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By

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ABSTRACT

During the tabulation of votes in the 2000 presidential election, the world was shocked at the technological inadequacy of electoral equipment in many parts of the US. In reaction to public dismay over "hanging chads", Congress quickly enacted the Help America Vote Act (HAVA), legislation to fund the acquisition of advanced vote-counting technology. However, the intention was to enable, rather than mandate, choices of new electoral equipment. This paper takes advantage of a unique historical opportunity to test whether electoral equipment follows the pattern predicted by well-established models of innovation diffusion, merging electoral data with census data on socioeconomic characteristics. We infer that fiscal constraints to acquisition are strong but are not the only limitations to technology adoption, particularly within certain types of easily identifiable populations.

JEL Codes: H0, H1, K0, O33, O38, P11
Keywords: election, vote, innovation, diffusion, Help America Vote Act (HAVA), voting equipment

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"Those who cast the votes decide nothing. Those who count the votes decide everything."
Attributed to Josef Stalin (1879 - 1953)

1. Introduction

In the aftermath of the remarkably close and hotly contested 2000 U.S. presidential elections, there was widespread national soul-searching. How had the nation come to a place where the presidency would be determined based on legal decisions regarding the counting of ballots with hanging or dimpled chads? Were voters making the choice of president, or was the choice instead effectively being made by machinery and the officials who tallied the votes?

During the tabulation of votes in the 2000 US presidential election, the nation was shocked at the technological inadequacy of the electoral equipment in many parts of the nation. Butterfly ballots and "hanging chads" quickly caught the public's attention and the media focused on the problems with punchcard voting technology. In the weeks that followed, obscure details of voting technology, counting standards, error rates and accessibility were eagerly explored and important questions emerged about voting systems and the administration of US elections. The election called the public's attention to a fact that election officials knew for years, namely that a variety of elector equipment exists concurrently across and within counties across the nation.

In reaction to the very public dismay over the Florida debacle, Congress acted quickly to enact legislation intended to fund the acquisition of more advanced vote-counting technology across the nation. The Help America Vote Act (HAVA, P.L. 107-252) was enacted in October 2002, authorizing $3.86 billion to fund new equipment, advance accessibility, and improve election administration. HAVA both enables the replacement of punchcard and lever voting systems and focuses on strengthening election administration. However, this legislation was designed to enable, rather than mandate, choices of new electoral equipment. "HAVA does not require any particular voting system, but it sets requirements that will influence what systems election officials choose. Beginning in 2006, voting systems used in federal elections must provide for error correction by voters, manual auditing, accessibility, alternative languages, and federal error-rate standards." (Coleman & Fischer, p.2) There is great variation in the requirements for ballots and vote tabulation across states and local jurisdictions. Moreover, there is no consensus on which technology is best.

This is a classic example of demand-push technological change in which a sudden, obvious shift in demand leads to a dramatic increase in the number of consumers (in this case, election authorities) considering the adoption of new technology. Demand-push changes traditionally lead to an interesting set of inter-related choices regarding adoption. First, there is the decision regarding which, if any, new technology to choose. Since the choice is to move away from something old, there is not a single obvious new technology with which to replace the incumbent. There is generally uncertainty at this early stage (e.g. VHS versus Betamax case) about which new system will best fulfill the population's needs. A myriad of varieties of optical scanning machines and electronic systems such as touch-screens were suddenly being discussed and evaluated simultaneously by large groups of consumers.

Second, there is the decision about when to switch. After all, there is tremendous uncertainty involved in the transition to any new technology. Election officials believing the original technology functioned without mishap, may find no pressing need for change. In addition, new technologies often have early-stage technical concerns. There may be competing advantages to recommend the adoption of various different new technologies, where only one should be chosen. Alternatively, it may be the case that decision-makers are unable to reach a consensus on which new technology to adopt. Moreover, even after HAVA's financial support, the costs of adoption may still be significant.

Indeed, four years after HAVA was enacted, only eighty percent of the voting electorate is confirmed to be using advanced voting technologies. Table 1 summarizes the state of equipment in 2006.[1] The technologies are divided into two groups: primitive (punch-card, lever, paper ballots, data-vote machines) and advanced (optical and electronic). In addition, there are a small number of counties utilizing a mix of different voting equipment.

Table 1: Voting Equipment in 2006

Voting Equipment	Counties		Registered Voters	
	Number	Percent	Number	Percent
Punch Card	124	3.98	5,166,247	3.03
Lever	119	3.82	17,356,729	10.18
Paper Ballots	176	5.65	653,704	0.38
Optical Scan	1502	48.23	69,517,991	40.79
Electronic	1050	33.72	66,573,736	39.06
Mixed	143	4.59	11,154,765	6.55
Total	**3,114**	**100.0**	**170,423,172**	**100.0**

(Source: Election Data Service, Inc., 2006)

Given historic differences in resources and election administration, the newly available federal funding and the variation in election requirements, is it not surprising that the adoption of advanced technologies has not been uniform. This paper takes advantage of this unique historical opportunity to test whether electoral equipment follows the pattern predicted by well-established models of innovation diffusion. Merging electoral data with census data on socioeconomic characteristics, we find that the adoption of advanced voting technologies is decidedly different across the US.

[1] The state of equipment in 2008 reflects further adoption of advanced technologies. The 2008 data are drawn from a different source (described in section 3) which described the types of voting equipment with fewer categories.

This paper focuses primarily on the question of timing. In particular, we ask whether traditional models of technology diffusion (outlined in Section 2 below) apply to this case of election equipment. With county-level data spanning 28 years (described in Section 3), we use multivariate regression analysis to explore whether counties with particular socioeconomic characteristics are more likely to quickly adopt new equipment. Tests of several different models offer complementary conclusions (Section 4). As part of that analysis, we establish whether HAVA changed that pattern, and in what respects. Finally, we offer conclusions (Section 5) about the nation's voting equipment status for the upcoming 2008 elections. Policy recommendations spring out of those conclusions.

2. Models of technology diffusion

It is commonly acknowledged that the pioneering study of technology diffusion was Griliches (1957). His work described for the first time the perfectly rational reasons for both incomplete diffusion within and between populations, and also slower adoption within some populations than in others. The now-familiar S-shaped curve plotting dispersion against time has been noted in various industries since then (Hall, 2005). Hybrid corn seed was more immediately appropriate in Iowa, offering obvious higher yields and profit margins than existing seed stocks. That difference was less obvious in states such as Alabama, applying mostly on the margin and often requiring additional complementary inputs to obtain those higher yields. Thus, it was perfectly rational for Alabama to be a slower adopter of this technology than Iowa was.

In addition, within each population (state), adoption did not spike to one hundred percent immediately. In Iowa, where applicability was most obvious, it still took ten years for all decision-makers to choose to adopt. That delay is due to communication delays, risk-aversion among potential adopters, and those decision-makers exercising the option value of simply waiting to see if a next generation of hybrid seed would follow hard on the heels of the initial change. After all, why make two switches if you could wait and simply choose once to skip over the intervening technological generation? Less developed nations are successfully following this strategy now, adopting cell phones and bypassing landline telephone technology altogether. In some populations, adoption rates are not only slower but will never reach one hundred percent. In the context of hybrid seed, in some portions of Alabama, hybrid seed never offered an appreciable advantage over previous seed stocks, and those regions have never switched.

A host of studies have followed Griliches (see Hall (2005) for a terrific review), all pointing to the fact that adoption is slow and potentially incomplete, depending on the characteristics of the adopting agents. The provocative question for this study is: which characteristics of the voting population act to speed up or slow down the adoption process?

In contrast, the physics literature has proposed a somewhat simpler model of diffusion, one based upon epidemiological models of disease. The most elegant version (Bettencourt et al., 2006) simply states that populations fall into one of three categories: susceptible, infected or recovered. Susceptible populations are potential adopters, infection is akin to adoption of the new technology, and those who recover are those who previously adopted but choose to return to the old technology. Each population can be modeled simply: a measurable share of those susceptible is newly infected (adopt the new technology) each period, and a similarly measurable share of adopters recover (recant the new technology) in each period. The simple version of this model does not distinguish populations by characteristics, but treats all susceptible constituents as equally probable adopters of the new technology.

In a similar vein, Hall (2004) makes the excellent point that the decision to (not) adopt is not a once-and-for-all choice. Instead, each decision-maker holds the equivalent of an option contract. If they decide to execute the option, they adopt the new technology with all attendant costs and benefits. If they decide not to adopt, they still hold the option to adopt next period, so may forego benefits this period while postponing the costs of adoption into the future and waiting for a more valuable version of new technology to arrive. Many information technology departments face this option regularly in deciding upon a particular renewal/depreciation cycle for computer equipment.

There are several observations in the literature that would suggest a rapid increase in the rate of technology diffusion since 2000. Tellis et al. (2002) suggest that status-enhancing goods are quicker to diffuse. In their European study, information consumer durable goods (electronics) in particular diffused faster than household appliances, controlling for many other factors. Perhaps, they suggest, this is akin to conspicuous consumption, as consumption observable by others adopts advanced technology faster than more private consumption does. In our case, the choice of electoral equipment has always been publicly known, but has been increasingly widely publicized since the 2000 elections, even with pejorative coverage for counties that held to the primitive technologies associated with the 2000 election mishaps. We should perhaps expect faster adoption of advanced voting technology post-2000 as a result, even in the absence of HAVA.

