAAQ $5.64$ RichlandABQ $5.21$ SummitADX $11.49$ MonroeAAI $5.71$ RichlandABU $5.22$ SummitADX $11.49$	Jefferson	AAM	7.17	Montgomery	ATX	4.40	Summit	ACB	12.74
LawrenceACY6.02NobleAAI6.72SummitACF6.00LawrenceADD5.78NobleAAP6.87SummitACG10.46LickingAEL5.37NobleAAZ5.19SummitACH4.06LorainABW4.29PikeAAL6.23SummitACO7.73LorainACZ4.23PikeAAQ5.76SummitACQ6.59LorainAEA7.28PikeAAV7.07SummitACV4.79LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAQ5.64RichlandABQ5.21SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitADX11.49MonroeAAI5.71RichlandABW4.92SummitAFE4.85MonroeAAI5.71RichlandABW4.92	Jefferson	AAN	4.83	Morgan	AAO	4.33	Summit	ACC	5.28
LawrenceADD5.78NobleAAP6.87SummitACG10.46LickingAEL5.37NobleAAZ5.19SummitACH4.06LorainABW4.29PikeAAL6.23SummitACO7.73LorainACZ4.23PikeAAQ5.76SummitACQ6.59LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitADX11.49MonroeAAI5.71RichlandABW4.92SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFE4.85MonroeAAQ4.06RichlandABW4.92 <td>Lawrence</td> <td>ABP</td> <td>4.00</td> <td>Morrow</td> <td>AAL</td> <td>5.81</td> <td>Summit</td> <td>ACE</td> <td>7.59</td>	Lawrence	ABP	4.00	Morrow	AAL	5.81	Summit	ACE	7.59
LickingAEL5.37NobleAAZ5.19SummitACH4.06LorainABW4.29PikeAAL6.23SummitACO7.73LorainACZ4.23PikeAAQ5.76SummitACQ6.59LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAQ5.64RichlandABQ5.21SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandABW4.92SummitAFN18.04MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG	Lawrence	ACY	6.02	Noble	AAI	6.72	Summit	ACF	6.00
LorainABW4.29PikeAAL6.23SummitACO7.73LorainACZ4.23PikeAAQ5.76SummitACQ6.59LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFN18.04MontgomeryABP4.29RichlandABE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACV4.47StarkAAG<	Lawrence	ADD	5.78	Noble	AAP	6.87	Summit	ACG	10.46
LorainACZ4.23PikeAAQ5.76SummitACQ6.59LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABW4.92SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACF5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Licking	AEL	5.37	Noble	AAZ	5.19	Summit	ACH	4.06
LorainAEA7.28PikeAAV7.07SummitACT7.84LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	ABW	4.29	Pike	AAL	6.23	Summit	ACO	7.73
LorainAEW6.31PrebleABD4.22SummitACV4.79LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABU5.22SummitADX11.49MonroeAAI5.71RichlandABW4.92SummitAFE4.85MontgomeryABP4.29RichlandABW4.92SummitAFN18.04MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	ACZ	4.23	Pike	AAQ	5.76	Summit	ACQ	6.59
LorainAEY4.26RichlandABG5.51SummitACY5.65LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAQ4.06RichlandABW4.92SummitAFE4.85MontgomeryABP4.29RichlandABW4.92SummitAFI18.04MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACF5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AEA	7.28	Pike	AAV	7.07	Summit	ACT	7.84
LorainAEZ5.13RichlandABH4.60SummitADD8.37LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AEW	6.31	Preble	ABD	4.22	Summit	ACV	4.79
LorainAFB5.59RichlandABJ6.60SummitADN4.35LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AEY	4.26	Richland	ABG	5.51	Summit	ACY	5.65
LorainAFG4.67RichlandABL6.11SummitADQ7.08MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AEZ	5.13	Richland	ABH	4.60	Summit	ADD	8.37
MadisonAAQ8.71RichlandABM6.09SummitADS8.42MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AFB	5.59	Richland	ABJ	6.60	Summit	ADN	4.35
MadisonAAV5.64RichlandABQ5.21SummitADV6.59MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Lorain	AFG	4.67	Richland	ABL	6.11	Summit	ADQ	7.08
MercerAAI4.18RichlandABR6.46SummitADX11.49MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Madison	AAQ	8.71	Richland	ABM	6.09	Summit	ADS	8.42
MonroeAAI5.71RichlandABU5.22SummitAFE4.85MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Madison	AAV	5.64	Richland	ABQ	5.21	Summit	ADV	6.59
MonroeAAQ4.06RichlandABW4.92SummitAFN18.04MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Mercer	AAI	4.18	Richland	ABR	6.46	Summit	ADX	11.49
MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Monroe	AAI	5.71	Richland	ABU	5.22	Summit	AFE	4.85
MontgomeryABP4.29RichlandADE5.34SummitAIJ6.52MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	Monroe	AAQ	4.06	Richland	ABW	4.92	Summit	AFN	18.04
MontgomeryACF7.00SciotoADR4.04SummitAJL7.36MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71		-							
MontgomeryACP5.51StarkAAG7.65SummitAJS7.48MontgomeryACV4.47StarkABA4.80SummitAPT10.71	••••								
Montgomery ACV 4.47 Stark ABA 4.80 Summit APT 10.71	••••			Stark					
	•••								

Table 21: Outliers, Punchcard Machine Technology II: Residual Vote: Machines per Voter Regressor

Table 22: Outliers, Punchcard Machine Technology III: Residual Vote: Machines per Voter Regressor

Punchcard									
County	Code	SRes	County	Code	SRes				
Summit	AVY	7.29	Trumbull	AEE	4.94				
Trumbull	AAW	5.75	Trumbull	AEF	4.22				
Trumbull	ABG	5.37	Trumbull	AEH	6.80				
Trumbull	ACG	7.03	Trumbull	AEM	4.99				
Trumbull	ACM	7.65	Trumbull	AGZ	4.40				
Trumbull	ACR	4.24	Trumbull	AHO	4.24				
Trumbull	ACW	4.07	Trumbull	AJZ	4.35				
Trumbull	ADK	4.79	Trumbull	AKJ	4.37				
Trumbull	ADN	4.75	Union	AAQ	5.63				
Trumbull	ADP	4.11	Vinton	AAB	4.19				
Trumbull	ADX	4.31	Vinton	AAG	4.85				
Trumbull	AEB	10.66	Vinton	AAK	4.32				
Trumbull	AEC	5.14	Wayne	ADH	4.20				

		DRE		
Variable	Coef.	SE	t-ratio	
(Intercept)	-4.650	0.0436	-107.00	
Machines per Registered Voter	-20.400	10.3000	-1.97	
Proportion African American	0.878	0.0559	15.70	
	Optical Central			
Variable	Coef.	SE	t-ratio	
(Intercept)	-4.550	0.0533	-85.200	
Machines per Registered Voter	-6.270	8.1000	-0.775	
Proportion African American	-0.212	0.0905	-2.340	
	Optical Precinct			
	Op	tical Preci	nct	
Variable	Op Coef.	tical Preci SE	nct t-ratio	
Variable (Intercept)	-			
	Coef.	SE	t-ratio	
(Intercept)	Coef. -4.70	SE 0.204	<i>t</i> -ratio -23.00	
(Intercept) Machines per Registered Voter	Coef. -4.70 -74.20 1.46	SE 0.204 32.600	<i>t</i> -ratio -23.00 -2.28 5.51	
(Intercept) Machines per Registered Voter	Coef. -4.70 -74.20 1.46	SE 0.204 32.600 0.266	<i>t</i> -ratio -23.00 -2.28 5.51	
(Intercept) Machines per Registered Voter Proportion African American	Coef. -4.70 -74.20 1.46	SE 0.204 32.600 0.266 Punchcard	<i>t</i> -ratio -23.00 -2.28 5.51	
(Intercept) Machines per Registered Voter Proportion African American Variable	Coef. -4.70 -74.20 1.46 Coef.	SE 0.204 32.600 0.266 Punchcard SE	<i>t</i> -ratio -23.00 -2.28 5.51 <i>t</i> -ratio	

