Does Context Trump Individual Drivers of Voting Behavior? Evidence from U.S. Movers

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Abstract

This paper assesses the relative influence of contextual drivers of voter behavior, such as economic growth, voting rules, and media consumption, vs. individual factors, such as race and education. We use individual-level panel data covering the vast majority of the U.S. voting-age population from 2008 to 2014 and track changes in movers’ behavior as they cross state lines to estimate a value-added model including voter, state, and election fixed effects, and allowing movers’ behavior to be arbitrarily different, both in levels and average trend, than non-movers’. We find that state characteristics explain about 52 percent of the observed cross-state variation in turnout, and voter characteristics the residual 48 percent. The factors most strongly correlated with state fixed effects are the availability of Election Day voter registration and no-excuse absentee voting, as well as electoral competitiveness. Education is the only variable showing a significant correlation with average voter effects.

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1 Introduction

People’s partisan affiliation and their level of electoral participation are influenced by individual factors, such as race and education (e.g., Schlozman et al., 2012), and contextual factors, such as economic growth, voting rules, and media consumption (e.g., Brender and Drazen, 2008; DellaVigna and Kaplan, 2007). To determine which of these two sets of factors matters the most, we use individual-level panel data covering the vast majority of the U.S. voting-age population from 2008 to 2014, follow movers as they cross state lines, and test whether and to what extent their behavior adjusts to their destination’s context. Our findings shed light on the drivers of voter behavior, which in turn determines election outcomes and public policies, and on the reasons underlying large differences in participation and partisanship across groups and locations.

Electoral participation varies greatly by race, age, education, and other individual factors: Black, Hispanic, and Asian citizens are much less likely to vote than Whites, young people than seniors, and turnout is positively correlated with education, occupation, religiosity, and income (e.g., Wolfinger and Rosenstone, 1980; Verba et al., 1995; Schlozman et al., 2012). But socio-demographic characteristics also strongly correlate with vote choices and policy preferences (e.g., Alesina and La Ferrara, 2005; Hersh and Nall, 2016; Marshall, 2018; Pew Research Center, 2016). Unequal participation across groups might thus lead to election outcomes and policies that differ substantially from the preferences of the majority of the population (Meltzer and Richard, 1981; Husted and Kenny, 1997; Mueller and Stratmann, 2003; Miller, 2008; Hansford and Gomez, 2010; Fujiwara, 2015), which can in turn weaken the legitimacy of elected officials and democratic regimes and further reduce the participation of groups that feel excluded (Lijphart, 1997).

Importantly, voters with different characteristics are not evenly spread out across space. In-

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2 While preferences stated in surveys by non-voters tend to be relatively similar to voters’ (Highton and Wolfinger, 2001), large shifts in vote shares and policies typically ensue from higher and more equal turnout (Tucker et al., 1986; Mueller and Stratmann, 2003; Hajnal and Trounstine, 2005; Hansford and Gomez, 2010; Fowler, 2013; Bechtel et al., 2016), in particular after the enfranchisement of women (Miller, 2008), ethnic minorities (Husted and Kenny, 1997; Cascio and Washington, 2014), or less educated citizens (Fujiwara, 2015). This indicates that the combination of group differences in participation and in preferences can have decisive policy consequences.
stead, segregation by ethnicity, age, or income is salient at any geographical level, with different streets, neighborhoods, counties, and states showing large differences in their racial mix-up, average age, or affluence (e.g., Massey and Denton, 1998; Enos, 2017). Turnout and partisanship differences across groups are thus mirrored in a second type of differences, across locations (e.g., Johnston et al., 2016; Brown and Enos, 2018). For example, state-level turnout in the 2014 midterm election ranged from 27.8 percent in Indiana to 58.1 percent in Maine (McDonald, 2018), encouraging politicians to pay uneven attention to the needs and desires of different places as much as different groups (Cascio and Washington, 2014). Differences in partisanship between “blue” and “red” states are just as strong and they can be equally consequential, due for instance to national politicians favoring politically aligned locations (e.g., Grossman, 1994; Berry et al., 2010; Brollo and Nannicini, 2012; Bracco et al., 2015; Corvalan et al., 2018).

Geographical segregation makes identifying the factors responsible for differences in voter behavior even more important, but it also makes the task difficult. Indeed, beyond differences in average education or racial composition, states also differ in their voter registration laws (such as their registration deadline and whether they allow Election Day registration), voting rules (such as early and absentee voting and voter ID laws), polling station density, media coverage, campaign intensity, electoral competitiveness, and economic growth. Starting with Harold Gosnell’s work on differences between electoral systems in Europe and in the US (Gosnell, 1930), cross-country and cross-state comparisons have established that these contextual factors are themselves associated with large differences in participation and vote choice (e.g., Rosenstone and Wolfinger, 1978; Powell, 1986; Jackman, 1987; Radcliff, 1992; Knack, 1995; Gray and Caul, 2000; Lewis-Beck and Stegmaier, 2000; Wolfinger et al., 2005; Blais, 2006; Johnston et al., 2016).

It is thus difficult to separate the share of differences in voter behavior that results from such place characteristics from the share that results from voter characteristics. But disentangling the role played by these two sets of factors is important to understand voters’ decisions and inform election-related policies. For instance, changes in voting rules will not affect voter behavior if differences are primarily driven by individual characteristics. Conversely, civic education programs
will not equalize voter participation if institutional factors are its main driver.