Often the advantages of a technology are most clearly displayed by early adopters, as pointed out by Rosenberg (1972; 1982) and Nelson et al. (2002). In our case, the advantages of advanced technology were obvious in the 2000 elections through the lack of controversy in those counties. Once might again expect a rapid rise in the adoption rate of election equipment after any very public and embarrassing disclosure of counting woes, administrative difficulties or voting access problems.

Alternatively, the benefits may in fact be linked to the number of adopters, the network externalities familiar in a variety of contexts. See Saloner and Shepard (1995) for an evaluation of the power of these effects in the case of automated teller machine diffusion, or David (1985) for the classic, and often argued, case of the QWERTY keyboard. In the case of electoral equipment, the case to be made for network effects is perhaps weaker, except for the shared labor pool of technology experts needed to service and install machinery.

Another theme prevalent in the diffusion literature centers on standards (e.g. Katz and Shapiro, 1985 or Arthur, 1989 on the VHS/Betamax case). As HAVA sets baseline standards for supportable technology, one might expect a legislation-enabled surge in adoption merely due to the standards, peripheral to any funding provided by HAVA.

Most studies relating diffusion to competitive pressures find that large firms in more concentrated industries adopt earlier. However, there have been some notable exceptions, in steel (Oster, 1982), coal, rail and brewing (Mansfield, 1961) and machine tools (Romeo, 1977). We do not have a strict comparator in our non-industrial venue, but we are able to compare the adoption of new voting technology across urban and rural counties. In so much as more urban counties parallel large firms, we find that they do adopt advanced voting technologies more rapidly.

Several authors have pointed out the complementary investments required in human capital in order for advanced technology to reach its potential (Caselli and Coleman, 2001; Shaw, 2002). In a similar vein, Lleras-Muney and Lichtenberg (2002) conclude that more educated agents in the medical sector adopt advanced technology more quickly. Mulligan and Sala-i-Martin (1996) find a similar result in the financial sector. Our case is no different, as election officials will undoubtedly require training on how to aid voters with advanced technology. We hypothesize that more educated counties will adopt more quickly, either because they have more educated decision-makers and/or because they feel a lower cost of adoption given their educated electorate.

The age of the decision-maker may have a bearing as well. Mulligan and Sala-i-Martin (1996) found that older households were less likely to adopt advanced financial technologies. In the context of a social psychology study, Brown et al. (1995) found that due to a “heightened motive for emotional harmony, older individuals are especially likely to prefer consistent activities, cognitions, and people”(Brown et al., p.517). That is, older decision-makers were more likely to remain with the status quo, and generally were more fearful of change than their younger peers.

If we consider the literature from the point of view of technology suppliers, oligopolistic providers such as exist in electronic voting equipment may in fact lead to an overly quick diffusion. Each will have an obvious incentive to under-price in order to capture market share (Farrell and Saloner, 1992). Particularly given HAVA legislation, which relaxes the budget constraint for counties wishing to adopt, we find that adoption has indeed been amazingly rapid in the post-HAVA years.

Obviously, there are cultural determinants which bear upon the question as well. Strang and Soule (1998) identify the popular media and other change agents such as communities of experts as potent forces for diffusion. They also suggest that potential adopters look at the decisions made by others that they view similar to themselves, as indicators for whether they should adopt. Rogers’ (1995) conclusions mirror this, suggesting that culture plays a large role in the adoption, or non-adoption, of health-related innovations. However, evidence is mixed. Tellis et al. (2002) conclude that most socioeconomic variables offer little to predict the rate of diffusion, or at least the timing of changes in that rate of diffusion.

Drawing on each of these strands of literature, the analysis which follows in Section 4 presents three different models. First, we offer estimates for the parameters of a simple epidemiological model. Next, we present parameters for a logistic estimation of the importance that socioeconomic factors play in the decision to adopt. Finally, we treat the adoption decision as an option, and present parameters for a duration model in which socioeconomic factors play a role in delaying the decision to adopt.

In the case of hybrid corn, the reasons for differential adoption rates seem obvious in retrospect (different climates and soil types). The reasons are less obvious in the case of electoral equipment. The factors that drive differential adoption rates likely include, but are not limited to the following.

Implementation costs. Estimates place the costs of new election equipment between \$0.5 and \$5 billion nationwide, depending upon exact choices and timing. (Coleman & Fischer, p.2) These include equipment and transitional / training costs. Prior to the passage of HAVA in October 2002, limited federal support was available to cover those costs.

Administrative inertia or deadlock. There are excellent studies showing that decision-makers often stay with the default (in this case, existing technology) even when it does not match their preferences. See Thaler and Sunstein (2008) for a study of the choice to sign organ donor cards where a majority opt for the default option (wherever it is placed), or for a study of those who do not take advantage of generous employer-matched retirement plans, in return for the low cost of filling out a single form. In a more active example, decision-makers may be unable to reach a consensus about which new technology to adopt, so rely on the incumbent technology until a decision is reached.

Lack of knowledge. Faced with decisions about complex systems with far-reaching implications, it is possible that jurisdictions do not adopt new technology for lack of adequate technical knowledge about how they are different than the status quo. It may also be unclear how difficult new systems will be to install, repair or maintain. While there is no consensus on which technology is best, adoption decisions are further complicated by states' vastly different requirements. For example, some require that the full ballot must be displayed on one page, some require tabulation in precincts versus a central location and jurisdictions vary greatly on how accessibility requirements are met.

Option value. It may be optimal to wait for an even better next-generation machine, or to wait to see which line of new technology (optical or electronic) really works better elsewhere, generates fewer problems and requires less maintenance.

Uncertainty / risk. There is genuine technical uncertainty with any new product or process. In addition, there may be doubts or suspicions about election equipment in particular given recent past experience. Fears run from the passive (e.g. if we choose a technology that does not leave a paper trail, how will we recount if called upon to do so as we were in 2000?) to the paranoid (e.g. will computer programmers be able to insert a backdoor allowing them to manipulate elections at will?). Some argue that a diversified electoral system limits the possibility of widespread election manipulation or technical failure.

Maximizing chances of re-election. Decision-makers may prefer a technology that caters to a specific portion of the electorate. For example, they may prefer familiar, old technology to court old voters.

Regrettably, many of these potential reasons are not measurable, but Section 3 outlines our unique matched dataset which will shed some light on potential reasons for the decision to adopt new election equipment.

3. Data

We have merged data from six distinct sources for this project. First, we purchased election equipment data from Election Data Services, Inc. on the type of equipment used to tabulate votes. This is the same vendor used by the federal government for this purpose. These data include the type of equipment in place during popular elections for the years 1980, 1988, 1992, 1996, 2000, and 2004. Unfortunately, data for 1984 were unavailable. The surveys classify voting equipment according to seven categories: (1) DataVote punchcards, (2) other punch cards, (3) mechanical lever machines, (4) hand-counted paper ballots, (5) optical scan systems, (6) electronic systems, and (7) mixed systems. Figure 2 shows examples of these types of equipment.

We augmented these data with information for 2008 voting equipment from the VerifiedVoting.org website.[2] VerifiedVoting.org is a nonpartisan, nonprofit 501(c)(4) corporation, which lobbies for reliable and publicly verifiable election systems. The site provides county-level data on the polling place equipment in use. Their list of technologies differs only slightly from the EDS data. The categories include (1) punchcards, (2) lever machines, (3) hand-counted paper ballots, (4) optical scan systems, (5) ballot-marking devices, (6) electronic touch-screen systems, (7) electronic direct dial systems, (8) digital scans, and (9) mail-in ballots counted by optical scan.

Utilizing these data, the electoral map of the US may be painted to identify a variegated patchwork of equipment uses, ranging from hand-counted paper ballots through lever machines and punch cards and on to optical scanners and electronic touch-screens. Figure 3 reveals the variety of electoral equipment in place immediately before and immediately after the implementation of HAVA, in 2000 and 2008. For the purposes of intertemporal comparison, we present only six aggregated categories of equipment in the two maps here.

The near universal adoption of advanced technologies (electronic and optical scans) is very apparent in Figure 3, with the exception of Idaho, New England, New York, and Wisconsin. Between 2000 and 2008 many states passed legislation to implement a uniform voting technology statewide.

Within the election equipment data, all counties reporting mixed systems were eliminated from consideration since no information is available on the composition of machines in use. The number of counties with mixed technologies varies by year: averaging 145, with a low of 95 in 1980 and a high of 192 in 1988. In addition, the Alaskan data were eliminated because county lines were redrawn between the 1980 and 2000 elections. For the remaining counties, the election technologies were divided into two groups: primitive (punchcard, level, paper ballots, data-vote machines) and advanced (optical and electronic).