 Table 23: Residual Vote: Machines per Voter and Precinct Racial Composition Regressors

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct, the dependent variable counts the number of residual votes versus the number of votes for one of four presidential candidates (Bush, Kerry, Bedarnik or Peroutka). The residual vote is the number of ballots cast that did not include a vote for one of those four candidates. DRE: LQD  $\sigma = 0.91$ ; tanh  $\sigma = 1.05$ ; n = 1,535 precincts; 68 precincts are outliers. Optical Central: LQD  $\sigma = 0.86$ ; tanh  $\sigma = 0.98$ ; n = 807 precincts; 40 precincts are outliers. Optical Precinct: LQD  $\sigma = 0.68$ ; tanh  $\sigma = 0.89$ ; n = 139 precincts; 13 precincts are outliers. Punchcard: LQD  $\sigma = 1.18$ ; tanh  $\sigma = 1.26$ ; n = 7,865 precincts; 226 precincts are outliers. Punchcard precincts include Cuyahoga and Hamilton precincts.

Expected Residual Vote Rate at Machine Ratio Quartiles with Median African American Proportions

		Quartile	
Technology	25%	50%	75%
DRE	0.0090	0.0089	0.0088
Centrally Tabulated Optical Scan	0.0101	0.0101	0.0101
Precinct Tabulated Optical Scan	0.0065	0.0059	0.0054
Punchcard	0.0150	0.0149	0.0148

	-	-						
				DRE				
County	Code	SRes	County	Code	SRes	County	Code	SRes
Auglaize	AAF	4.48	Franklin	AIQ	4.34	Franklin	AYU	9.14
Franklin	AAQ	4.37	Franklin	AJJ	5.82	Franklin	AYZ	5.99
Franklin	ABK	5.11	Franklin	AKG	6.04	Franklin	AZD	5.09
Franklin	ABU	9.03	Franklin	AKL	4.32	Franklin	AZE	4.18
Franklin	ACP	4.35	Franklin	AKT	4.03	Franklin	AZH	8.80
Franklin	ACQ	8.83	Franklin	AKY	7.63	Franklin	AZK	4.61
Franklin	ADF	5.06	Franklin	AML	8.28	Franklin	BAB	5.22
Franklin	AEJ	8.17	Franklin	AOF	4.31	Franklin	BAG	5.08
Franklin	AEN	4.46	Franklin	AOW	13.78	Franklin	BAJ	5.09
Franklin	AER	4.12	Franklin	AQQ	4.47	Franklin	BAK	5.66
Franklin	AES	4.29	Franklin	ATD	4.41	Franklin	BBB	4.29
Franklin	AEU	5.83	Franklin	ATE	5.87	Franklin	BBE	5.67
Franklin	AEY	4.53	Franklin	ATF	5.28	Franklin	BBK	5.48
Franklin	AFD	4.40	Franklin	ATM	4.35	Franklin	BBV	4.21
Franklin	AFI	5.28	Franklin	ATN	6.75	Franklin	BCV	4.04
Franklin	AFN	4.37	Franklin	AUK	5.43	Knox	AAJ	4.21
Franklin	AFO	4.32	Franklin	AWA	5.64	Knox	AAR	4.76
Franklin	AFS	4.14	Franklin	AXE	4.45	Lake	ADN	6.49
Franklin	AGG	5.59	Franklin	AXK	6.88	Mahoning	AOV	4.27
Franklin	AGQ	6.37	Franklin	AXM	4.18	Mahoning	ARC	16.97
Franklin	AHF	5.20	Franklin	AXP	4.75	Mahoning	ASC	4.36
Franklin	AHW	4.30	Franklin	AXZ	5.45	Ross	AAH	5.63
Franklin	AIK	4.57	Franklin	AYQ	5.91			

Table 24: Outliers, DRE Machine Technology: Residual Vote: Machines per Voter and Precinct Racial Composition Regressor

			Opt	ical Cen	tral			
County	Code	SRes	County	Code	SRes	County	Code	SRes
Ashland	AAC	12.28	Ashland	ABT	12.58	Hardin	ABE	4.73
Ashland	AAD	10.24	Ashland	ABY	8.32	Lucas	ASN	4.89
Ashland	AAH	4.91	Ashland	ABZ	6.84	Lucas	ABV	4.77
Ashland	AAK	4.09	Ashland	ACC	12.58	Lucas	AAB	4.27
Ashland	AAQ	5.24	Ashland	ACD	5.78	Lucas	ANQ	7.70
Ashland	AAR	9.86	Ashland	ACG	11.84	Lucas	AHJ	5.38
Ashland	AAU	10.93	Ashland	ACH	5.45	Lucas	AFC	4.27
Ashland	AAV	9.79	Ashland	ACK	6.83	Ottawa	ACE	4.21
Ashland	ABA	10.55	Ashland	ACL	6.55	Sandusky	AAM	4.21
Ashland	ABB	8.45	Ashland	ACO	10.93	Sandusky	ABE	6.03
Ashland	ABI	11.84	Ashland	ACP	7.87	Sandusky	ABK	6.51
Ashland	ABK	8.36	Ashland	ACS	12.90	Sandusky	ACS	4.13
Ashland	ABN	5.82	Erie	ADN	10.71			
Ashland	ABQ	11.69	Erie	AEG	4.33			
			Opti	cal Prec	inct			
County	Code	SRes	County	Code	SRes	County	Code	SRes
Allen	ABF	4.25	Allen	ADF	4.14	Allen	AFJ	5.30
Allen	ABI	4.36	Allen	ADQ	4.11	Allen	AGI	11.21
Allen	ABX	4.67	Allen	ADT	4.63	Allen	AGK	6.90
Allen	ACG	9.53	Allen	AEK	8.39			
Allen	ACZ	5.32	Allen	AEV	4.07			

Table 25: Outliers, Optical Scan Machine Technologies: Residual Vote: Machines per Voter and Precinct Racial Composition Regressor