We separate the role of voter vs. state factors by exploiting migration of U.S. voters and using the largest individual-level dataset ever assembled to study voter participation. These novel administrative data, collected and maintained by the political data vendor Catalist, cover the vast majority of voting-age individuals in the U.S. from 2008 to 2014 and track them over time, resulting in a total of about 1 billion observations (over 240 million observations per election times four general elections). We first track changes in voter behavior for individuals who move across states in an event-study setting. If geographic heterogeneity in voter behavior is entirely driven by individual characteristics, then post-move changes in movers’ registration, turnout and partisanship will be uncorrelated with differences in average behavior across states of origin and destination. Conversely, if this heterogeneity is attributable to contextual factors, then movers’ behavior will, after move, converge toward the average in the destination state. We find that movers’ turnout jumps discretely by 0.5 (or about 50% of the difference in average participation between origin and destination) at the first post-move election and remains flat thereafter.

We then use our full sample to estimate a value-added model including voter, state, and election fixed effects, and allowing movers’ behavior to be arbitrarily different, both in levels and average trend, than non-movers’. In line with the event study, we find that state characteristics explain about 52 percent of the observed variation in participation between states with above-median and below-median voter turnout, and voter characteristics the residual 48 percent. We obtain similar estimates of the relative contributions of voter and state effects when comparing other groups of high- and low-turnout states. In sum, context matters at least as much as individual drivers of voting behavior.

Our empirical strategy allows us to make three important contributions to the literature studying the determinants of voters’ behavior and attitudes. First, existing studies tend to focus on a specific factor, and they exploit exogenous variation to isolate its impact from the influence of correlated variables. A number of studies rely on state-level changes in voter registration laws (Burden et al., 2014), compulsory voting (Fowler, 2013; Hoffman et al., 2017), early voting (Burden et al., 2014; Kaplan and Yuan, 2018), Election Day Registration (Keele and Minozzi,
2013), or voter ID requirements (Highton, 2017), while others leverage variation – either naturally occurring or introduced by experimental manipulation – in localities and individuals’ exposure to voting rules (Holbein and Hillygus, 2016; Braconnier et al., 2017), voting technologies (Fujiwara, 2015), electoral campaigns (e.g., Ansolabehere et al., 1994; Gerber and Green, 2000, 2015; Pons, 2018; Spenkuch and Toniatti, 2018), media coverage (e.g., Gentzkow, 2006; DellaVigna and Kaplan, 2007; Gentzkow et al., 2011; Falck et al., 2014; Adena et al., 2015), and favorable economic context (e.g., Brunner et al., 2011; Charles and Stephens, 2013; Bagues and Esteve-Volart, 2016; Wolfers, 2018) to isolate the impact of these contextual factors. Another set of studies focus on voter characteristics and use exogenous variation to assess the influence of a specific factor such as education (e.g., Dee, 2004; Milligan et al., 2004; Sondheimer and Green, 2010), income (e.g., Doherty et al., 2006; Peterson, 2016), stock ownership (Kaustia et al., 2016; Jha and Shayo, 2016), or religiosity (Gerber et al., 2016). Our goal is diametrically different, as we endeavor to assess the overall importance of all relevant state and voter factors.

Second, existing research designs are unable to assess the role of factors that are unobserved or that do not offer credible exogenous variation, for instance voting rules that vary across space but not time, or biological factors such as race, gender, or age, which unlike income or education are inherent to an individual. Instead, our estimates take all factors varying across states or individuals into account.

Third, we build on multivariate regressions of voter turnout or partisanship by identifying observable correlates of their state and voter components. The factors most strongly correlated with the estimated state fixed effects are the availability of Election Day voter registration and no-excuse absentee voting, as well as electoral competitiveness. Meanwhile, education is the only variable showing a significant correlation with average voter effects.

Methodologically, we draw on value-added models estimated in other settings, in particular on a number of recent studies which, like ours, track movers across states, companies, or schools to investigate the sources of spatial variation in health care utilization (Finkelstein et al., 2016) and intergenerational mobility (Chetty and Hendren, 2018a,b), wage differences across workers and com-

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panies (Abowd et al., 1999; Card et al., 2013), and variations in students’ outcomes (Chetty et al., 2014). We are particularly indebted to the empirical framework laid out in Finkelstein et al. (2016). While our focus on movers is primarily driven by the goal to disentangle the influence of individual-level and state-level factors, it also allows us to make a substantial contribution to the literature on the political motives (e.g., Hirschman, 1970; Bishop, 2009; Abrams and Fiorina, 2012; Sussell, 2013; Tam Cho et al., 2013) and effects (e.g., Gay, 2012) of spatial mobility: we do not find evidence that spatial sorting across states is driven by gradual changes in movers’ level of political participation but we do observe a systematic drop in participation after the move, in line with Gay (2012).

The remainder of the paper is organized as follows. Section 2 provides more information on Catalist’s voter-level panel data. Section 3 lays out the empirical specifications and Section 4 presents the corresponding results. Section 5 identifies the correlates of average voter and state effects, and Section 6 concludes.

2 Data

2.1 Catalist’s Voter-Level Panel Data

Our empirical strategy requires observing both individual turnout and place of residence for the universe of the U.S. voting-eligible population at multiple elections to track movers’ participation as they cross state boundaries. Building such a panel is challenging, because files commercialized by political data vendors typically contain voters’ residential information as of the day of a customer’s request, but lack any information on movers’ previous addresses. Fortunately, Catalist’s data allow us to overcome this limitation.

Catalist is a political data vendor that maintains a national database of over 240 million unique voting-age individuals. Information on registered voters comes from voter registration and turnout records collected from all 50 states and the District of Columbia. These administrative data are supplemented by commercial records on about 55 million unregistered individuals provided by
data aggregation firms and based on customer files from retailers and direct marketing companies.

Over time, Catalist continually updates its database to incorporate new state voter files released after each election as well as commercial data refreshes, and it identifies deceased voters based on the Social Security Death Master File (SSDMF) datasets. Crucially for our ability to follow movers across states, Catalist also identifies people changing addresses based on records in the USPS National Change of Address (NCOALink®) and by systematically comparing the voter lists and commercial records of different states. Catalist gives each person a unique ID, invariant across years and files. Data matching procedures are run to ascertain potential matches across files. For example, if a voter registered with the first name “Tom,” but commercial records include an individual called “Thomas” with the same address and sociodemographic characteristics, Catalist will recognize that it is the same individual and reconcile the two sources of information (Ansolabehere and Hersh, 2014).