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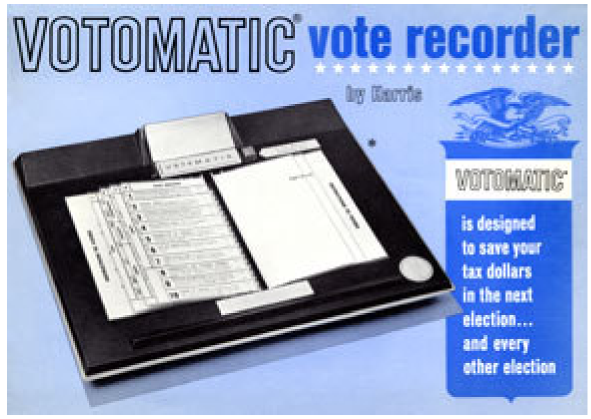
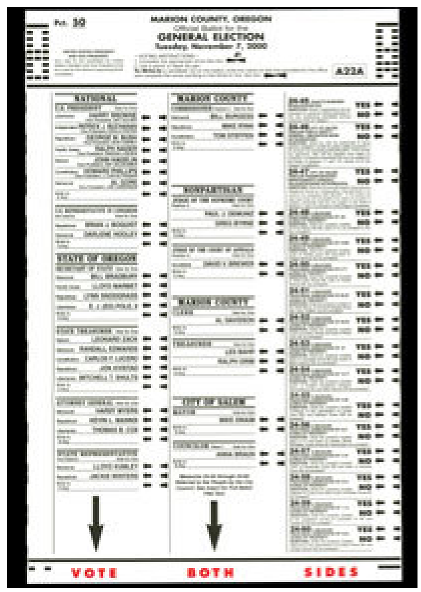
[2] These data were collected between August 15 and 17, 2008. (http://verifiedvoting.org/)

Figure 2: Forms of electoral equipment



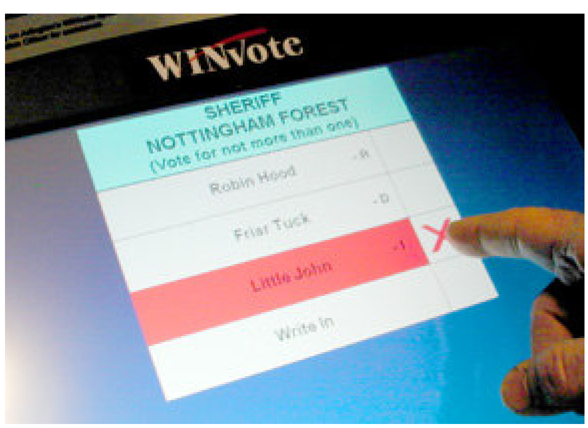
Datavote Punchcard (type 1)

Votomatic Punchcard (type 2)



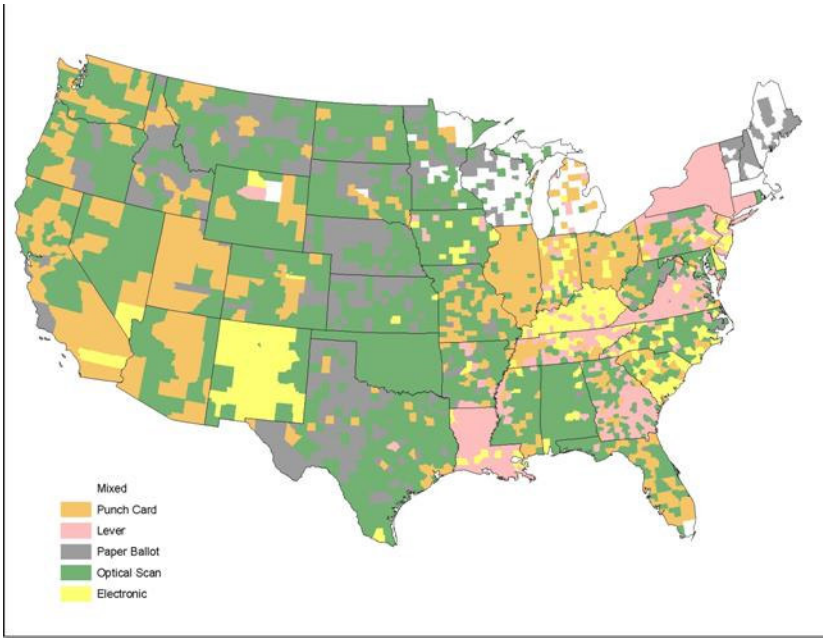
Gear & Lever Voting Machine (type 3)

Optical scan card (type 5)

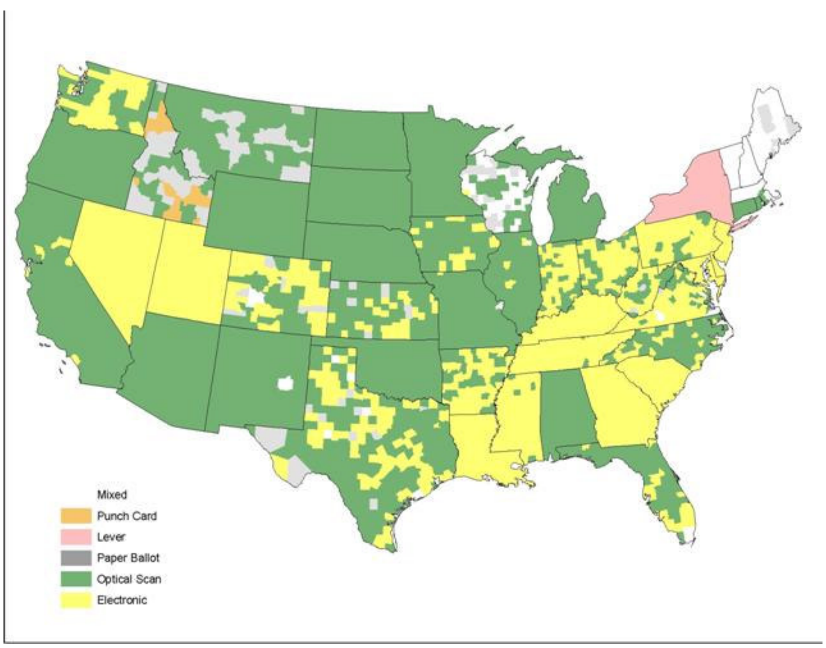


Touchscreen (type 6)

Figure 3: Variety of electoral equipment, 2000 and 2008



2000



2008

Next, we merged information from CQ Press about the precise number of votes for each party's presidential candidate, tabulated by county, for the presidential elections 1980 through 2008 (except 1984) (CQ Press, 2008). Figure 4 presents a time progression of maps, tracing primitive versus advanced electoral equipment against the major political party winning the most votes in the presidential election that year. Dark colors denote advanced equipment (while light colors denote primitive equipment), while blue and red reflect the traditional colors of the Democratic and Republican parties respectively. Mixed-technology counties are left white. The final panel represents advanced and primitive equipment as shades of gray in advance of the 2008 election results. Notice that the darkening/advancing of equipment adoption is not clearly associated with one region or one political party. Instead, darkening appears fairly random over time, perhaps clustering geographically next to other counties that have adopted, but not uniformly. Notice for example, that Florida (site of the notorious hanging chads in 2000) uniformly adopted advanced technologies before 2004, along with much of the southeast. On the other hand, the Midwest and Rocky Mountain regions are quite speckled with a combination even through 2004.

One obvious pattern has been the increase in uniform statewide electoral equipment standards. According to Election Data Services, Inc. recent years have shown a rapid increase in such legislation. Oklahoma was the first, adopting a uniform optical scan in the early 1990s. This was followed by Delaware's 1996 implementation of an electronic system and optical scans adopted in Hawaii (1998) and Rhode Island (1998). Between 2002 and 2006, Georgia, Nevada and Maryland established uniform electronic voting systems and North Dakota adopted a uniform optical scan system in 2006. (Election Data Services, p.3) Across the board, counties are increasingly utilizing advanced election technologies. Table 2 summarizes the distribution of technology use over time, from 1980 to 2008.

Table 2: Diffusion of Advanced Voting Equipment Technology

Year	Number of Counties (not mixed)	Counties using Advanced Technologies	
1980	3088	33	1.07%
1988	2991	221	7.39%
1992	3022	635	21.01%
1996	3030	1220	40.26%
2000	3045	1576	51.76%
2004	3033	2114	69.70%
2008	3038	2884	94.93%

Source: Author calculations

Finally, we merged those data with census data from 1980 and 2000 on a range of socioeconomic characteristics of the county population. In particular, we have constructed variables to measure median household income, education (percentage of population that has at least completed college), ethnicity (percentage of population that is white), age (percentage of population that is 18-21 years old), urbanization (percentage of population that lives in urban areas), and census region indicators (nine multi-state census groupings). The regression results reported here do not include urbanization since it was highly correlated with education. We use 1980 census data in the results presented here, to reflect the historical status of counties, and to avoid some minor statistical correlation challenges in the 2000 data. It is important to note that