			Pur	nchcard				
County	Code	SRes	County	Code	SRes	County	Code	SRes
Adams	AAM	8.43	Cuyahoga	BQW	4.59	Hamilton	AQK	4.87
Adams	AAQ	4.48	Cuyahoga	CFQ	8.08	Hamilton	AQW	6.63
Adams	AAX	4.22	Cuyahoga	CGD	6.12	Hamilton	AUJ	5.52
Adams	ABC	5.02	Darke	AAG	71.15	Hamilton	AVF	4.13
Ashtabula	AAQ	6.65	Fairfield	ADY	6.34	Hamilton	AVK	7.59
Ashtabula	AAS	4.69	Fairfield	AEN	4.31	Hamilton	AVV	4.77
Ashtabula	ABA	4.05	Gallia	AAZ	4.14	Hamilton	AWP	4.23
Ashtabula	ABK	4.35	Gallia	ABA	4.26	Hamilton	AYW	4.28
Ashtabula	ACG	4.13	Greene	ADP	5.11	Hamilton	BBQ	6.28
Athens	ABC	5.49	Hamilton	AAF	5.72	Hamilton	BEG	4.71
Athens	ACO	4.37	Hamilton	AAQ	5.44	Hamilton	BFA	4.54
Belmont	AAC	7.45	Hamilton	ACV	5.92	Hamilton	BFK	6.14
Belmont	AAF	4.04	Hamilton	ADC	5.13	Hamilton	BLJ	5.74
Belmont	AAQ	4.30	Hamilton	ADH	4.00	Hamilton	BLK	6.75
Belmont	ACH	5.79	Hamilton	ADW	5.24	Hamilton	BON	6.91
Butler	ADJ	9.08	Hamilton	AEF	4.14	Harrison	AAX	7.76
Butler	AKV	4.04	Hamilton	AFK	6.19	Harrison	ABF	5.06
Carroll	AAJ	4.56	Hamilton	AFP	4.51	Highland	AAF	5.17
Carroll	AAS	6.08	Hamilton	AGE	7.24	Hocking	ABA	5.38
Carroll	AAY	4.58	Hamilton	AGP	6.78	Holmes	AAA	7.63
Clark	AAO	4.28	Hamilton	AGU	5.20	Holmes	AAB	6.51
Clark	ACI	5.62	Hamilton	AHA	6.48	Holmes	AAC	30.66
Clark	ACM	6.70	Hamilton	AID	5.68	Holmes	AAM	23.89
Crawford	AAB	4.63	Hamilton	AIE	8.01	Holmes	AAP	21.09
Crawford	ABF	4.20	Hamilton	AIV	4.62	Holmes	AAR	4.93
Cuyahoga	ABM	11.64	Hamilton	AJF	5.43	Holmes	AAW	21.98
Cuyahoga	AHY	4.16	Hamilton	AJN	7.63	Huron	AAV	4.35
Cuyahoga	ANX	6.34	Hamilton	AJS	4.01	Huron	ACB	5.59
Cuyahoga	APT	4.58	Hamilton	AKK	10.27	Jackson	AAC	4.60
Cuyahoga	APY	16.24	Hamilton	ALO	5.27	Jackson	AAQ	7.24
Cuyahoga	ASL	7.69	Hamilton	ALU	9.96	Jefferson	AAA	4.70
Cuyahoga	AXU	4.72	Hamilton	ALZ	4.82	Jefferson	AAM	6.96
Cuyahoga	AYJ	4.05	Hamilton	AMD	8.06	Jefferson	AAN	4.38
Cuyahoga	AYX	4.11	Hamilton	AMI	4.00	Lawrence	ABP	4.64
Cuyahoga	BAC	4.86	Hamilton	AMS	5.33	Lawrence	ACY	6.83
Cuyahoga	BAJ	5.02	Hamilton	ANU	7.70	Lawrence	ADD	6.18
Cuyahoga	BBQ	7.27	Hamilton	ANZ	8.80	Licking	AEL	6.21
Cuyahoga	BCI	4.31	Hamilton	AOK	6.53	Lorain	AEA	6.55
Cuyahoga	BEF	4.49	Hamilton	APA	6.61	Lorain	AEW	5.26
Cuyahoga	BQB	12.35	Hamilton	APQ	8.52	Lorain	AEZ	5.36
e a j'anogu	- 22			· •• X	0.02			0.00

Table 26: Outliers, Punchcard Machine Technology I: Residual Vote: Machines per Voter and Precinct Racial Composition Regressor

			Pun	nchcard				
County	Code	SRes	County	Code	SRes	County	Code	SRes
Lorain	AFB	5.88	Preble	ABD	4.93	Summit	ADQ	4.85
Lorain	AFG	4.94	Richland	ABG	5.22	Summit	ADS	6.51
Lorain	AIP	4.39	Richland	ABJ	5.30	Summit	ADV	4.28
Madison	AAQ	9.74	Richland	ABL	4.89	Summit	ADX	10.00
Madison	AAV	6.60	Richland	ABM	5.10	Summit	AFE	5.18
Marion	AAI	4.17	Richland	ABQ	4.96	Summit	AFN	18.68
Meigs	ABA	4.16	Richland	ABR	6.05	Summit	AIJ	5.54
Mercer	AAI	4.75	Richland	ABW	5.05	Summit	AJL	7.15
Mercer	AAQ	4.32	Richland	ADE	6.01	Summit	AJS	8.56
Monroe	AAB	4.65	Richland	ADJ	4.31	Summit	APT	12.31
Monroe	AAI	6.64	Richland	ADV	4.08	Summit	ATZ	4.26
Monroe	AAJ	4.19	Scioto	ADR	4.64	Summit	AVS	6.78
Monroe	AAQ	4.70	Shelby	AAB	4.60	Summit	AVY	4.07
Montgomery	ABP	4.43	Shelby	ABD	4.19	Trumbull	AAR	4.46
Montgomery	ACF	4.37	Stark	AAG	7.58	Trumbull	AAW	6.65
Montgomery	ADT	5.52	Stark	AAW	4.34	Trumbull	ABG	6.22
Montgomery	ADW	4.26	Stark	ABA	4.76	Trumbull	ACG	7.35
Montgomery	AHZ	4.14	Stark	ABB	7.89	Trumbull	ACM	7.73
Montgomery	AQS	4.68	Stark	ABQ	8.28	Trumbull	ACR	4.75
Montgomery	ATX	5.11	Stark	ABV	6.20	Trumbull	ADK	5.16
Morgan	AAC	4.07	Stark	ACA	4.77	Trumbull	AEB	9.41
Morgan	AAO	4.89	Stark	ACF	7.21	Trumbull	AEH	4.69
Morrow	AAL	6.92	Stark	AEH	5.74	Trumbull	AGZ	5.01
Morrow	AAM	4.25	Stark	AFU	4.67	Trumbull	AHO	4.92
Noble	AAI	7.92	Summit	AAC	5.48	Trumbull	AII	4.09
Noble	AAP	7.91	Summit	AAI	5.70	Trumbull	AJZ	5.05
Noble	AAY	4.45	Summit	AAS	6.23	Trumbull	AKJ	5.12
Noble	AAZ	6.20	Summit	ABL	4.11	Tuscarawas	AAS	4.24
Paulding	AAG	4.09	Summit	ABW	6.89	Union	AAQ	6.52
Pike	AAF	4.58	Summit	ACB	8.98	Vinton	AAB	4.77
Pike	AAH	4.19	Summit	ACE	4.68	Vinton	AAG	5.55
Pike	AAL	6.40	Summit	ACG	7.17	Vinton	AAK	4.96
Pike	AAQ	6.47	Summit	ACO	4.13	Vinton	AAP	4.02
Pike	AAV	8.02	Summit	ACT	4.63	Wayne	ADH	4.82
Pike	AAX	4.33	Summit	ACY	5.08			
Preble	AAJ	4.22	Summit	ADD	4.44			

Table 27: Outliers, Punchcard Machine Technology II: Residual Vote: Machines per Voter and Precinct Racial Composition Regressor

	Mediar	n Rate
Technology	Outliers	Rest
DRE	0.0290	0.0094
Optical Central	0.0409	0.0099
<b>Optical Precinct</b>	0.0240	0.0067
Punchcard	0.0593	0.0159

Table 28: Median Residual	Vote Rates Among the Residual Vote Outliers

Notes: Median residual vote rates among precincts using outliers identified in the analysis reported in Tables 23, 24, 25, 26 and 27. Punchcard precincts include Cuyahoga and Hamilton precincts.

		DRE		
Variable	Coef.	SE	t-ratio	
(Intercept)	-3.48	0.41	-8.6	
Proportion Voting Kerry	0.74	0.69	1.1	
	Optical Central			
Variable	Coef.	SE	t-ratio	
(Intercept)	-0.36	0.61	-0.6	
Proportion Voting Kerry	-5.27	1.32	-4.0	
	Optical Precinct			
	Opti	cal Pre	cinct	
Variable	1		cinct t-ratio	
Variable (Intercept)	Coef.	SE		
	Coef. -2.71	SE	<i>t</i> -ratio -4.0	
(Intercept)	Coef. -2.71 1.17	<b>SE</b> 0.68	<i>t</i> -ratio -4.0 0.7	
(Intercept)	Coef. -2.71 1.17	SE 0.68 1.60 unchca	<i>t</i> -ratio -4.0 0.7	
(Intercept) Proportion Voting Kerry	Coef. -2.71 1.17 Pt Coef.	SE 0.68 1.60 unchca SE	<i>t</i> -ratio -4.0 0.7	

## Table 29: Residual Vote Outliers and Proportion Voting for Kerry

Notes: Binary logit regression estimates. For each precinct, the dependent variable has the value 1.0 if the precinct is an outlier in the analysis reported in Tables 23, 24, 25, 26 and 27, otherwise zero. DRE: n = 1,535 precincts. Optical Central: n = 807 precincts. Optical Precinct: n = 139 precincts. Punchcard: n = 7,865 precincts. Punchcard precincts include Cuyahoga and Hamilton precincts.

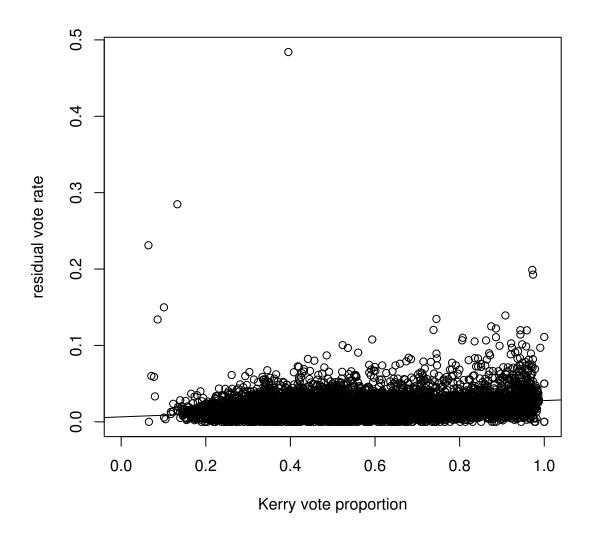


Figure 27: Residual Vote Rate in Ohio 2004 Precincts by Democratic President Proportion

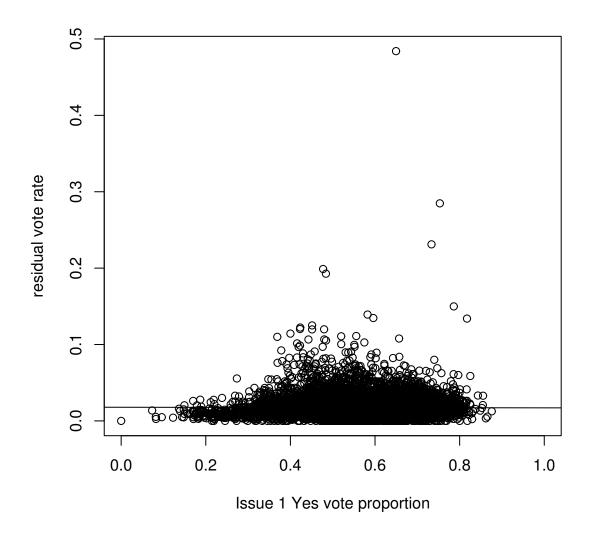


Figure 28: Residual Vote Rate in Ohio 2004 Precincts by Issue 1 Proportion Yes

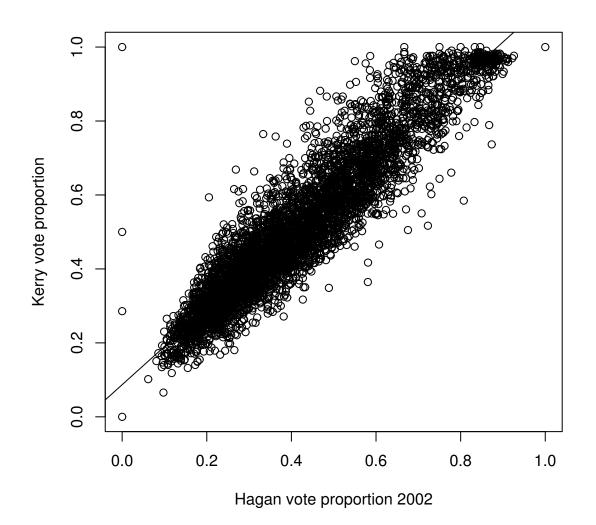


Figure 29: Democratic President Proportion by 2002 Democratic Governor Proportion in Precincts with Constant Boundaries Since 2002

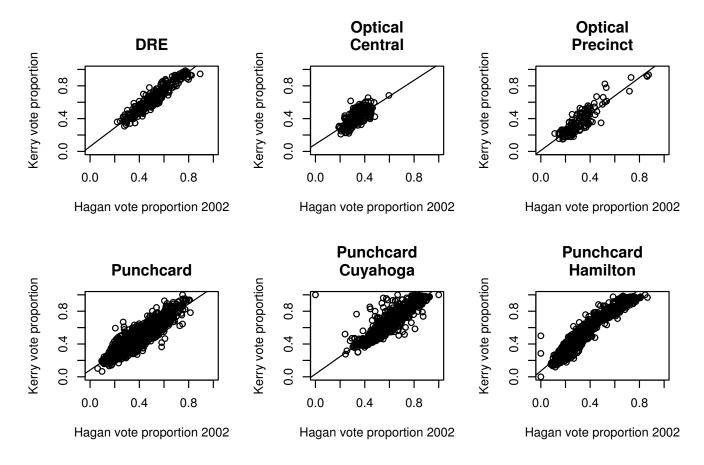


Figure 30: Democratic President Proportion by 2002 Democratic Governor Proportion in Precincts with Constant Boundaries Since 2002, by Machine Type

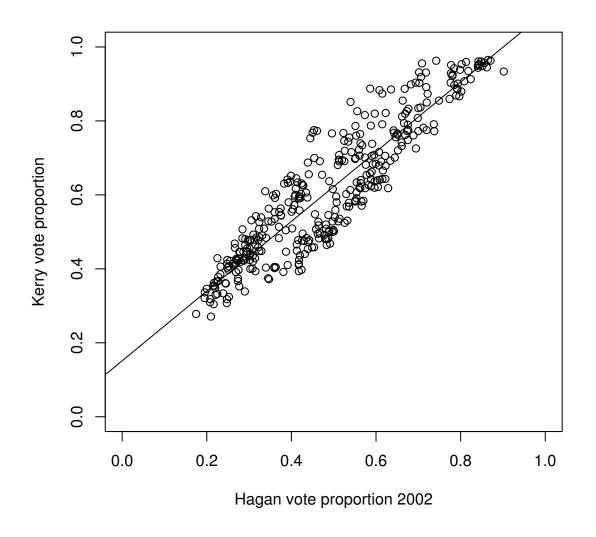


Figure 31: Democratic President Proportion by 2002 Democratic Governor Proportion in Wards with Constant Boundaries Since 2002

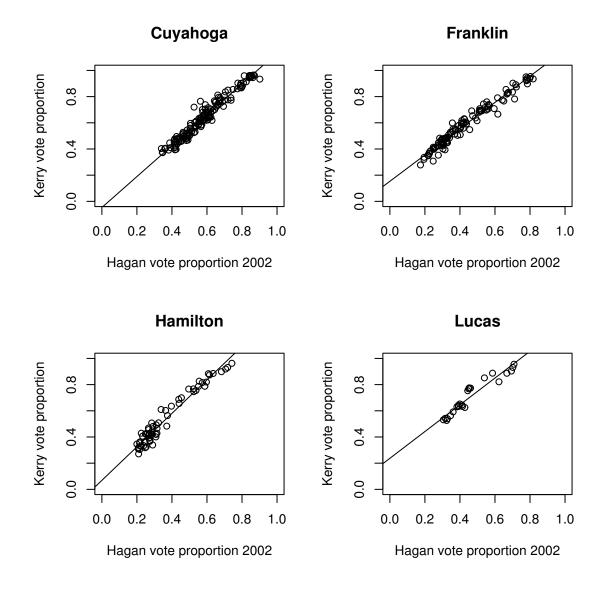


Figure 32: Democratic President Proportion by 2002 Democratic Governor Proportion in Wards with Constant Boundaries Since 2002, by County