The information Catalist shares with its clients usually stems from a cross-sectional “live file,” containing the present-day address and information and the full voter turnout history of every individual who ever appeared in its database. Since 2008, however, Catalist has also been saving “historical files”: snapshots of its live file as of the date of each biennial nationwide election.3

We received four historical files, corresponding to the 2008, 2010, 2012, and 2014 nationwide elections, and matched them with the current live file. The live file constitutes our source of longitudinal information on voter turnout and the historical files our source of longitudinal information on voters’ residence. To the best of our knowledge, we are the first researchers to use voter-level panel data on turnout and geographic residence covering the vast majority of the U.S. voting-eligible population.

For each election, the historical files we received from Catalist report voters’ state and county of residence at that time, a flag for whether the voter was deceased,4 registration status,5 partisan

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3Since it takes two to five months after Election Day for election administrators to process and give Catalist individual-level voter turnout information, historical files are copies of the live file as of two to five months after the corresponding Election Days. For instance, the 2008 historical file was saved between January and March 2009.

4Voters are flagged as deceased when they appear in the SSDMF.

5Voter registration features five possible values: A, I, D, M, or U. “A” and “I” denote voters appearing on a state registration file with, respectively, “active” or “inactive” registration status. “D” stands for “dropped” and indicates
affiliation (for voters registered in the 28 states with partisan registration), an indicator for permanent absentee status, and a flag for “best state.”

According to these data, about 3.9 million voters moved across state boundaries between 2008 and 2010, 5.3 million between 2010 and 2012, and 4.6 million between 2012 and 2014. From the Catalist live file, we received the following variables: full turnout history, the state where the voter cast her ballot in each general election in our sample, if any, age, race, source of race information, and gender. Catalist’s information on age, race and gender is available for nearly all voters and has been shown to be very reliable (Fraga, 2016a). Other variables in the Catalist’s full database are only available for a subset of individuals or at a more aggregate level (such as the census block). We did not request them out of budgetary considerations.

### 2.2 Data Limitations

While an in-depth assessment of the Catalist’s database is beyond the scope of this project, it is important to note two limitations of the data. First, Catalist's coverage of the unregistered population is imperfect. In fact, Catalist acknowledges that the commercial data used for unregistered citizens cover the voting-age (VAP), rather than the voting-eligible population (VEP). Moreover, Jackman and Spahn (2018) estimate that at least 11% of the adult citizenry does not appear in commercial voter lists like Catalist’s. Second, Ansolabehere and Hersh (2014) argue that Catalist’s deceased flag misses some dead voters, making the total number of deceased voters in the voter individuals who appeared on past state voter files, but not in the most recent one. “M” stands for “moved, unregistered”, that is, voters who, according to NCOA or commercial data, have moved into the state, but are not found re-registered for that state. “U” are voters whose status is “unregistered” as they do not appear on current or past voter files but are known to reside in the state.

6When a voter is observed moving across states, Catalist creates a new record, and updates the original record (e.g., recoding the voter’s registration status from “active” to “dropped”) instead of erasing it. Consequently, the Catalist database is uniquely identified by voter ID and state. After using voter ID and state to match the historical files with the live file, we use the “best-state” flag to deduplicate on voter ID. Specifically, we deduplicate the matched historical files using the following lexicographic rules: we privilege the record corresponding to the state where a voter voted, if any; then records flagged as “best state”; then we use voter registration, privileging voter registration statuses in this order: “A”, “M”, “U”, “I”, and “D”; then we privilege the record with the oldest registration date; finally, among residual duplicates, we keep a reproducibly random record. All results are virtually identical when we deduplicate ignoring the voter turnout criterion.

7See Ansolabehere and Hersh (2014) for a thorough discussion of Catalist’s database and the underlying data collection and maintenance practices. Other papers using cross-sectional extractions of Catalist’s data include: Fraga (2016b,a); Hersh and Ghitza (2016); Hersh and Nall (2016).
file lower than it really is. The mis-categorization of some deceased voters and commercial data covering the VAP instead of the VEP likely explain why Catalist’s state turnout rates are lower than McDonald (2018)’s.\(^8\)

Despite this discrepancy in levels, two-way and Spearman’s rank correlations between Catalist’s and McDonald’s turnout rates are very high (respectively .7382 and .7403), assuaging concerns that cross-state heterogeneity in the quality of Catalist’s state registration records may bias our estimates. Moreover, our event-study results are very similar when we compute mean state turnout using McDonald’s instead of Catalist’s data (see Section 4.2).

### 2.3 Summary Statistics

Figure 1 shows average turnout rates across the fifty states and the District of Columbia. State averages are computed by first calculating the percentage of individuals in the state who turn out in each election, and then taking a simple average across elections. The mean state has an average turnout rate of 43.8 percent, with a standard deviation of 4.8 percentage points. Minnesota has the highest turnout rate (58.1 percent), while Mississippi trails all other states with an average turnout of only 33.8 percent. Figure 1a reveals a striking geographic clustering of average turnout rates. In particular, the map hints at a North-vs.-South turnout divide, with states in the northern half of the country characterized by higher voter participation than their southern counterparts.

Figure 2 plots the distribution of destination-minus-origin differences in mean state turnout for movers who cross state boundaries exactly once.\(^9\) The distribution is roughly symmetric and the average difference in turnout is approximately zero, which implies that moves from low- to high-turnout states are as frequent as moves in the opposite direction.

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\(^8\)McDonald’s turnout figures are widely considered the most reliable estimates of the share of the state voting-eligible population turning out in a particular election. See McDonald and Popkin (2001) for a discussion on how these rates are computed.

\(^9\)For simplicity, all analyses exclude voters who change states more than once.
3 Empirical Specifications

3.1 Main Decomposition

Our decomposition is based on the following equation:

\[ y_{ijt} = \alpha_i + \gamma_j + \tau_t + \rho_{r(i,t)} + \epsilon_{ijt}, \]  

where \( y_{ijt} \) equals 1 if voter \( i \) living in state \( j \) voted at election \( t \), and 0 otherwise. \( \alpha_i, \gamma_j \) and \( \tau_t \) denote voter, state, and election fixed effects, respectively. Election fixed effects are normalized to be equal to 0 on average. For movers, \( r(i,t) = t - t_i^* \) is the election relative to the first post-move election \( t_i^* \) (so \( r(i,t) = 0 \) if \( t \) is the first election after the move, \( r(i,t) = -1 \) if \( t \) is the last election before the move, etc.) and \( \rho_{r(i,t)} \) indicates fixed effects for election relative to move. Under the assumption of additive separability in \( i, j, \) and \( t \) embedded in equation 1, \( E(\epsilon_{ijt}|i,j,t) = 0. \)

We estimate the parameters in this equation using all movers and stayers in the Catalist database. The equation is only identified if the data include movers because otherwise the state fixed effects \( \gamma_j \) would be absorbed by the individual fixed effects \( \alpha_i \). We can separately identify both sets of parameters by tracing changes in voter turnout as voters cross state boundaries.

Estimating equation 1, we pursue two objectives. First, we want to estimate the total contribution of state-specific characteristics (such as voter ID laws and economic growth) and the contribution of voter-specific factors (such as voters’ age and education) to cross-state variation in voter turnout. Second, we aim to decompose the share of variation in voter turnout due to these two sets of factors and, so, determine the relative influence of state- and voter-characteristics on turnout.

Our decomposition between these two types of factors follows Finkelstein et al. (2016). Let \( \bar{y}_{jt} \) be the expectation of \( y_{ijt} \) across voters living in state \( j \) in election \( t \), and \( \bar{y}_j \) be the average of \( \bar{y}_{jt} \) across \( t \). \( \bar{y}^{\text{vot}}_{jt} \) and \( \bar{y}^{\text{vot}}_j \) denote the analogous expectations for the part of voter turnout imputable to voter characteristics, \( y^{\text{vot}}_{it} = \alpha_i + \rho_{r(i,t)} \). Using this notation, equation [1] implies that \( \bar{y}_j = \bar{y}^{\text{vot}}_j + \gamma_j \)
and, for any two states $j$ and $j'$,

$$
\bar{y}_j - \bar{y}_{j'} = (\gamma_j - \gamma_{j'}) + (\bar{y}_{j'}^\text{vot} - \bar{y}_j^\text{vot}).
$$

(2)

Equation 2 shows that the difference in average voter turnout across states $j$ and $j'$, $\bar{y}_j - \bar{y}_{j'}$, is the sum of two components. The first component, imputable to state-specific factors, is given by the difference between the corresponding state fixed effects: $\gamma_j - \gamma_{j'}$. The second component, due to voter characteristics, is given by the difference between the voter-specific components: $\bar{y}_{j'}^\text{vot} - \bar{y}_j^\text{vot}$.

The shares of the difference in turnout between states $j$ and $j'$ attributable to states and voters are then given by, respectively:

$$
S^{\text{state}}(j, j') = \frac{\gamma_j - \gamma_{j'}}{\bar{y}_j - \bar{y}_{j'}},
$$

(3)

$$
S^{\text{voter}}(j, j') = \frac{\bar{y}_{j'}^\text{vot} - \bar{y}_j^\text{vot}}{\bar{y}_j - \bar{y}_{j'}} = 1 - S^{\text{state}}(j, j').
$$

(4)

Although $S^{\text{state}}(j, j')$ and $S^{\text{voter}}(j, j')$ sum to 1, neither needs to be within the unit simplex, since $\gamma_j - \gamma_{j'}$ and $\bar{y}_{j'}^\text{vot} - \bar{y}_j^\text{vot}$ can have opposite signs. When we apply our decomposition to the difference in turnout between groups of states, $\bar{y}_R$, $\bar{y}_R^\text{vot}$, and $\gamma_R$ denote the simple averages of $\bar{y}_j$, $\bar{y}_j^\text{vot}$, and $\gamma_j$ across the states in group $R$. Similarly, we define $S^{\text{state}}(R, R')$ and $S^{\text{voter}}(R, R')$ as the shares of turnout differences between states in groups $R$ and $R'$ attributable to states and voters, respectively.

We compute the sample analogues of $\bar{y}_j$ directly from the Catalist data and denote them $\hat{y}_j$. We obtain consistent estimates $\hat{\gamma}_j$ of $\bar{y}_j$ from estimating regression [1] and derive consistent estimates of $\bar{y}_j^\text{vot}$ by subtracting $\hat{\gamma}_j$ from $\hat{y}_j$: $\hat{y}_j^\text{vot} = \hat{y}_j - \hat{\gamma}_j$.

Equation [1] allows for arbitrary differences in turnout levels across voters. In particular, via the $\alpha_i$’s, movers’ mean turnout can be arbitrarily different from non-movers’ without biasing our estimates. Moreover, fixed effects for election relative to move $\rho_{r(i,t)}$ permit differential trends in voter turnout across movers and non-movers. Such differential trends may arise, for example, if movers face a cost of re-registering to the voter rolls of the state of destination (Squire et al., 1987) or if the loss of pre-existing social ties associated with moving decreases civic engagement (Gay,
Despite the flexibility given by the voter and relative election fixed effects, our model is restrictive in at least three important ways. First, like in other studies using movers to estimate value-added models (e.g., Finkelstein et al., 2016; Molitor, 2018), the crucial identifying assumption required to uncover unbiased estimates from equation [1] is that changes in individual drivers of voter turnout for movers do not correlate systematically with differences in average participation between their states of origin and destination. We do not have direct ways to test for the presence of shocks to movers’ turnout that correlate with differences in turnout between origin and destination and coincide exactly with the year of the move. However, we can reject changes in individual drivers of movers’ turnout that correlate with participation in the origin and destination and that develop gradually, which would occur for example if voters who become more politically engaged over time respond by moving to relatively high-turnout states. Such changes would appear as pre-trends in the event-study analysis described in Section 3.2, of which we find no evidence. This indicates that our event-study estimates do not mistakenly capture underlying changes in movers’ political activism and it reinforces our confidence in the decomposition of cross-state differences in turnout based on equation [1].

Second, equation [1] assumes that voter turnout is additively separable in its voter- \((\alpha_i + \rho_{r(i,t)})\) and state-specific components \((\gamma_j)\). Since relative-election effects \(\rho_{r(i,t)}\) do not depend on the specific states of origin and destination, additive separability of voter and state effects implies that the absolute change in voter turnout for voters moving from \(j\) to \(j'\) (experiencing change in state factors equal to \(\gamma_{j'} - \gamma_j\)) should be the same as for voters moving from \(j'\) to \(j\) (experiencing change in state factors equal to \(\gamma_j - \gamma_{j'}\)). We present a test of this implication in Section 4.1.

Finally, we assume that movers and non-movers face identical state effects \(\gamma\). If movers differ from non-movers in ways that alter the relevant state effects, then our decomposition between state- and individual-level determinants of turnout only applies to movers, and not to the rest of the population.
3.2 Event-Study Specification

To trace out changes in voter turnout around moves, we also estimate an event-study equivalent of equation [1]. For voter $i$ who moves from origin state $o(i)$ to destination state $d(i)$, equation [1] can be rearranged as:

$$y_{ijt} = \alpha_i + \gamma_o(i) + I_{r(i,t)\geq 0} \times S_{\text{state}}(d(i), o(i)) \times \delta_i + \tau_t + \rho_{r(i,t)} + \epsilon_{ijt},$$

(5)

where $\delta_i$ is the difference in average turnout between $i$’s states of destination and origin, $\bar{y}_d(i) - \bar{y}_o(i)$, and $I_{r(i,t)\geq 0}$ is an indicator for post-move elections.\(^{10}\)

Combining $\alpha_i + \gamma_o(i)$ into a single voter fixed effect $\tilde{\alpha}_i$, replacing $I_{r(i,t)\geq 0}$ with indicators for election relative to move, and replacing $\delta_i$ with its sample analogue $\hat{\delta}_i = \bar{y}_d(i) - \bar{y}_o(i)$ (computed using both movers and non-movers), we obtain the following event-study specification:

$$y_{it} = \tilde{\alpha}_i + \theta_{r(i,t)} \hat{\delta}_i + \tau_t + \rho_{r(i,t)} + \epsilon_{it}.$$  

(6)

The parameters of interest are the $\theta_{r(i,t)}$’s. In relative election $r(i,t)$, $\theta_{r(i,t)}$ measures movers’ response to differences in average turnout between states of destination and origin. Assuming heterogeneity in $S_{\text{state}}$ is orthogonal to the other covariates in the model, $\theta_{r(i,t)}$ is a weighted average of $S_{\text{state}}(d(i), o(i))$, with weights given by the relative frequency of all pairs of origin and destination states.

The pattern of estimated effects offers indirect tests of our identification assumption: if move-induced changes in state characteristics cause changes in movers’ turnout, then $\theta_{r(i,t)}$ should be approximately flat in all pre-move elections. For $r(i,t) \geq 0$, $\theta_{r(i,t)}$’s describe the extent to which post-move voter behavior adjusts to the difference in average turnout between states of destination and origin. Namely, a discontinuity in the level of $\theta_{r(i,t)}$ after the move indicates how much state-level factors influence individual-level voter participation. Moreover, the pattern of post-move coefficients can illuminate the underlying mechanisms: effects that appear suddenly on move and

\(^{10}\)To recover equation [1], observe that $S_{\text{state}}(d(i), o(i)) \times \delta_i = \frac{\gamma_d(i) - \gamma_o(i)}{\bar{y}_d(i) - \bar{y}_o(i)} \times (\bar{y}_d(i) - \bar{y}_o(i)) = \gamma_d(i) - \gamma_o(i)$. 

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then remain stable suggest that discrete factors that are easy to get accustomed to (e.g., election laws) are important drivers of voter turnout, while effects that increase over time underscore the importance of “slow-moving” factors such as the influence of other voters or learning about the candidates in the destination state. Because we include voter fixed effects, the \( \theta_{r(i,t)} \) coefficients are only identified up to a constant term; we therefore normalize \( \theta_{-1} \) to 0.

In all event-study specifications, we compute two-way clustered standard errors by states and voters, thus accounting for the possibility that regression residuals are serially correlated at the individual level and spatially correlated at the state level.

4 Main Results

4.1 Descriptive Analysis

As a preliminary look at how voter behavior changes after move, Figure 3 plots the change in movers’ turnout against the destination–origin difference in voter participation \( \hat{\delta}_i \). For each mover, we compute the change in voter turnout as the difference between average turnout in all post-move elections minus average turnout in all pre-move elections. If states explained individual-level turnout entirely, we would expect the slope of the graph to be 1. Conversely, if voter turnout were independent of state characteristics, we would expect the slope to be 0.

Figure 3 shows that the slope is exactly .5, suggesting that state characteristics explain half of the observed variation in voter participation. The relationship is symmetric around zero and linear, thus lending support to our model, which implies identical absolute changes in voter turnout for voters moving from state \( j \) to \( j' \) and for voters moving in the opposite direction.

With an ×, we also plot average changes in voter turnout for a sample of matched non-movers. Following Finkelstein et al. (2016), the matched sample is constructed by randomly drawing, for each mover-election, a non-mover in the same election who shares the mover’s state of origin, sex, race, and age ventile bin\(^{11}\). To construct Figure 3, the matched sample is assigned \( \delta = 0 \).

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\(^{11}\)Age ventile bins are computed using all movers and non-movers with non-missing values of age. Along with these 20 bins, we have another category for voters with missing age.
matched sample and all points for movers lie vertically below 0, which reflects an overall decline of voter participation occurring in our sample period. Moreover, the matched sample lies vertically above all points for movers, suggesting that cross-state moves are associated with a decline in voter participation (Squire et al., 1987). In our model, this negative effect of moving is captured by the relative election dummies $\rho_{r(i,t)}$.

The relationship shown in Figure 3 could be spuriously driven by trends in voter turnout that vary along socio-demographic traits. To test for this possibility, Figure 4 replicates Figure 3 replacing the mover sample with the matched sample. Specifically, we replace changes in movers’ turnout on the $y$-axis with changes in voter turnout from the matched sample. To do so, we assign matched observations the value of $\hat{\delta}_i$ of the corresponding mover (instead of $\hat{\delta}_i = 0$, as in Figure 3). The intuition is that, if changes in movers’ turnout are driven by changes in the characteristics of states of residence rather than by trends in voter participation that vary by demographic groups, then there should be no systematic relationship between changes in turnout in the matched sample and $\hat{\delta}_i$ of the corresponding movers. In line with this prediction, the fitted line in Figure 4 has a slope of roughly 0.

4.2 Event Study

Our main event-study results are shown in Figure 5, which plots the estimated $\theta_{r(i,t)}$ coefficients from equation [6]. Whiskers indicate 95-percent confidence intervals constructed from two-way clustered standard errors at the voter and state levels. Event-study regressions use $\hat{\delta}_i$’s estimated using all movers and stayers in each state, but, for computational ease, they are run using the movers sample only.\(^\text{12}\)

The plot reveals no (partial) correlation between pre-move turnout and destination-minus-origin differences in average state turnout: estimates of $\theta_{-3}$ and $\theta_{-2}$ are centered around zero and statistically insignificant. The pattern of $\theta_{r(i,t)}$ then jumps discretely by approximately .5 at the first

\(^{12}\)Estimating two-way clustered standard errors (by voters and states) using both movers and non-movers is in fact computationally very costly. However, we find virtually identical point estimates while estimating regression 6 on the full sample (results available upon request).
post-move election and remains flat thereafter.

The pre-move effects help identify differences in turnout trends as a function of where voters move (as described by $\delta_i$). The lack of pre-trends supports the key identifying assumption that changes in individual drivers of voter turnout are not systematically correlated with differences in average participation between origin and destination. In other words, moves are not systematically preceded by gradual changes in individual determinants of voter turnout (e.g., increases in political activism before moving to high-turnout states) which would complicate the causal interpretation of post-move estimates.

The sharp positive change in $\theta_{r(i,t)}$ in the first post-move election (i.e., at $r(i,t) = 0$) indicates a significant and immediate effect of state factors on voter turnout. Consistent with the slope of Figure 3, the magnitude of the jump is approximately .5, suggesting that state characteristics explain approximately 50 percent of the observed cross-state variation in voter turnout. Moreover, the lack of post-move adjustments is consistent with the state characteristics driving turnout being “discrete” (e.g., the availability of early or absentee voting) and easy for voters to adapt to.

State average turnout rates computed from the Catalist data enter in the $\hat{\delta}_i$’s used as regressors in the event study and they directly affect the estimated $\theta_{r(i,t)}$ as a result. For this reason, limitations of the Catalist data discussed earlier may affect the $\hat{\delta}_i$’s and thus the event-study results. To assess whether this is the case, we estimate a specification in the form of equation [6] replacing the $\hat{\delta}_i$’s computed using the Catalist data with $\hat{\delta}_i$’s constructed using Michael McDonald’s turnout figures (McDonald, 2018). Figure 6, which relies on $\hat{\delta}_i$’s computed using the McDonald’s data, is very similar to the event-study plot based on the Catalist data. Like in Figure 5, there is no evidence of pre-trends, as pre-move estimates are small and insignificant. $\theta$ jumps upwards by approximately .4 on move and increases to .5 in the third election since moving across states. The overall similarity of Figures 5 and 6 assuages the concern that the data limitations discussed in Section 2.2

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13 We use McDonald’s rates defined as ballots cast for the highest office in a given state-election divided by the estimated voting-eligible population in the same state-year. Michael McDonald also reports two other turnout rates: the total number of ballots counted divided by the voting-eligible population, which is not available for all states-years, and the count of votes cast for the highest office divided by the voting-age population. Results (available upon request) based on the latter turnout rates are very similar to those we report in the paper.
dramatically affect our results and increases our confidence in the event-study estimates and in the related decomposition of turnout between voter and state factors, which we present now.

4.3 Decomposing Cross-State Variation in Voter Turnout

We exploit the variation underlying Figure 5 to implement two decompositions of voter turnout in its state- and voter-driven components. We start with the linearly additive decomposition discussed in Section 3.1. Using both movers and non-movers, we run a specification in the form of equation [1] to estimate place and voter effects for all 50 states and the District of Columbia. For different sets of high- and low-turnout states, we then estimate the overall and relative contributions of state and voter characteristics. That is, for different groups of states $R$ and $R'$ (with high and low turnout, respectively), Table 1 reports estimates of the following quantities: the total difference in average voter turnout ($\bar{y}_R - \bar{y}_{R'}$), the difference due to voters ($\gamma^{\text{voter}}_R - \gamma^{\text{voter}}_{R'}$), the difference due to states ($\gamma_R - \gamma_{R'}$), the share of difference due to voters ($S^{\text{voter}}(R, R') = (\gamma^{\text{voter}}_R - \gamma^{\text{voter}}_{R'}) / (\bar{y}_R - \bar{y}_{R'})$), and the share of difference due to states ($S^{\text{state}}(R, R') = (\gamma_R - \gamma_{R'}) / (\bar{y}_R - \bar{y}_{R'})$).

Column 1 reports the comparison between states with above-median and below-median turnout. The difference in average turnout across the two groups is 7.4 percentage points, of which 3.6 and 3.9 percentage points are due to voter and place characteristics, respectively. This translates to voter factors accounting for approximately 48 percent of the overall difference and state factors for the residual 52 percent. Standard errors are computed using a voter-level bootstrap with 50 repetitions. Thanks to the large number of cross-state movers (approximately 35 million) and the large total number of observations (approximately 1 billion), the estimated shares are extremely precise: their standard error is equal to 0.4 percentage points, which is two orders of magnitude smaller than the corresponding point estimates.

In columns 2–5, we report comparisons for other groups of high- and low-turnout states. Column 2 compares the 15 highest- and 15 lowest-turnout states. The overall difference in turnout is 10.9 percentage points, of which 4.5 and 6.4 percentage points are due to voter and state characteristics, respectively. The overall difference grows to 13.2 percentage points in the top-10-vs.-bottom-
10 comparison (column 3), and to 16.3 percentage points in the top-5-vs.-bottom-5 comparison (column 4), with voter and state characteristics accounting for 6.1 and 7.1 percentage points and 8.2 and 8.2 percentage points respectively. Column 5 compares Mississippi to Minnesota, namely the states with lowest and highest mean turnout. The overall difference in average turnout is 24.4 percentage points, of which 10.3 and 14.1 percentage points are due to voters and states, respectively.

The corresponding relative contributions of voter and state factors are very similar across comparisons, with states accounting for 49.9 to 58.8 percent of the overall variation in voter turnout. These figures are in line with the slope of .5 on Figure 3 and with the on-move discontinuity of .48 in the event study shown in Figure 5, which both suggested a place share of about 50%. Along with the linear relationship shown in Figure 3, the stability of the state shares estimated using different groups of high- and low-turnout states suggests that $S^{state}(j, j')$ is not strongly correlated with $\bar{y}_j - \bar{y}_{j'}$.

Table 2 presents a second, alternative decomposition to assess the relative importance of state and voter factors. We first compute the cross-state variance of average voter turnout and estimate the cross-state variances of voter and state effects, along with their correlation: $\text{Var}(\bar{y}_j), \text{Var}(\bar{y}^{vot}_j), \text{Var}(\gamma_j)$, and $\text{Corr}(\bar{y}^{vot}_j, \gamma_j) = \frac{\text{Cov}(\bar{y}^{vot}_j, \gamma_j)}{\sqrt{\text{Var}(\bar{y}^{vot}_j)\text{Var}(\gamma_j)}}$. To estimate the variance of $\gamma_j$ and $\bar{y}^{vot}_j$ and the covariance between these variables we use a split-sample approach to take into account the fact that the underlying parameters are themselves estimated.\footnote{We randomly assign movers within each origin-destination pair and non-movers within each state to either of two subsamples of approximately identical size. We then estimate equation 1 separately on each subsample. We estimate $\text{Var}(\gamma_j)$ (resp. $\text{Var}(\bar{y}^{vot}_j)$) as the covariance between the estimated $\gamma_j$ (resp. $\bar{y}^{vot}_j$) from the two subsamples. To estimate $\text{Cov}(\gamma_j, \bar{y}^{vot}_j)$, we take the simple average of the covariances between the estimated $\gamma_j$ from one subsample and the estimated $\bar{y}^{vot}_j$ from the other subsample.} We then estimate the share of cross-state variance in voter turnout due to voter characteristics, defined as the share of the total variance that would be eliminated by erasing differences in voter characteristics. Since $\bar{y}_j = \bar{y}^{vot}_j + \gamma_j$, the variance in $\bar{y}_j$ remaining after erasing differences in voter characteristics is $\text{Var}(\gamma_j)$ and the share of the
total variance due to voter characteristics is given by:

\[ S_{\text{voter}}^{\text{var}} = 1 - \frac{\text{Var}(\gamma_j)}{\text{Var}(\bar{y}_j)}, \]  

(7)

Similarly, the share of the total variance due to place characteristics is given by

\[ S_{\text{state}}^{\text{var}} = 1 - \frac{\text{Var}(\bar{y}_{j\text{vot}})}{\text{Var}(\bar{y}_j)}. \]  

(8)

The advantage of this decomposition is that, unlike \( S_{\text{voter}} \) and \( S_{\text{state}} \), \( S_{\text{voter}}^{\text{var}} \) and \( S_{\text{state}}^{\text{var}} \) do not require choosing specific sets of states to be compared. However, differently from \( S_{\text{voter}} \) and \( S_{\text{state}} \), the variance decomposition is not additive: \( S_{\text{voter}}^{\text{var}} \) and \( S_{\text{state}}^{\text{var}} \) will not sum to 1 as long as \( \text{Cov}(\gamma_j, \bar{y}_{j\text{vot}}) \neq 0 \).

The variance decomposition delivers two key results. First, equalizing voter effects would eliminate 44.8 percent of the cross-state variance in voter turnout; equalizing state effects would reduce the variance by 51.8 percent. Second, the correlation between voter and state effects is negative, which explains why \( S_{\text{voter}}^{\text{var}} \) and \( S_{\text{state}}^{\text{var}} \) sum to less than 1. For example, this negative correlation could signal that states with politically disengaged voters try to bridge the turnout gap with higher-turnout states by approving forms of convenience voting. To explore possible mechanisms behind our results, the next section explores observable correlates of the estimated place and voter effects.

5 Correlates of Voter and Place Effects

Our estimated state \( \hat{\gamma}_j \) and average voter effects \( \hat{y}_{j\text{vot}} \) may capture the influence of a wide range of individual and contextual factors. To assess the relative importance of these factors, we now use the \( \hat{\gamma}_j \)’s and \( \hat{y}_{j\text{vot}} \)’s as independent variables in regressions that control for observable state and voter characteristics. While the results do not necessarily represent causal evidence, we improve upon multivariate regressions of voter turnout or partisanship by identifying observable correlates of their state and voter components.
We explore three sets of state characteristics: voting and registration rules, characteristics of the electoral landscape, and population density. Among voting rules, we focus on strict voter identification laws and on the availability of same-day registration, no-excuse absentee voting, and early voting.\footnote{We follow the National Conference of State Legislature (NCSL)’s classification of early and no-excuse absentee voting. Early (in-person) voting means that any eligible voter may cast a ballot in person during a designated period before Election Day, without providing an excuse. No-excuse absentee voting means that the state will mail an absentee ballot to all registered voters who request one. The voter, who does not need to offer an excuse (e.g., being out of town on Election Day), may return the ballot by mail or in person. \url{http://www.ncsl.org/research/elections-and-campaigns/absentee-and-early-voting.aspx} Accessed: 6/25/2018.} While our regressions are cross-sectional, some states changed these voting rules during our sample period. We therefore construct time-invariant regressors by measuring the share of elections in our sample covered by each rule. The second group of state factors includes the share of 2008–2014 elections concurring with gubernatorial and U.S. Senate elections and average electoral competitiveness in presidential elections.\footnote{We use electoral competitiveness in presidential elections because Washington D.C. elects no voting member of Congress (though it holds mayoral elections concurrently with midterm federal elections). Results are virtually identical when we use average electoral competitiveness in congressional elections and drop D.C.} Finally, population density might matter for at least two reasons: low density might limit interpersonal discussions about politics and hence voters’ interest in elections, and it also correlates with larger average distance to the polling station (Gimpel and Schuknecht, 2003), thus making voting more costly.

For voters, we include socio-demographic predictors of voter turnout (age, minority status, education, and income; Leighley and Nagler, 2013), the state incarceration rate (Gerber et al., 2017), and the Republican two-party vote share in presidential elections.

Figure 7 summarizes the correlates of the estimated state effects. Each row represents a different correlate. The left panel reports estimates and 95-percent confidence intervals from bivariate OLS regressions of the estimated state effects ($\hat{\gamma}_j$) on state and voter correlates. All covariates are standardized by subtracting the mean and dividing by the standard deviation. There are 51 observations, corresponding to the 50 states and the District of Columbia. In the right panel, we present estimates and standard errors from a multivariate OLS regression on regressors chosen with
a first-stage Lasso regression (Belloni and Chernozhukov, 2013).\textsuperscript{17}

Among state characteristics, the strongest predictors of state effects are the availability of Election Day voter registration and no-excuse absentee voting, as well as electoral competitiveness. All three variables are positively correlated with state effects, consistent with intuition and the existing literature. We find weaker bivariate correlations with population density, the concurrence of gubernatorial or U.S. Senate elections, and the presence of strict voter ID requirements.

The correlation between the Republican two-party vote share in presidential elections and place effects is very low. By contrast, the share of minority population, educational attainment, and the incarceration rate display significant bivariate correlations with place effects. Interestingly, these relationships shrink to statistical insignificance in the right panel, which controls for electoral competitiveness, same-day registration, and no-excuse absentee voting.

Figure 8 reports analogous results for the estimated average voter effects ($\hat{y}_{\text{vot}}^j$). We find no obvious relationship between state characteristics and average voter effects. Conversely, bivariate correlations with voter characteristics are broadly consistent with intuition: average voter effects are higher in states with more U.S.-born, non-Hispanic white, older, richer, and more educated voters. This is particularly true for education, which is the only variable showing a significant correlation with average voter effects. Similarly with state effects, the state partisan leaning in presidential elections has virtually zero correlation with the estimated voter effects.

6 Conclusion

This paper assesses the overall influence of contextual factors on voter behavior relative to the influence of individual drivers. We use a dataset assembled by political data vendor Catalist to identify voters who move across states and to track their behavior over time. Event-study graphs show that movers’ participation is stable before move, suggesting that changes in individual drivers of voter turnout do not correlate systematically with differences in average participation between

\textsuperscript{17}In the first stage, we select regressors using a Lasso regression with a penalty chosen by a 10-fold cross-validation to minimize the mean squared error. In the second stage, we estimate coefficients and standard errors through a multivariate OLS on the selected covariates.
movers’ states of origin and destination. Movers’ turnout jumps by half of this difference in the first election after the move and remains flat thereafter, indicating that differences in state characteristics exert a large influence over individual-level turnout and that state factors with immediate effects, such as voting rules or distance to the polling station, matter more than variables expected to affect behavior more gradually, such as peer pressure.

Exploiting the variation underlying these event-study results, we decompose voter turnout in its state and voter components with a value-added model that includes voter, state, and election fixed effects and allows movers’ behavior to be arbitrarily different, both in levels and average trend, than non-movers. We find that state characteristics explain about 52 percent of the observed variation in participation between states with above-median and below-median voter turnout, and voter characteristics the residual 48 percent. We obtain similar estimates of the relative contributions of voter and state attributes when comparing other groups of high- and low-turnout states. In an alternative decomposition, we estimate the share of cross-state variance in voter turnout due to voters vs. states and find that equalizing voter effects would eliminate 44.8 percent of the cross-state variance in voter turnout, compared to a 51.8 percent reduction when equalizing state effects. The observable factors most strongly correlated with the estimated state effects are the availability of Election Day voter registration and no-excuse absentee voting, as well as electoral competitiveness. