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MEASURING THE IMPACT OF VOTING TECHNOLOGY ON RESIDUAL VOTE RATES

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Summary

In the wake of the 2000 election, the importance of knowing the impact of voting equipment on the number of uncounted ballots became evident. Using data from the 1988-2004 presidential elections, this paper estimates the effects of voting technologies on residual vote rates using several measurement techniques: a difference-in-differences estimator, fixed effects regression models and a propensity score matching technique. The pattern of the results is robust to the different methods. Paper ballots and lever machines produce the lowest rates of residual votes followed by optically scanned ballots, direct recording electronic machines and punch cards.

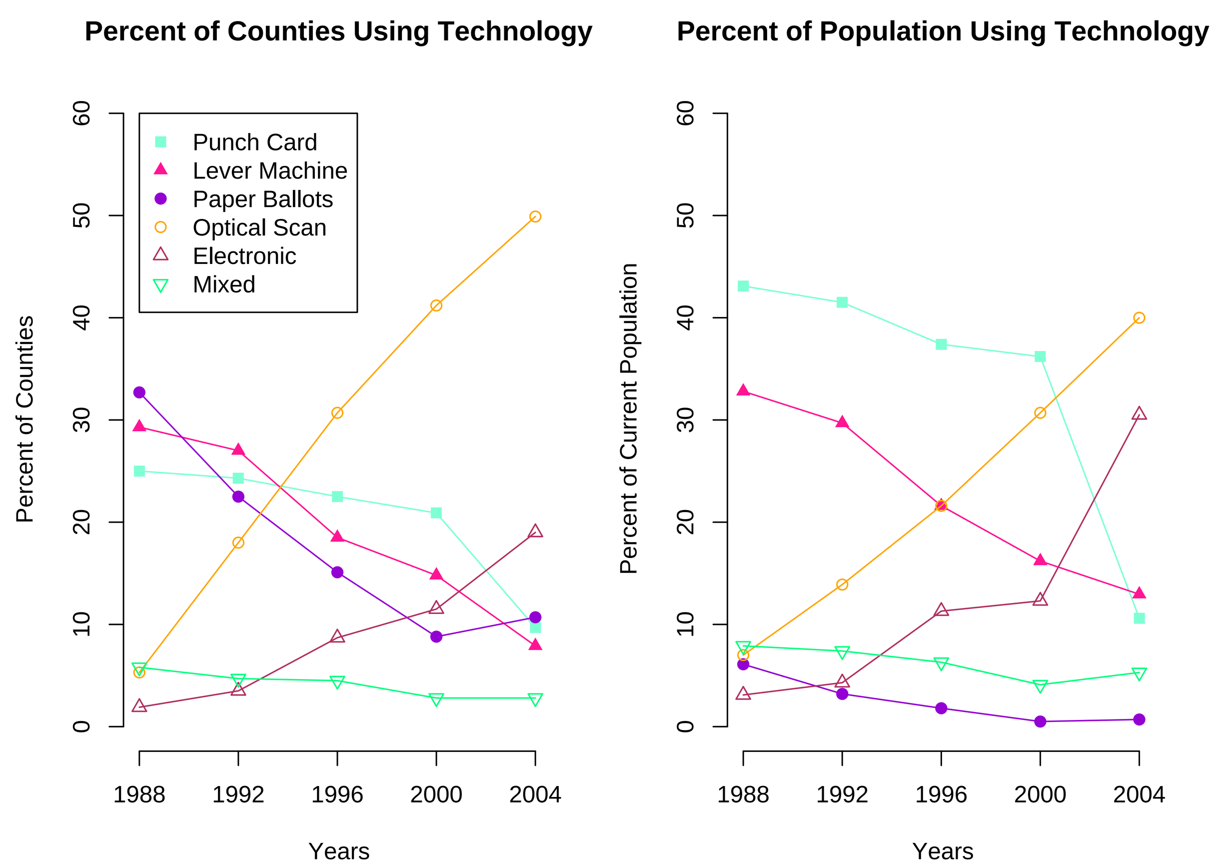
Data

- 1988-2004 Presidential Elections
- Election Returns
- Voting Technology
- Demographics
- Data on approximately $\frac{1}{2}$ of U.S. Counties
- Residual Votes

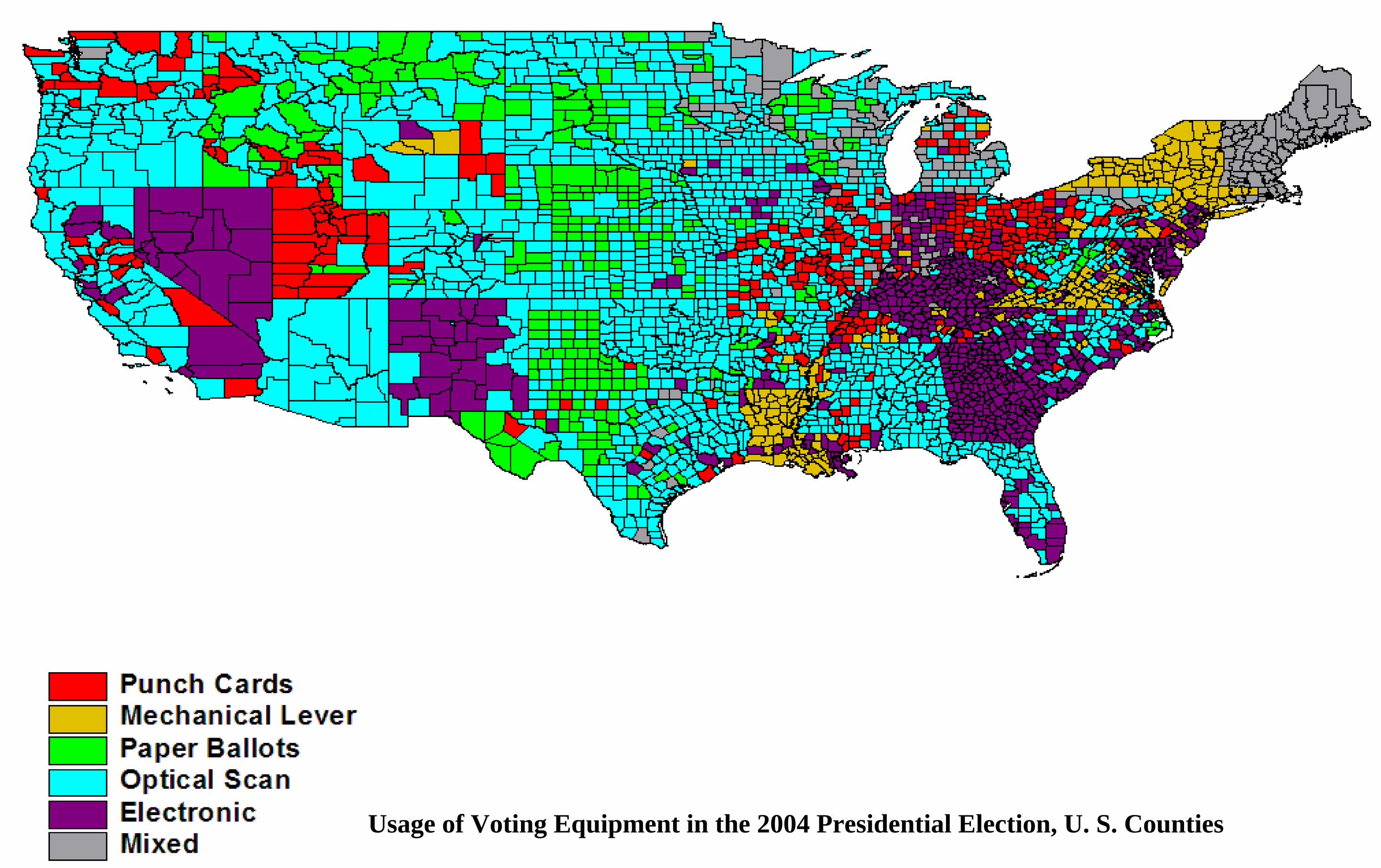
  * the fraction of total ballots cast for which no vote for president was counted.

Average Residual Vote by Machine Type and Year in U.S. Counties
1988-2004 Presidential Elections.

	Counties				
Machine Type	1988	1992	1996	2000	2004
Punch Card	3.5%	2.7%	3.1%	2.6%	2.0%
Lever Machine	1.8%	1.7%	2.2%	2.2%	1.1%
Paper	2.7%	1.9%	2.6%	2.2%	2.2%
Optical Scan	3.1%	3.1%	2.4%	2.1%	1.4%
Electronic	3.6%	3.8%	3.3%	2.4%	1.6%
Total	2.9%	2.4%	2.7%	2.3%	1.6%



Distribution of Voting Technologies across the U.S., 1988-2004



Usage of Voting Equipment in the 2004 Presidential Election, U. S. Counties

Methods

- Difference-in-differences

  Exploit the natural experiment that occurs when counties change technology

  Four time periods: 1988-1992, 1992-1996, 1996-2000, 2000-2004
  Focus only on counties that switch from Punch Cards to Optical Scanners

$$\mathrm{DD} = [\hat{E}(Y_1|\mathrm{OS}) - \hat{E}(Y_0|\mathrm{OS})] - [\hat{E}(Y_1|\mathrm{P}) - \hat{E}(Y_0|\mathrm{P})]$$

- Fixed Effects

All specifications are variations on the following equation:

$$\ln(\mathcal{F}(Y_{it})) = \alpha_i + \gamma_t + T_{it}^j \lambda_j + X_{it}\beta + \varepsilon_{it}$$

1. state and year fixed effects
2. county and year fixed effects
3. county and year fixed effects as well as lagged dependent variable

- Propensity Score Matching

  Propensity score estimated via logistic regression of T_{it} on X_{it}

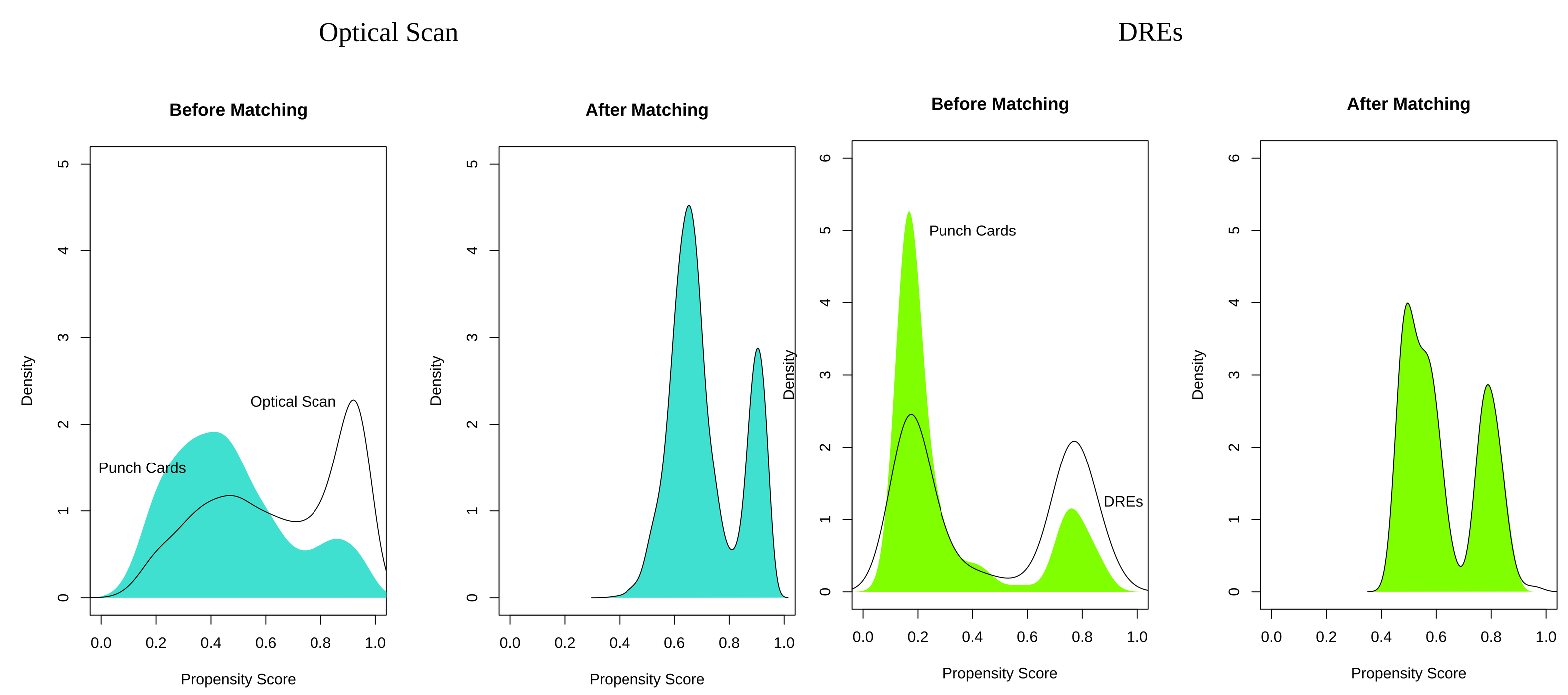
  Nearest-neighbor matching with replacement, using *Matching* package for R (Sekhon 2005).

  Estimated average treatment effect (ATE): $\tau = E[Y_i^{\mathrm{OS}} - Y_i^{\mathrm{P}}]$

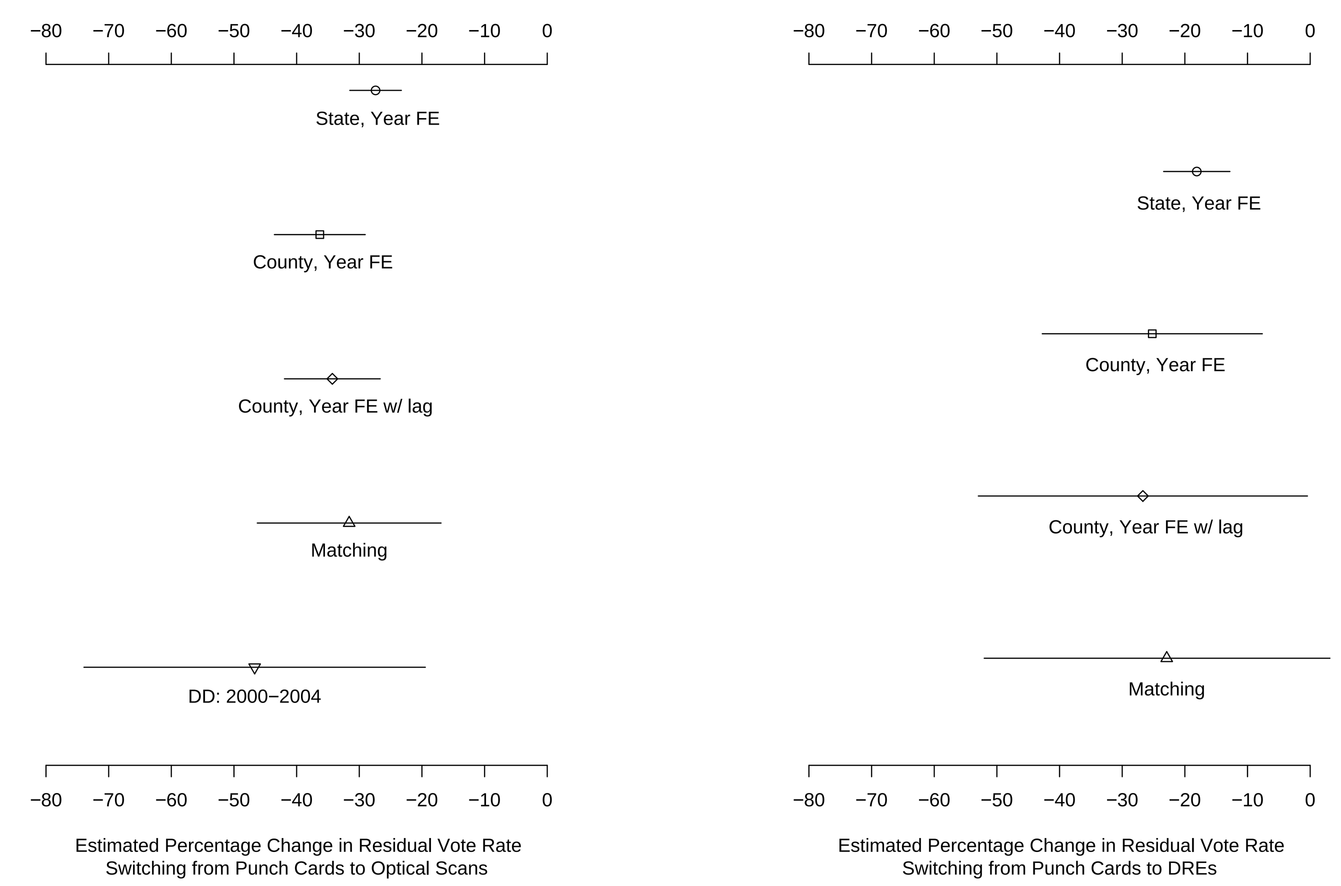
  Multi-valued treatment – measured change from Punch Cards to each other technology individually

Empirical Results

Propensity Score Distributions



Estimated Effects



Conclusions

- Pattern of the results is consistent across estimators.
- Matching estimates do not differ significantly from the linear models, suggesting that the linear specification is appropriate.
- Difference-in-differences estimators theoretically appropriate, but not enough data to distinguish estimates from zero.