Figure 4: Primitive/Advanced electoral equipment and political parties

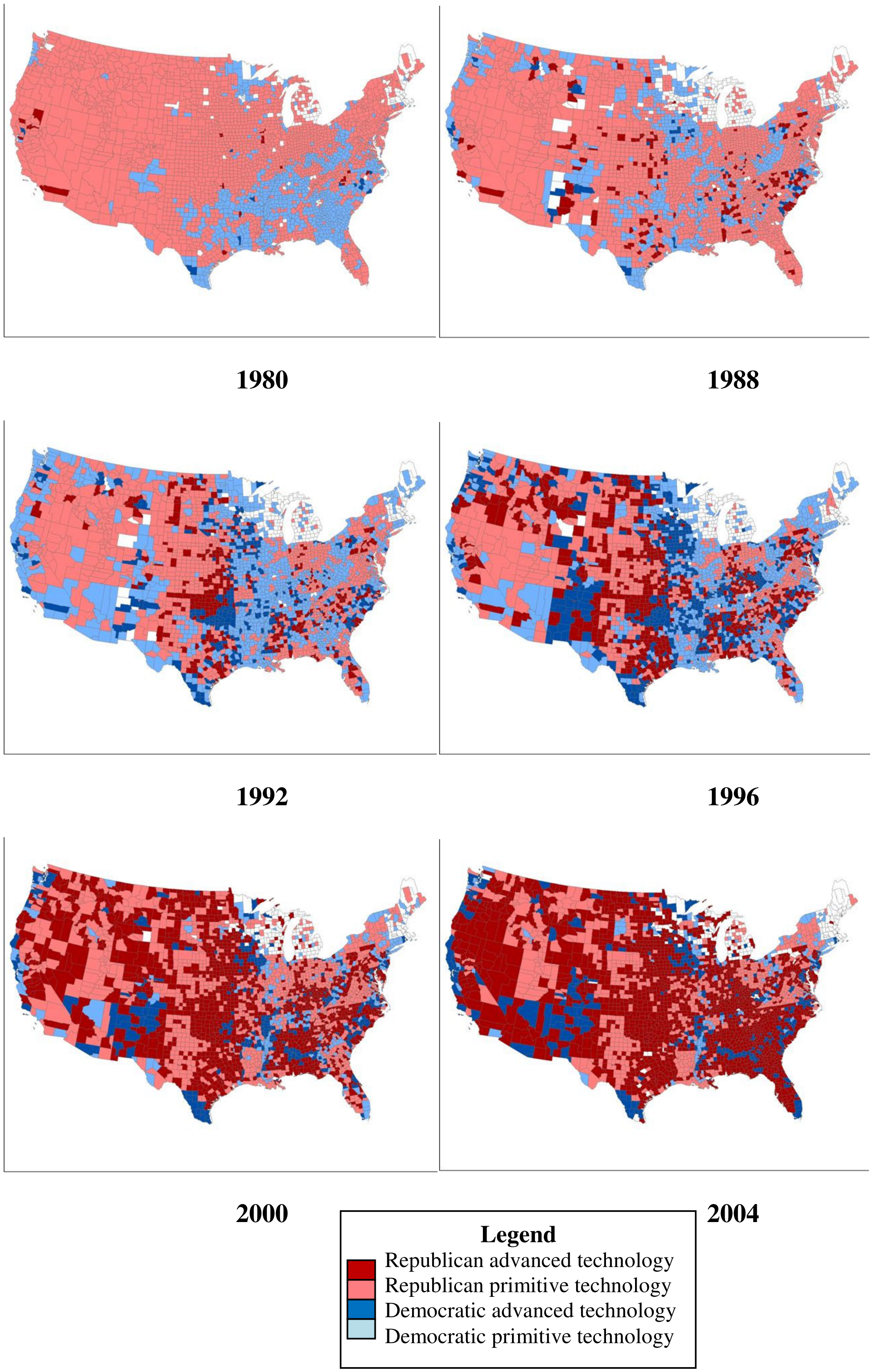
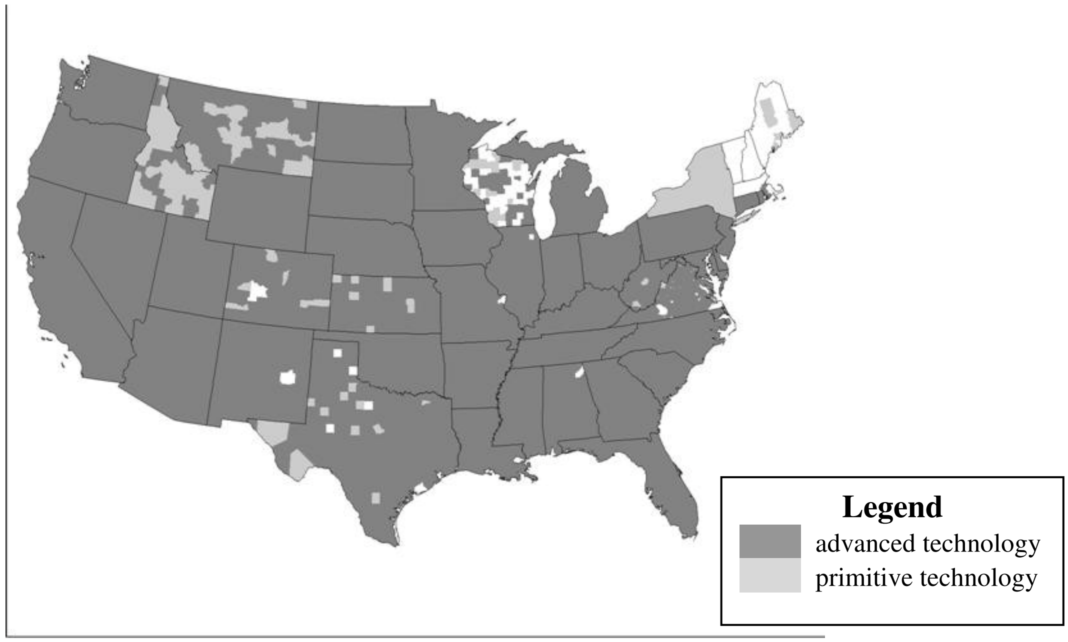


Figure 4 (cont.): Primitive/Advanced electoral equipment and political parties



2008

the size and sign estimated coefficients does not depend upon which census year is chosen.

In early work, data were also collected on religiosity by county from the Association of Religion Data Archives. However, we found that variables such as the number of religious adherents per capita or number of distinct religious communities in a county were either hopelessly correlated with other variables in our list and/or yielded no explanatory power in the model below. Future work might still consider effort in this direction.

We are left with an unbalanced panel of observations for 3114 counties over time, with the lack of balance arising from the decision by some counties to adopt mixed technologies.[3] In the absence of a clear-cut geographic or political explanation, such as uniform adoption legislated by the state, we explore below a list of socioeconomic variables, to determine their role (if any) in the diffusion of electoral equipment innovation. A summary of our key variables across 18,684 observations (3,114 counties across 6 time periods) is presented in Table 3.

RedMajority takes the value of zero if the Democratic candidate wins the county, while in the case of a Republican win it is the difference between votes cast for the Republican and Democratic candidates as a percent of the total votes cast. It is recorded with a one election lag, i.e. for the preceding presidential election. We hypothesize that close races (small majorities) may encourage advanced technology adoption, perhaps because the population actively discusses the election and considers the cost of slight miscounting higher. Alternatively, the cynical reader

[3] The number of counties with mixed technologies varies by year: averaging 145, with a low of 95 in 1980 and a high of 192 in 1988. We have also dropped the few counties that reverted from an advanced voting technology to a primitive. At some point 91 counties reverted.

might believe that large incumbent majorities will be less likely to change anything, including the voting technology, which brought them to power. Since this partisan effect may be asymmetric, we next construct a similar variable for a Democratic win.

Table 3: Summary statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
RedMajority	13.47	16.88	0	85.64
BlueMajority	4.20	9.59	0	79.84
Youth	7.128	2.73	0	36.97
Education	6.67	3.10	0.68	31.95
Ethnicity	88.22	15.23	6.60	100.00
Income	14454.74	3421.16	5750.00	31911.00

Source: Author calculations.

BlueMajority takes the value of zero if the Republican candidate wins the county, while in the case of a Democratic win it is the difference between votes cast for the Democratic and Republican candidates as a percent of the total votes cast. It is recorded with a lag, i.e. for the preceding presidential election.

Youth is the percent of the county's population aged 18 to 21 years, as reported by census in 1980. Thus it is an indicator of historically young counties (although there may have been change in the age composition since that 1980 measurement). Since census data are only available for 1980 and 2000 presidential election years, we chose not to change measurement variables within the dataset for fear of introducing unpredictable measurement bias.[4] There is empirical evidence that younger populations are more likely to embrace new technology and older populations are averse to change (Mulligan and Sala-i-Martin, 1996; Brown et al., 2005). Moreover, there are other reasons to believe that younger and older counties may adopt at different rates. Older voters are represented by a strong, organized lobby organization in the AARP, and they may very well be able to influence the decision on whether to adopt advanced technology. Thus we hypothesize that younger counties will adopt more rapidly than older counties.

Education is the percent of the county's population whose highest educational status is a bachelor's degree or higher, as reported by census in 1980. Again, this is an indicator of historically educated counties. We hypothesize that more educated counties will be more likely to adopt new technology earlier, in confirmation of the existing literature (e.g. Mulligan and Sala-i-Martin, 1996; Lleras-Muney and Lichtenberg, 2002; Croppenstedt et al., 2003).

Ethnicity is the percent of the county's population that self-identifies as 'Caucasian' for purposes of the census in 1980, denoting historically Caucasian counties. We hypothesize (and hope) that this variable will be unrelated to technological status, but present tests to be sure. To our knowledge, there is no literature supporting the claim that certain ethnicities are more likely to

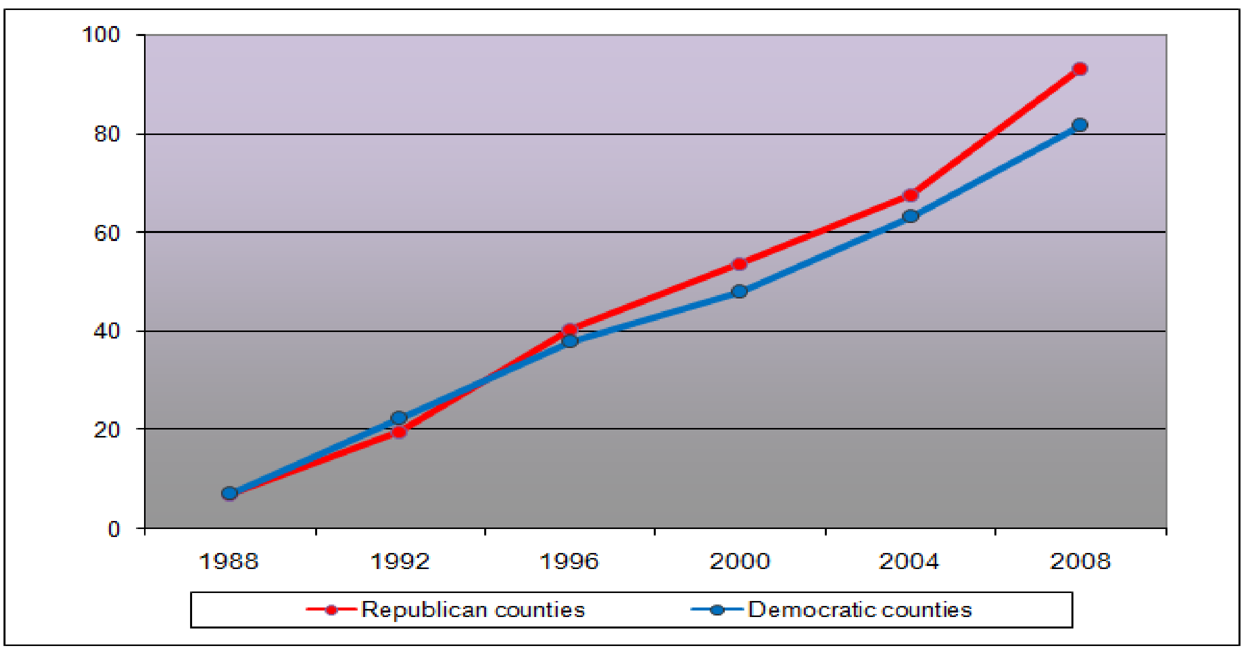
[4] The correlation between 1980 and 2000 of the percentage of population aged 18 to 21 years is 0.89.

adopt advanced technologies (once appropriate controls for geography and cultural norms have been included in the analysis).

Income is the median household income of the county, as reported in US dollars by census in 1980. We hypothesize that high income counties will adopt more quickly. We know from the data that higher-income counties also tend to be more educated and more urban, so we propose that educated, urban populations are more likely to adopt perhaps due to increased exposure to electronic and computerized equipment or due to more conversation within the community or city-centric media sources. Alternatively, higher-income counties may have higher tax revenues to support purchase of new technology in the pre-HAVA era. Income is highly correlated with youth and education, so the analyses which follow we do not combine them in the same equation.

Given these data, our early analysis of technology adoption very much resembles that of Griliches (1957). As an initial exploration of the data, we examine several socioeconomic characteristics and identify the share of counties (as a percentage of all US counties) using new election technology. Figures 5 though 9 reveal how different levels of a particular characteristic (winning political party, youth, education, ethnicity, and income) correspond to the percent of counties using new election technology over the last twenty years.[5]

Figure 5: Adoption rates by winning political party (%)



[5] For each socioeconomic variable (Figures 6-9, for youth, education, ethnicity and income respectively), divisions were drawn between counties lower than half of one standard deviation below the mean and counties higher than half of one standard deviation above the mean. The resulting characterizations of counties as 'younger' or 'highly educated' are therefore descriptions relative to the national average among counties. The lone exception is the category of 'below mean degree of Caucasian ethnicity', which is defined as a full standard deviation below mean for purposes of graphical presentation.

Figure 5 shows the adoption rates across counties who voted Republican in the previous presidential election, compared to counties that voted Democratic. The only noticeable difference is in the last four years, as counties that voted Republican have adopted more thoroughly than their Democratic peers. There is a clear difference in the percentage of counties utilizing new technology and red states appear to have adopted more rapidly. Following the passage of HAVA, the rate of adoption in blue states markedly increases.

Figure 6: Adoption rates by age of population (%)

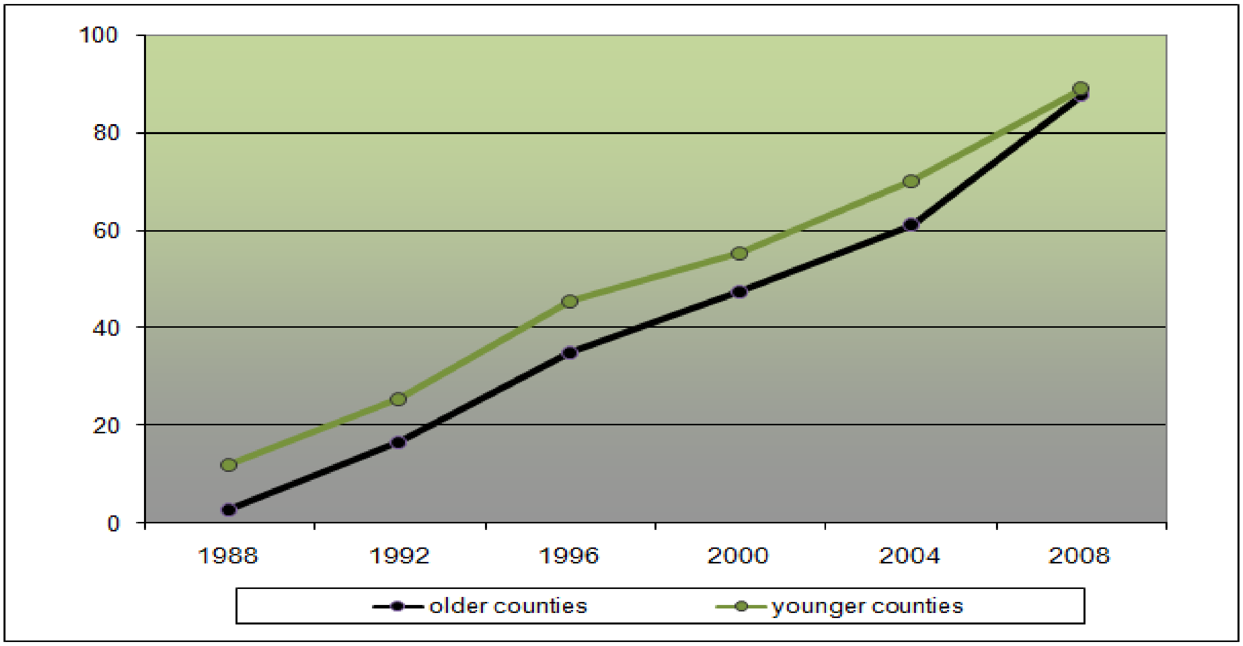


Figure 6 compares adoption rates across counties with older and younger populations, relative to the national average in 1980. The figure reveals that younger counties have historically adopted more thoroughly than their elders, a gap which has closed in the last four years. This corresponds with an expectation that younger individuals may be more technologically savvy and more readily accepting of change and new technology.

Figure 7 depicts the adoption rates by the level of education of the population of the counties, relative to the national average in 1980. The figure shows no significant difference between education cohorts, except for the last four years in which less educated counties have adopted both more thoroughly and more rapidly than their more educated peers.

Figure 8 indicates that ethnically diverse counties initially adopted more rapidly than historically Caucasian counties, but that this effect disappeared in the mid 1990s. Following the passage of HAVA in 2002, it appears that more ethnically diverse counties once again adopted new technology more rapidly and more thoroughly than their more Caucasian peers.

Figure 7: Adoption rates by education of population (%)

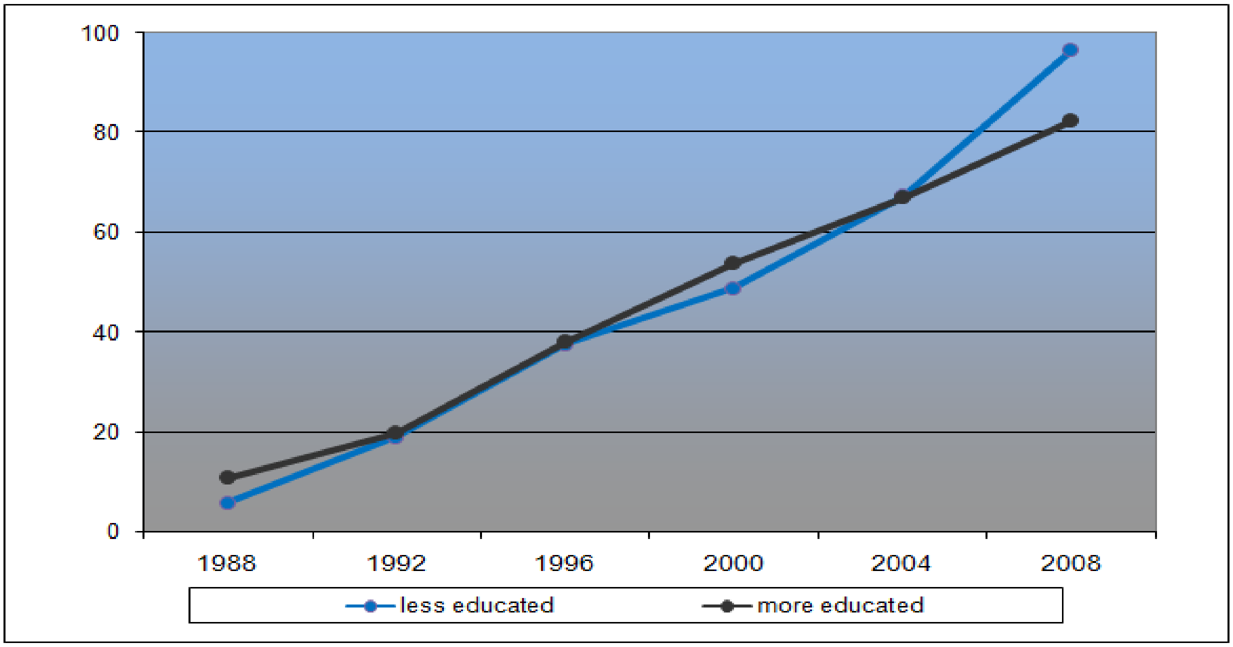


Figure 8: Adoption rates by ethnicity of population (%)

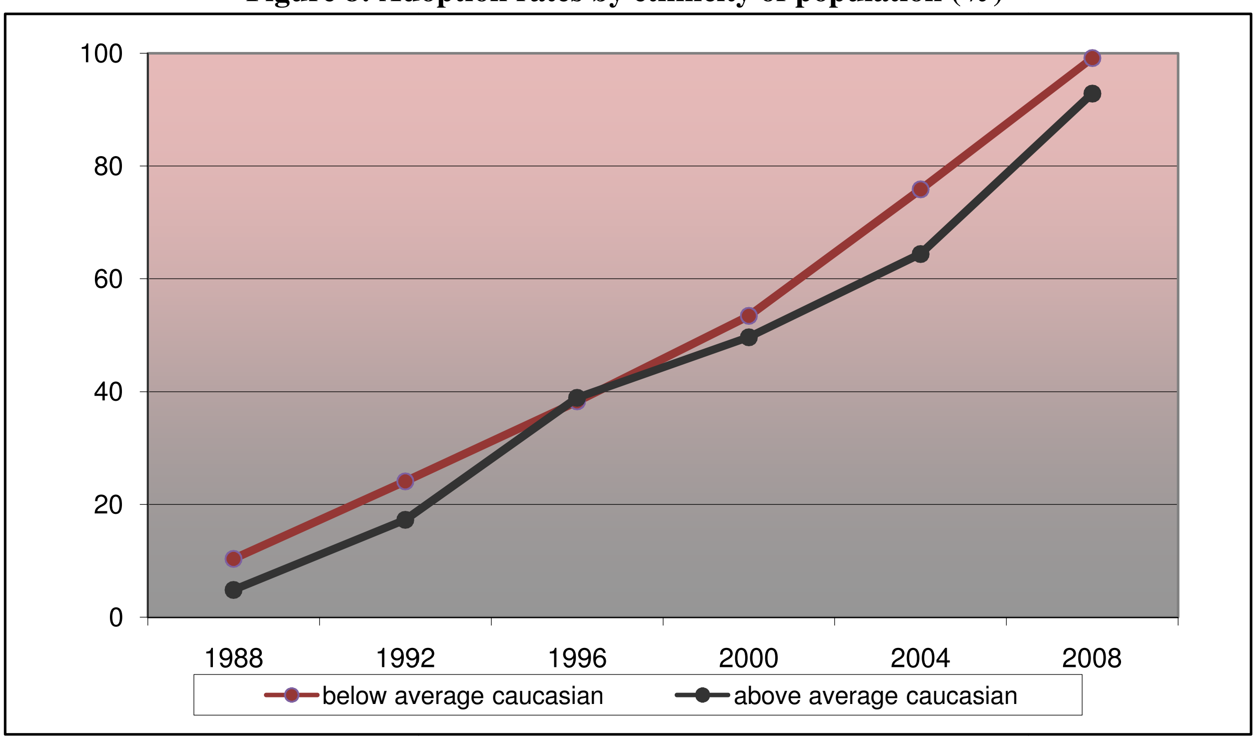
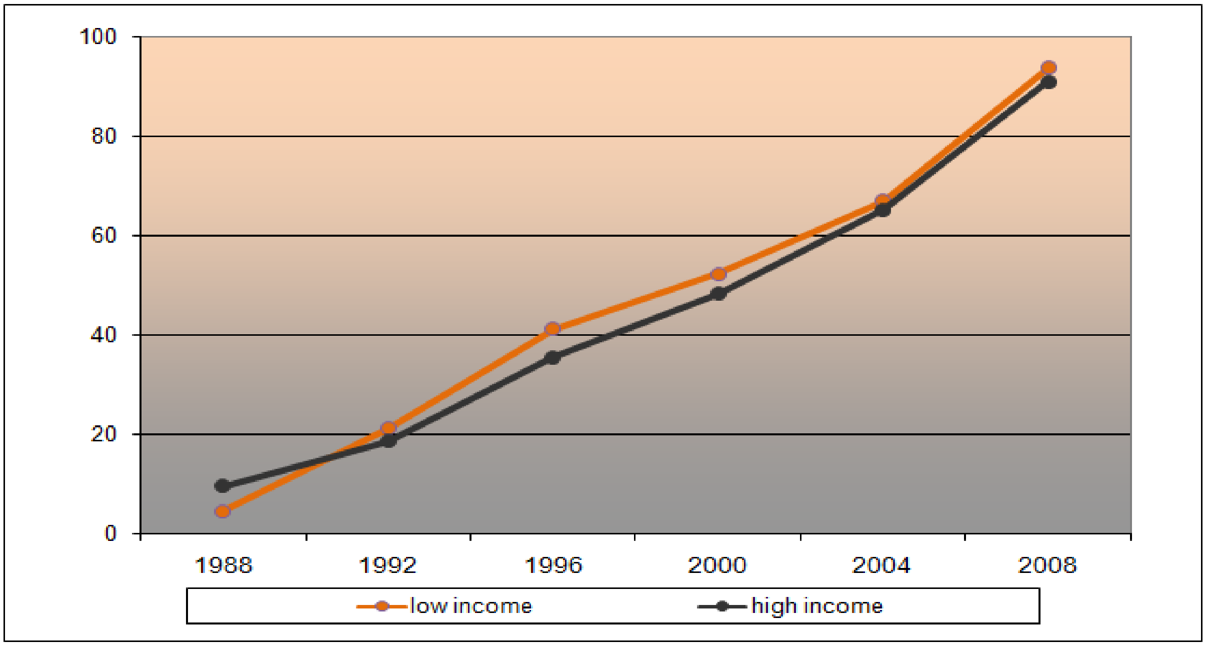


Figure 9 depicts the adoption rates by income level, relative to the national average in 1980. The difference between historically high-income counties and low-income counties is difficult to discern. Following the passage of HAVA in 2002, both types of counties appear to have increased their rate of adoption of new technology, at about the same rate. Obviously, all of these graphs await the confirmation of multiple regression analysis in the section that follows here.

Figure 9: Adoption rates by income of population (%)



4. Modeling and Analysis

This section offers four modes of analysis. First, we present evidence on the fit of a simple epidemiological model of diffusion, concluding that while it is interesting for future analysis, it does not offer the richness needed for the current question. Next, we suggest a logistic model of adoption, modeling whether a county decides to switch during a given period, taking each inter-election period as a possible period of change. Third, we build a duration model of adoption, which explicitly accounts for the nature of the adoption decision--- to adopt, or to forego temporarily in order to consider adoption next period. Finally, we present the results of a logistic model that considers a different question--- at any particular point in time, how likely is it that a county of particular attributes already has advanced electoral equipment in place.

The first three therefore approach the question from a 'flow' perspective, analyzing the changes between periods. The final approach treats technology as a 'stock', inferring from what we know about counties how likely they are to have already adopted.

4.a. Epidemiology SIR model

Bettencourt et al. (2006) find a good fit between their simple three-equation model and the empirical diffusion of physics techniques among practitioners in the field. They propose that the diffusion of ideas can be treated as though it were a virus between infected and susceptible populations. Consider the following:

$$\Delta S = -\beta S\left(\frac{I}{N}\right) \tag{1}$$

$$\Delta I = \beta S\left(\frac{I}{N}\right) - \gamma I \tag{2}$$

$$\Delta R = \gamma I \tag{3}$$

where S is the susceptible population (users of primitive technology), I is the infected population (users of advanced technology), N is the total population and R is the recovered population (former users of advanced technology who now use primitive technology again). Let $N = S+I+R$. Further, define β as the per capita adoption rate and let γ denote the recant rate (rate of recovery from infection). β and γ are estimated model parameters.

Intuitively, the number of susceptible individuals decreases based on the likelihood of exposure (share of the total population who are infected) and the rate of infection. The number of recovered individuals increases based on the rate of recovery (γ) multiplied by the number of infected individuals. The change in the number of infected individuals is the sum of those who transition from susceptible to infected less those who recover.

We find this paradigm provocative, and estimate the system for several subsets of our data, with parameters presented in Table 4. The first row treats all counties in the US as members of a single population. The second row treats each state as a separate population, and counties as members of their respective state. The remaining rows consider specific states in isolation.

Table 4: Epidemiological SIR model estimated parameters

Sample	**Estimated β**	**Estimated γ**
All counties as separate populations	0.726	-2.47×10^{-3}
All states as separate populations	0.833	4.68×10^{-3}
Alabama	1.312	-2.75×10^{-3}
California	0.963	4.17×10^{-3}
Colorado	0.983	1.46×10^{-2}
Iowa	1.298	1.98×10^{-3}
Texas	0.536	1.37×10^{-2}
Wyoming	0.449	1.29×10^{-3}

This approach and the parameters estimated in Table 4 clearly raise more questions than they answer. Perhaps most importantly, they motivate a deeper look and demand a more sophisticated approach in order to consider the factors that may influence rates of adoption. The results point to clear differences between national results and those at the state level. Moreover, the differences across states are surprisingly large, presumably for socioeconomic reasons. Alabama and Iowa adopted (or were infected) most quickly, at a rate almost three times that of the states that reacted most slowly, Wyoming and Texas. Table 4 suggests that a consideration of the national rate of adoption is inadequate, that there are important distinctions across states. The models that follow take this one step further, examining the differences which persist across counties and considering the socioeconomic characteristics at the county level to explore different rates of adoption.

While future work might dig more deeply into this model, categorizing populations (counties) by socioeconomic characteristics, we find two other models more immediately useful in making use of the census data outlined above to explain the differences between populations.

4.b. Logistic model of adoption

We alternatively consider the probability, at a given point in time, that a county has new rather than old technology. That probability is clearly an accumulation of past decisions to adopt or not adopt, and presumably is a function of socioeconomic factors each of which affected those decisions. Generally, we suggest that

$$Prob(change\ to\ advanced\ tech\ in\ a\ given\ time\ period) = f(political\ factors, socioeconomic\ factors, regional\ factors, time\ factors) \quad (4)$$

In lieu of a structural model, we propose a simple linear first-order approximation to recognize the inherent impact of political factors (β), socioeconomic factors (γ), regional factors (δ) and time (η). As there are multiple aspects of each theme to explore, we will permit multiple variables per category. We welcome the literature to follow, expanding and improving upon our first attempt here. We propose the following specification, at the county level:

$$Prob(change\ to\ advanced) = \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Youth + \gamma_2 Education + \gamma_3 Ethnicity + \sum_{n=1}^{49} \delta_n state_n + u_i \quad (5)$$

where $state_n$ is a set of dummy variables for each state, omitting Alaska in all analysis as previously explained, and omitting DC for the purpose of comparison. Each of the remaining variables was defined above in section 3.

While we could estimate a time trend instead, that would force a particular functional form on the diffusion path over time, an assumption that we would prefer to avoid. Interaction terms between variables would be interesting, but raise insurmountable issues of multicollinearity. We cluster all analyses by state to eliminate heteroskedasticity concerns. We use 1980 census values for each county here, but analyses run using 2000 census values are virtually identical.

We would have preferred to include a measure of household income into specification (5) but found that variable hopelessly intertwined with education, age and rural/urban measures. Thus we propose a separate specification here to reflect the impact of income:

$$Prob(change\ to\ advanced) = \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Income + \gamma_2 Ethnicity + \sum_{n=1}^{49} \delta_n state_n + u_i \quad (6)$$

where all variables are defined as above.

Obviously, these results take a 'flow' approach to advanced technology, rather than a 'stock' approach. In each time period, the sample includes only the counties that have not yet adopted advanced technology. That is, for each inter-election period we explore which variables are associated with the highest probability of a change (new technology adoption), given that new technology has not previously been adopted. A related question, concerning how these variables are associated with the ongoing inter-temporal choice to change or delay changing technologies, is answered in the next subsection.

Results of logistic estimation for these two specifications are presented in Tables 5 and 6 for the specification of equations (5) and (6) respectively. Each equation is estimated separately for three eight-year time periods, the baseline period (1980-1988), the pre-HAVA period (1992-2000), and the post-HAVA period (2000-2008). Estimation without state-specific effects results in coefficients similar in size, sign and significance.

Table 5: Estimated coefficients for logistic model using youth and education

Variable	***Baseline period (1980-1988)***			***Pre-HAVA (1992-2000)***			***Post-HAVA (2000-2008)***		
	Coefficient	***t-stat***		***Coefficient***	***t-stat***		***Coefficient***	***t-stat***	
RedMajority	-2.59×10^{-2}	(1.93)	**	-1.66×10^{-2}	(2.31)	**	7.87×10^{-3}	(1.12)	
BlueMajority	-3.20×10^{-2}	(2.50)	***	-4.64×10^{-3}	(0.68)		-9.29×10^{-3}	(0.60)	
Youth	4.46×10^{-2}	(1.90)	**	2.89×10^{-2}	(1.27)		2.44×10^{-3}	(0.07)	
Education	1.20×10^{-1}	(3.47)	***	5.18×10^{-2}	(1.66)	*	-4.04×10^{-2}	(1.40)	
Ethnicity	-1.51×10^{-2}	(1.81)	*	8.66×10^{-3}	(1.43)		-1.39×10^{-2}	(1.78)	*
Constant	-2.26	(3.10)	***	-1.55	(3.41)	***	1.57	(2.23)	**
Obs		**2286**			**2317**			**1240**	
Pseudo-R^2		**0.17**			**0.17**			**0.28**	
States perfectly explained[6]		**22**			**13**			**20**	

State dummies are not displayed here for presentation purposes, but are included in the analysis. Estimated errors are corrected for state-based heteroskedasticity. Statistical significance is denoted by * for the ten percent level, ** for the five percent level, and *** for the one percent level.

Politically, it appears that in the 1980s large majorities were less likely to change electoral equipment, as hypothesized. Democratic landslide counties were less likely to switch than Republican landslide counties, with closely contested counties most likely to switch. That effect fell away in the 1990s, as only Republican strongholds resisted advanced technology. Following

[6] States perfectly explained are those which have no variation within them. Either a state mandate is in place or simply all counties have chosen advanced (or primitive) technology.

the difficulties of the 2000 presidential election and the passage of HAVA, all political effects appear to have vanished.

Among socioeconomic factors, youth and education appear significant with signs as expected. Younger populations are significantly quicker to adopt new technology in the 1980s, and that effect stays positive but drops to insignificance by the 1990s. More educated counties adopt more quickly through the 1980s and 1990s, although that effect also subsides in significance in the post-HAVA era. There appears nice evidence then that HAVA is indeed at least temporally correlated with a period in which counties switch technologies regardless of socioeconomic or political factors. We view this as evidence that HAVA is having the intended effect of bringing technology to all, regardless of a county's attributes. Curiously, more ethnically diverse counties appear more likely to adopt than their homogeneously Caucasian peers in both the baseline and the post-HAVA periods.

Table 6 presents the results of the alternative specification, examining income and ethnicity in place of youth, education and ethnicity. As above, the equation is estimated separately for three eight-year time periods, the baseline period (1980-1988), the pre-HAVA period (1992-2000), and the post-HAVA period (2000-2008). This enables us to consider the impact over time, and focus, in particular, on whether the passage of HAVA matters.

Table 6: Estimated coefficients for logistic model using income

Variable	***Baseline period (1980-1988)***			***Pre-HAVA (1992-2000)***			***Post-HAVA (2000-2008)***		
	Coefficient	***t-stat***		***Coefficient***	***t-stat***		***Coefficient***	***t-stat***	
RedMajority	-2.99×10^{-2}	(2.53)	***	-1.89×10^{-2}	(2.76)	***	-8.77×10^{-3}	(1.15)	
BlueMajority	-2.79×10^{-2}	(2.14)	**	-3.90×10^{-3}	(0.58)		-1.19×10^{-2}	(0.83)	
Income	1.92×10^{-4}	(4.61)	***	7.17×10^{-5}	(2.52)	***	-4.18×10^{-5}	(1.96)	**
Ethnicity	-1.97×10^{-2}	(1.99)	**	7.44×10^{-3}	(1.38)		-1.50×10^{-2}	(1.95)	**
Constant	-4.90	(4.12)	***	-1.94	(3.99)	***	-1.44×10^{-2}	(0.02)	
Obs		**2286**			**2317**			**1240**	
Pseudo-R^2		**0.18**			**0.17**			**0.28**	
States perfectly explained		**22**			**13**			**20**	

State dummies are not displayed here for presentation purposes, but are included in the analysis. Estimated errors are corrected for state-based heteroskedasticity. Statistical significance is denoted by * for the ten percent level, ** for the five percent level, and *** for the one percent level.

As before, more ethnically diverse counties appear more likely to adopt new voting technology, relative to their more Caucasian counterparts, in both the baseline period and the one following HAVA. In the two periods before HAVA's inception, higher income counties were more likely to adopt advanced technology. Under HAVA, the pattern is reversed so that lower-income counties are more likely to adopt. Like ethnicity, political majorities show patterns similar in sign, size and significance to those in Table 5.

c) Duration model of adoption

In order to consider the genuinely sequential, and truly 'option value', nature of an adoption decision, we propose a duration model in this section. Since counties decide to either exercise the option to adopt, or to forego adoption today with the right to adopt next period, a duration (or survival analysis) model quite adeptly describes the impact of explanatory factors on the adoption decision. We use the same format as above to postulate

$$duration(primitive\ tech) = \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Youth + \gamma_2 Education + \gamma_3 Ethnicity + \sum_{n=1}^{49} \delta_n state_n + u_i \quad (7)$$

and

$$duration(primitive\ tech) = \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Income + \gamma_2 Ethnicity + \sum_{n=1}^{49} \delta_n state_n + u_i \quad (8)$$

where all variables are defined as above. To minimize the impact of our distributional assumptions, we assume a Weibull distribution for the arrival times, in keeping with the literature (Hall, 2004), allowing for the exponential distribution as a possible special case of the Weibull. We use years as the unit of analysis for duration. We present both the coefficients and the implied hazard ratios in Table 7.

Results here are almost entirely consistent with the previous section. Republican (Red) majorities do not appreciably slow or speed up adoption, while Democratic (Blue) majorities are associated with faster adoption. Younger counties, more educated counties, and higher-income counties all adopt faster than their peers.

Table 7: Estimated coefficients for duration model

Variable	***Using age and education*** *(specified in equation 7)*				***Using income*** *(specified in equation 8)*			
	Coefficient	***Hazard ratio***	***t-stat***		***Coefficient***	***Hazard ratio***	***t-stat***	
RedMajority	-6.59×10^{-4}	0.9993	(0.21)		6.88×10^{-4}	1.0001	(0.19)	
BlueMajority	-3.99×10^{-2}		(7.04)	***	-4.79×10^{-2}	0.9532	(8.18)	***
Youth	-2.05×10^{-1}	0.9609	(4.55)	***	---	---		
Education	-4.60×10^{-2}	0.8145	(2.02)	**	---	---		
Ethnicity	-4.09×10^{-2}	0.9599	(11.25)	***	-3.73×10^{-2}	0.9634	(10.79)	***
Income	---	---			-1.26×10^{-4}	0.9998	(7.49)	***
Obs			12779				12779	
Wald χ^2			344.86	***			765.81	***

State dummies are not displayed here for presentation purposes, but are included in the analysis. Estimated errors are corrected for state-based heteroskedasticity. Statistical significance is denoted by * for the ten percent level, ** for the five percent level, and *** for the one percent level.

However, ethnicity in these results shows an opposite effect, indicating that ethnically homogeneous (highly Caucasian) counties are quicker to adopt new technology. This result is rather surprising given that earlier results (recall Figure 8) seemed to show that more ethnically diverse counties initially adopted more rapidly and then again, following HAVA, adopted more quickly than their more Caucasian counterparts. Interestingly, those ethnically diverse counties which adopted early (1980) averaged twelve percent higher income than their equally ethnically diverse peers who chose not to adopt early. The comparative difference in 1988 had fallen to six percent. By 2000, that pattern had reversed, so that ethnically diverse counties with high incomes were actually less likely to have advanced technology than were their lower-income but ethnically diverse peers.

d) Logistic model of technology levels

The previous three approaches allow us to consider the decision to adopt new voting technologies. This section explores a somewhat different question. Given what we know about each county, how likely is a given voter to use advanced technology at the polling stations in November? For that matter, how likely is a representative voter to use advanced technology at any given point in time? Once again, we propose a logistic model, this time to explain the level of technology in place rather than the probability of change.

$$\begin{aligned} probability(advanced\ tech\ at\ time\ t) &= \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Youth + \gamma_2 Education \\ &\quad + \gamma_3 Ethnicity + \textstyle\sum_{n=1}^{49} \delta_n state_n + u_i \qquad (9) \end{aligned}$$

and

$$\begin{aligned} probability(advanced\ tech\ at\ time\ t) &= \alpha + \beta_1 RedMajority + \beta_2 BlueMajority + \gamma_1 Income + \gamma_2 Ethnicity \\ &\quad + \textstyle\sum_{n=1}^{49} \delta_n state_n + u_i \qquad (10) \end{aligned}$$

Results are presented in Table 8 (for youth and education) and Table 9 (for income), and tell the same story as previous models. As above, the equations are estimated separately for three eight-year time periods, the baseline period (1980-1988), the pre-HAVA period (1992-2000), and the post-HAVA period (2000-2008). Estimations without state-specific effects show similar signs, sizes and significance levels.

The results presented in Tables 8 and 9 both indicate that in the 1980s, counties with strong majorities in the previous election were less likely to have advanced technology in the current election. That effect lasted into the 1990s in counties experiencing strong Republican majorities. As expected, younger counties are more likely to have adopted advanced voting equipment, regardless of the time period. In addition, more educated or higher-income counties were more likely to have advanced equipment before 2000. This is not surprising, but that effect becomes insignificant following the passage of HAVA. Both tables 8 and 9 indicate that more ethnically diverse counties are more likely to have advanced equipment, at least in the 1980s and post-HAVA.

Table 8: Probability of using advanced technology, youth and education model

Variable	***Baseline, 1988***			***Pre-HAVA, 2000***			***Post-HAVA, 2008***		
	Coefficient	***t-stat***		***Coefficient***	***t-stat***		***Coefficient***	***t-stat***	
RedMajority	-2.41×10^{-2}	(1.83)	*	-2.21×10^{-2}	(2.98)	***	-1.93×10^{-5}	(0.01)	
BlueMajority	-3.06×10^{-2}	(2.65)	***	-6.63×10^{-3}	(1.08)		-1.39×10^{-2}	(0.50)	
Youth	3.90×10^{-2}	(1.72)	*	4.45×10^{-2}	(1.70)	*	2.66×10^{-1}	(1.87)	*
Education	1.24×10^{-1}	(3.43)	***	6.31×10^{-3}	(1.95)	**	9.67×10^{-2}	(1.43)	
Ethnicity	-1.82×10^{-2}	(2.36)	**	6.63×10^{-3}	(1.08)		-7.40×10^{-2}	(4.78)	***
Constant	-2.65	(4.32)	***	-6.46×10^{-1}	(1.20)		5.36	(3.75)	***
Obs		**2379**			**2757**			**706**	
Pseudo-R^2		**0.19**			**0.18**			**0.30**	
States perfectly explained		**21**			**13**			**43**	

Table 9: Probability of using advanced technology, income model

Variable	***Baseline, 1988***			***Pre-HAVA, 2000***			***Post-HAVA, 2008***		
	Coefficient	***t-stat***		***Coefficient***	***t-stat***		***Coefficient***	***t-stat***	
RedMajority	-2.89×10^{-2}	(2.60)	***	-2.53×10^{-2}	(3.47)	***	-3.13×10^{-3}	(0.28)	
BlueMajority	-2.50×10^{-2}	(2.07)	**	-5.24×10^{-3}	(0.84)		2.97×10^{-2}	(1.12)	
Income	2.11×10^{-4}	(5.18)	***	1.09×10^{-4}	(3.25)	***	3.17×10^{-4}	(2.44)	**
Ethnicity	-2.28×10^{-2}	(2.49)	**	3.72×10^{-3}	(0.69)		-9.39×10^{-2}	(4.27)	***
Constant	-5.07	(5.23)	***	-2.17	(3.69)	***	4.05	(1.51)	
Obs		**2379**			**2757**			**706**	
Pseudo-R^2		**0.21**			**0.18**			**0.33**	
States perfectly explained		**21**			**13**			**43**	

5. Conclusions

The tabulation of Florida votes in the 2000 US presidential election focused the nation's attention on the imperfections and challenges present in the voting process. While initial coverage reported on the technological fixes required, a consensus soon emerged that more wide-reaching improvements to the election administration were necessary. Although Congress responded with debates over federal election reform and the October 2002 passage of the Help America Vote Act, clearly many of the underlying issues remain to be resolved.

Evidence of this is strikingly present in the December 2007 decision to decertify thousands of Colorado's electronic voting machines. As the site of the 2008 National Democratic Convention, Colorado's voting technology problems are highly visible and emblematic of the difficulties many states continue to struggle with. Though Colorado's Secretary of State rescinded the December 2007 order and conditionally certified the electronic equipment in February 2008, questions remain as to whether the software patch fix used will be adequate and if the machines will function properly.

The national transition, state by state and county by county, to new voting technology raises important questions about the diffusion of technology and the socioeconomic characteristics that may be associated with more rapid adoption. To our knowledge, this is the first attempt to model the diffusion of a technology which requires local government decisions and action. Adoption is consistent with familiar patterns from within the economics literature, diffusing at differential rates to constituents who have varying abilities and desires to adopt. Socioeconomic characteristics clearly matter, perhaps more in this case than in other more traditional industrial technology adoption cases.

It appears that larger margins of political victory have served to slow down adoption in the subsequent elections, particularly for counties with Republican majorities. As expected, higher levels of education and income lead to faster adoption. Younger counties adopt more quickly as well.

An examination of the adoption of voting technology over time clearly demonstrates that policy matters. HAVA's introduction in 2002 was concurrent with broad wave of diffusion, ushering in a period in which adoption does not appear to be associated with any particular county characteristics. In particular, the initial effects of income and age and education have disappeared. The availability of federal funding seems to have enabled previously disadvantaged counties to introduce new voting technologies.

Advocates of decentralized government have embraced the variety of electoral equipment in simultaneous use across the US. However, their implicit assumption is that counties choose different technologies to best suit their local needs. If it is in fact constrained optimization that maintains the heterogeneity, through lack of knowledge or funding, then particular consideration must be given to those populations who are slower or less likely to adopt. In some cases, government intervention like the Help America Vote Act may be warranted to speed adoption and correct market or technological deficiencies.

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