Table 30: Vote for Ke	rrv versus Bush	: 2002 Gubernatorial	Vote Regressor

	Precincts				Wards		
Variable	Coef.	SE	t-ratio	Coef.	SE	t-ratio	
(Intercept)	0.456	0.00589	77.5	0.64	0.0224	28.6	
Logit(Democratic Vote in 2002)	1.040	0.00627	166.0	1.04	0.0266	39.1	

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of votes for Kerry versus the number of votes for Bush. Precincts: LQD  $\sigma = 2.98$ ; tanh  $\sigma = 2.87$ ; n = 5,384; 17 outliers. Wards: LQD  $\sigma = 9.09$ ; tanh  $\sigma = 8.91$ ; n = 357; no outliers.

The precinct estimation includes precincts with constant boundaries from the following counties: Adams, Allen, Ashland, Athens, Belmont, Butler, Carroll, Clermont, Clinton, Columbiana, Coshocton, Cuyahoga, Darke, Geauga, Greene, Hamilton, Hardin, Harrison, Hocking, Lawrence, Licking, Logan, Lorain, Madison, Mahoning, Marion, Meigs, Miami, Monroe, Morgan, Morrow, Noble, Ottawa, Paulding, Perry, Pike, Portage, Preble, Shelby, Trumbull, Tuscarawas, Van Wert, Vinton, Wayne, Williams.

The ward estimation includes wards with constant boundaries from the following counties: Cuyahoga, Franklin, Hamilton and Lucas.

County	Code	SRes	County	Code	SRes
Butler	AFD	-4.55	Hamilton	AQM	4.18
Cuyahoga	ABE	-5.12	Hamilton	BDN	810.96
Cuyahoga	AZY	512.89	Hamilton	BDQ	691.59
Cuyahoga	CQY	-4.79	Licking	ACV	4.75
Cuyahoga	CRG	-6.56	Licking	ACY	6.55
Cuyahoga	CRY	4.28	Lorain	AKV	-4.07
Cuyahoga	CWY	-4.22	Miami	AAN	-8.28
Greene	AHJ	4.52	Tuscarawas	AAX	-4.82
Hamilton	APT	4.37			

Table 31: Outliers: Vote for Kerry versus Bush: 2002 Gubernatorial Vote Regressor

Table 32: Vote for Kerry versus Bush: 2002 Gubernatorial Vote and Issue 1 Vote Regressor

	Precincts				Wards		
Variable	Coef.	SE	t-ratio	С	oef.	SE	t-ratio
(Intercept)	0.524	0.00653	80.2	0	.605	0.0239	25.40
Logit(Democratic Vote in 2002)	0.946	0.00684	138.0	1	.000	0.0285	35.20
Logit(Yes on Issue 1)	-0.283	0.01030	-27.3	-0	.225	0.0540	-4.16

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct or ward, the dependent variable counts the number of votes for Kerry versus the number of votes for Bush. Precincts: LQD  $\sigma = 2.78$ ; tanh  $\sigma = 2.68$ ; n = 5,384; 22 outliers. Wards: LQD  $\sigma = 8.33$ ; tanh  $\sigma = 8.49$ ; n = 357; no outliers.

The precinct estimation includes precincts with constant boundaries from the following counties: Adams, Allen, Ashland, Athens, Belmont, Butler, Carroll, Clermont, Clinton, Columbiana, Coshocton, Cuyahoga, Darke, Geauga, Greene, Hamilton, Hardin, Harrison, Hocking, Lawrence, Licking, Logan, Lorain, Madison, Mahoning, Marion, Meigs, Miami, Monroe, Morgan, Morrow, Noble, Ottawa, Paulding, Perry, Pike, Portage, Preble, Shelby, Trumbull, Tuscarawas, Van Wert, Vinton, Wayne, Williams.

The ward estimation includes wards with constant boundaries from the following counties: Cuyahoga, Franklin, Hamilton and Lucas.

Table 33: Outliers: Vote for Kerry versus Bush: 2002 Gubernatorial Vote and Issue 1 Vote Regressor

County	Code	SRes	County	Code	SRes
Athens	AAF	-4.33	Cuyahoga	CRY	4.52
Athens	AAG	-4.49	Cuyahoga	CSB	-5.19
Athens	AAK	-5.03	Cuyahoga	CWY	-4.92
Butler	AFD	-6.01	Hamilton	APT	4.14
Cuyahoga	ABE	-5.91	Hamilton	AQM	4.27
Cuyahoga	AZY	271.42	Hamilton	BDN	372.23
Cuyahoga	CQH	-4.10	Hamilton	BDQ	364.10
Cuyahoga	CQM	-4.16	Licking	ACZ	-4.17
Cuyahoga	CQY	-5.70	Lorain	AKV	-4.10
Cuyahoga	CRG	-7.97	Miami	AAN	-8.11
Cuyahoga	CRM	-4.00	Tuscarawas	AAX	-4.76

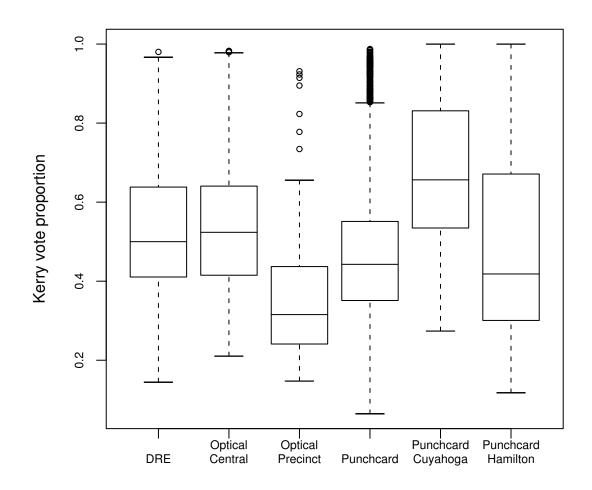


Figure 33: Democratic President Proportion in Ohio 2004 Precincts by Machine Type

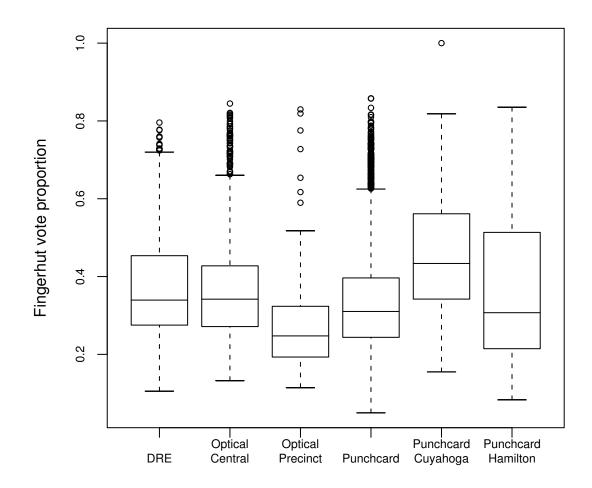


Figure 34: Democratic Senator Proportion in Ohio 2004 Precincts by Machine Type

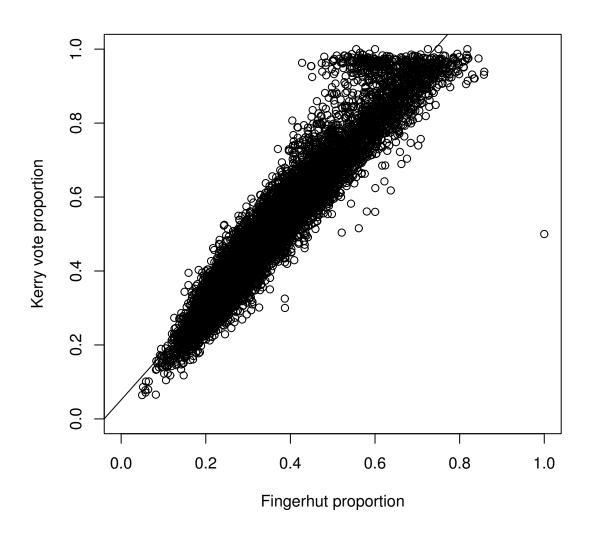


Figure 35: Democratic President Proportion by Democratic Senator Proportion in Ohio 2004 Precincts

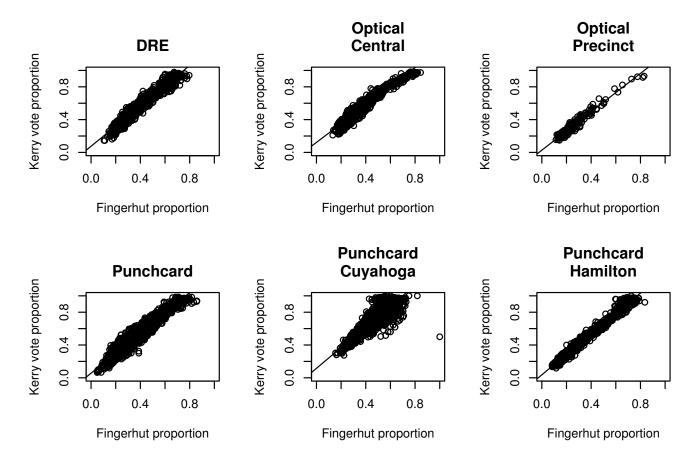
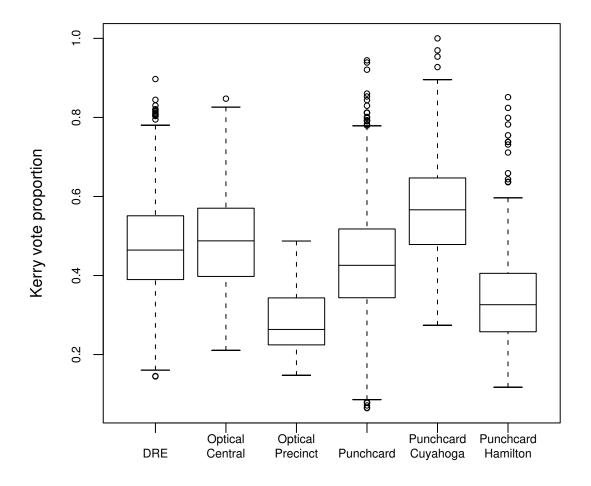
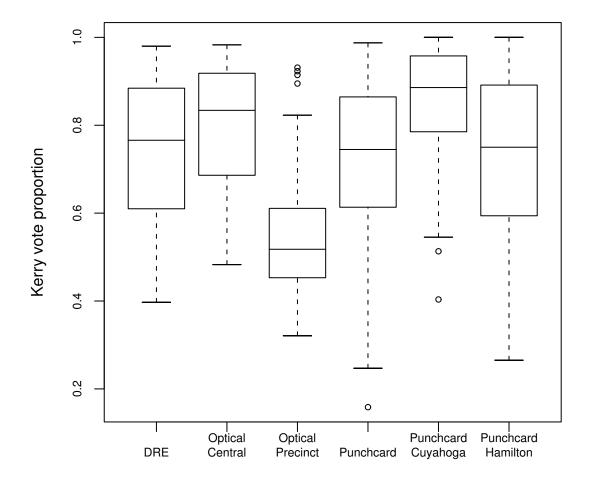


Figure 36: Democratic President Proportion by Democratic Senator Proportion in Ohio 2004 Precincts by Machine Type



# African American proportion less than .10

Figure 37: Democratic President Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Less Than 10 Percent



# African American proportion greater than .10

Figure 38: Democratic President Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Greater Than 10 Percent

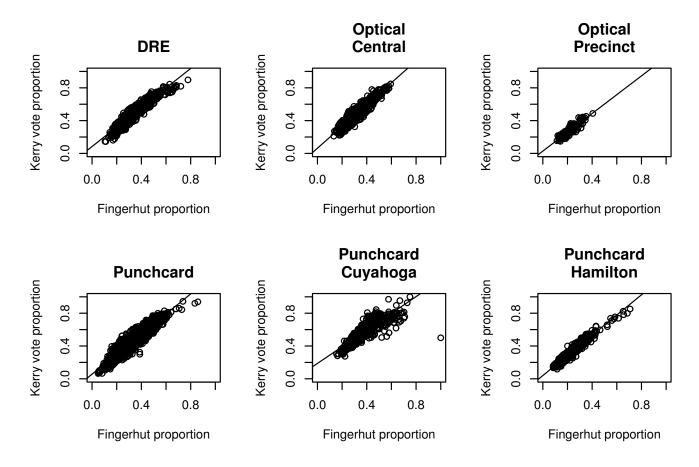


Figure 39: Democratic President Proportion by Democratic Senator Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Less Than 10 Percent

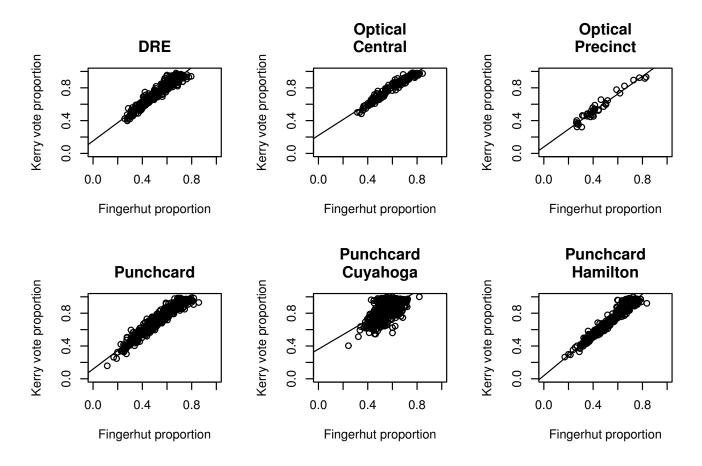


Figure 40: Democratic President Proportion by Democratic Senator Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Greater Than 10 Percent

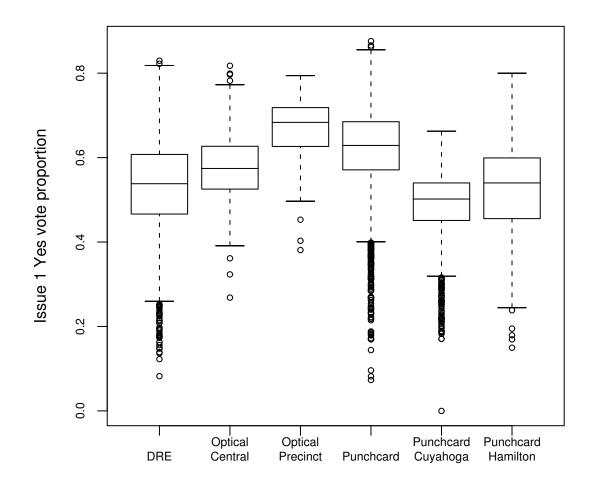


Figure 41: Issue 1 Proportion Yes in Ohio 2004 Precincts by Machine Type

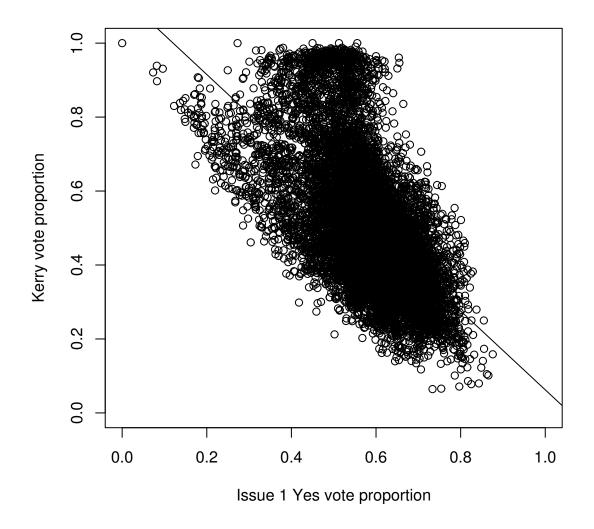


Figure 42: Democratic President Proportion by Issue 1 Yes Proportion in Ohio 2004 Precincts

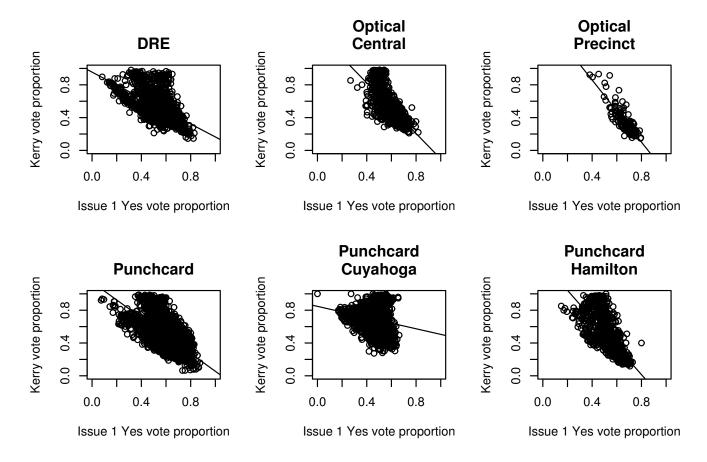


Figure 43: Democratic President Proportion by Issue 1 Yes Proportion in Ohio 2004 Precincts by Machine Type

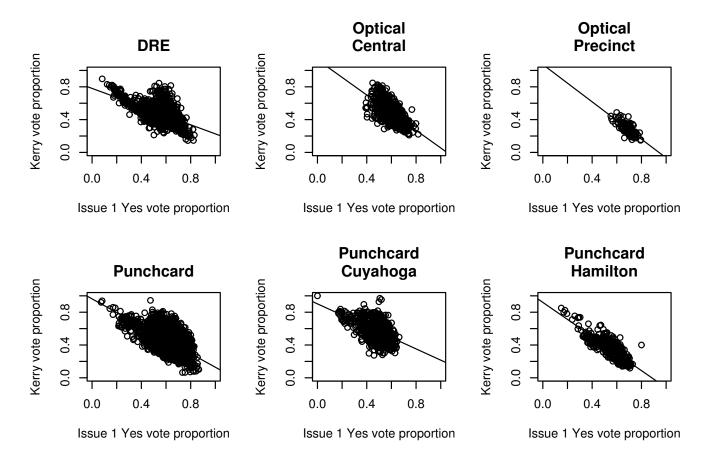


Figure 44: Democratic President Proportion by Issue 1 Yes Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Less Than 10 Percent

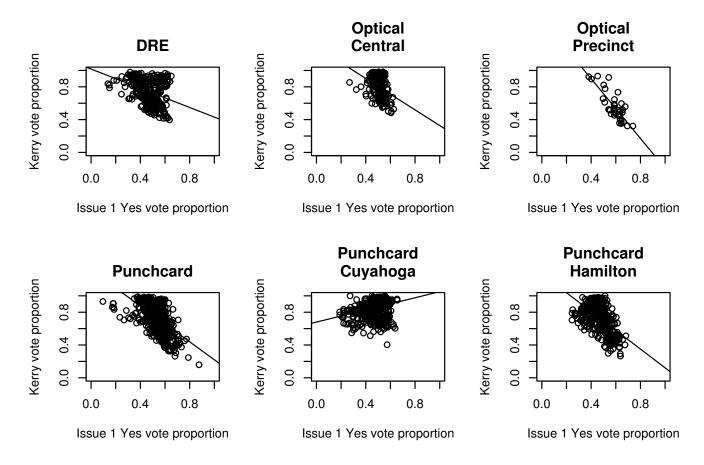


Figure 45: Democratic President Proportion by Issue 1 Yes Proportion in Ohio 2004 Precincts by Machine Type for African American Proportion in Precinct Greater Than 10 Percent

Table 34: Vote for Kerry versus Bush: 2004 Senatorial Vote, Issue 1 Vote and Precinct Racial Composition Regressors (Selected Counties)

	Hamilton County		
Variable	Coef.	SE	t-ratio
(Intercept)	0.272	0.0186	14.6
Logit(Democratic Vote for Senate)	0.796	0.0172	46.3
Logit(Yes on Issue 1)	-0.312	0.0193	-16.1
Proportion African American	1.440	0.0534	26.9
	Cuyahoga County		
	Coef.	SE	t-ratio
(Intercept)	0.7840	0.0145	54.10
Logit(Democratic Vote for Senate)	0.9970	0.0203	49.20
Logit(Yes on Issue 1)	0.0538	0.0222	2.42
Proportion African American	1.9800	0.0408	48.50
	Crawford County		
	Coef.	SE	t-ratio
(Intercept)	0.696	0.0435	16.00
Logit(Democratic Vote for Senate)	0.992	0.0576	17.20
Logit(Yes on Issue 1)	-0.335	0.0697	-4.81
Proportion African American	-4.560	1.5900	-2.87

Notes: Robust (tanh) overdispersed binomial regression estimates. For each precinct, the dependent variable counts the number of votes for Kerry versus the number of votes for Bush. Hamilton: LQD  $\sigma = 1.33$ ; tanh  $\sigma = 1.27$ ; n = 979; no outliers. Cuyahoga: LQD  $\sigma = 2.09$ ; tanh  $\sigma = 1.99$ ; n = 1,411; 16 outliers. Crawford: LQD  $\sigma = 0.94$ ; tanh  $\sigma = 0.84$ ; n = 46; 1 outlier.

Table 35: Outliers: Vote for Kerry versus Bush: 2004 Senatorial Vote, Issue 1 Vote and Precinct Racial Composition Regressors

County	Code	SRes	County	Code	SRes
Carroll	AAJ	-0.67	Cuyahoga	CRK	-7.89
Columbiana	ACK	-4.58	Cuyahoga	CRM	-6.82
Crawford	ABG	4.68	Cuyahoga	CRO	-4.09
Cuyahoga	ABE	-4.80	Cuyahoga	CWY	-4.96
Cuyahoga	ABJ	-4.32	Darke	AAO	8.26
Cuyahoga	ABQ	-4.07	Darke	ABL	10.63
Cuyahoga	APX	-5.27	Darke	ABP	13.38
Cuyahoga	AYV	-6.99	Franklin	ACN	4.79
Cuyahoga	AYZ	-4.63	Franklin	AMC	-8.18
Cuyahoga	BLH	-7.99	Greene	AIN	3.25
Cuyahoga	BLI	-6.03	Madison	ABN	-5.11
Cuyahoga	BLK	-7.36	Medina	AAG	4.78
Cuyahoga	CQY	-7.63	Montgomery	AQU	-4.13
Cuyahoga	CRC	-5.05	Trumbull	AJU	-5.36
Cuyahoga	CRG	-9.63			

#### **Appendix: Notes Regarding the Data**

By precinct we mean an election day location for casting votes. Some precincts share locations but we do not aggregate by location. Furthermore, some precincts are split, i.e., serve voters in different legislative districts for the Ohio lower house, but splitting is not relevant to our analysis since all Ohio voters had the chance to vote for presidential electors.

We ignore absentee precincts and federal-only precincts. In addition, we ignore all precincts that reported zero registered voters.

For the most part we take as given the accuracy of data supplied to us by the Ohio Secretary of State and by various county BoEs. In some cases we have verified data with multiple sources, and where discrepancies were found we have resolved them to the extent that we have been able. All of our election data is public.

Data regarding precinct racial composition are proprietary data prepared under contract for the DNC.

The condition of Ohio election data has both contributed to and been an impediment to our work. With respect to the former, we appreciate and have benefited greatly from the efforts that the Ohio Secretary of State makes in assembling precinct-level election returns for the entire state. The availability of these returns has obviated the need for us to collect and process a large number of different precinct canvasses. We have caught only a few errors in Secretary of State data, and the Secretary of State has resolved these problems immediately upon being informed of them. Data collected by the Ohio Secretary of State ignore presidential write-in candidates; we do the same.

On the other hand, the lack of uniformity in data formats and availability across Ohio's 88 counties has complicated our task considerably. For instance, some counties do not have records on the number of voting machines at each precinct; others sent us hand-written information with machine counts; and still others were able to send us electronic spreadsheets with machine counts. Similarly, some counties have consistent precinct naming conventions that correspond to codes used by the Ohio Secretary of State; others employ two or three naming conventions across their own records and do not link their data to Secretary of State codes.

The most severe data problems have been caused by a lack of standards in precinct names. We are puzzled as to why some Ohio counties use Secretary of State codes for their precincts while others do not. If this situation were addressed, so that each county identified its precincts with a three letter code, then compiling election data from Ohio would be immeasurably easier.

Another key data issue concerns the stability of precinct boundaries across time. Many precincts moved between the general elections of 2002 and 2004, and one of our tasks was trying to identify those that did not move. In some cases, counties informed us that none of their precincts had changed since November, 2002. We attempted to verify the accuracy of all such claims, and in many cases found them to be wanting. In such cases we attempted to determine which of a county's precincts did not move.

Electronic maps, often called shapefiles, would make the task of identifying temporal precinct changes simple. In general, however, it appears that Ohio counties do not produce maps of their precincts, particularly in non-census years.

### Appendix: Brief Explanation of Statistical Tools Used in this Report

- **Boxplots** For example see Figure 1. The middle line in each boxplot shows the median of the plotted data and the boundaries of the box below and above the median show the first and third quartiles. The whiskers at the ends of the dashed lines each spans a range 1.5 times the interquartile range (IQR) or extends to the most extreme point if that point is closer than 1.5 IQR to the median. Points further than 1.5 IQR from the median are shown individually. These points represent points that are unusually far from the bulk of the data.
- **Robust (tanh) overdispersed binomial regression estimates** For example see Table 3. The binomial regression model is used to assess the relationship between a set of counts for the number of occurrences and nonoccurrences of an event and a set of conditioning variables (so-called "regressors"). For instance, in Table 3 the event is voting by a registered voter and the nonevent is nonvoting by a registered voter. The model analyzes the number of votes and nonvotes by registered voters in each precinct.

The conditioning variables are assumed to affect the probability that events occur in a way that can be represented by a linear function. For instance, to model turnout as depending only on the type of voting technology, for each technology we may create a variable that takes the value one if a precinct used the technology and zero otherwise (a so-called "dummy variable"). We pick one technology to be the reference category. The model estimates a baseline for this category and the differences between that category and the others. For instance, if DRE is the reference category and OC, OP and P denote dummy variables for the other technologies, then a linear predictor for precinct i may be written as follows

$$Z_i = b_0 + b_1 \mathbf{OC}_i + b_2 \mathbf{OP}_i + b_3 \mathbf{P}_i$$

The value  $Z_i$  is a score that depends on the coefficients  $b_0$ ,  $b_1$ ,  $b_2$  and  $b_3$ . Alternately, we may estimate a separate model for each type of voting technology, using a linear predictor of the following form for each set of precincts:

$$Z_i = b_0 .$$

In this case the differences between the values estimated for  $b_0$  for each type of technology tell us about the performance differences of interest. One goal of the statistical estimation is to determine values for those coefficients, which otherwise are unknown. Given the score, we can compute the probability that an event occurs in precinct *i* by using the following function (the "logistic" function):

$$p_i = 1/(1 + \exp(-Z_i))$$
.

This value  $p_i$ , which is greater than zero and less than one, represents the probability that an event occurs at every occasion where the event is possible in precinct *i*.

In the voter turnout case, for example,  $p_i$  is the probability that each registered voter in precinct *i* votes, i.e.,  $p_i$  is the voter turnout rate. Notice that this rate is assumed to be the same for every voter in precinct *i*. In fact, the true probability varies from person to person. This variability is measured by a dispersion parameter that is estimated for each model.

The estimation is "robust" in the sense that the stipulated model is not assumed to be a good approximation for all of the observed data. Observations that have counts that differ greatly from the values the model predicts receive less weight in the estimation procedure. If an observed count is sufficiently far from the predicted value, its weight is reduced to zero. In this case the observation is declared to be an "outlier." An observed count may differ greatly from the predicted value for many reasons. With election data, it is always possible that there are otherwise innocuous reporting errors, either in the counts of events and nonevents or in the measurements of the conditioning variables. Or the data may accurately reflect the fact that unusual processes occurred in the place that has the discrepant count. In either case, further investigation is warranted.

The estimation method is derived in Mebane and Sekhon (2004a). Software implementing the method is available in the MultinomRob package for the statistical programming environment  $\mathbf{R}$  (Mebane and Sekhon 2004b).

- **studentized residual** For example see Table 4. This statistic takes the difference between the observed count of events and the count predicted by a model and rescales it to take into account the total number of events and nonevents in the precinct, the expected relative rarity of events in the precinct, the configuration of the regressors and the estimated dispersion. With these adjustments, different studentized residuals may be compared to one another. A negative residual means the observed number of events is smaller than the predicted number, and a positive residual means the observed number is larger than the predicted number. A studentized residual greater than 2.0 or smaller than -2.0 represents a count that is relatively unusual given the specified model. An outlier has a studentized residual greater than 4.0 or smaller than -4.0.
- **logit function** The logit or log-odds function is logit(p) = log(p/(1-p)). It is the inverse of the logistic function, i.e.,

$$\frac{1}{1 + \exp(-\log(p))} = \frac{1}{1 + \exp(-\log(p/(1-p)))} = \frac{1}{1 + (1-p)/p} = p$$

To understand the rationale for the model of Table 30 (Kerry tends to have "uniformly" more support than Hagen), let  $d_0 > 0$  and  $d_1 = 1$ , and for p = D2002 consider

$$q_K = \frac{1}{1 + \exp(-(d_0 + \operatorname{logit}(p)))} = \frac{1}{1 + e^{-d_0}(1 - p)/p} .$$

Because  $d_0 > 0$  implies  $0 < e^{-d_0} < 1$ , for  $0 we have that <math>0 < e^{-d_0}(1-p)/p < (1-p)/p$  and hence  $q_K > p$ . For instance, suppose p = 1/2:

$$q_K = \frac{1}{1 + e^{-d_0}(1 - (1/2))/(1/2)} = \frac{1}{1 + e^{-d_0}} > 1/2.$$

### References

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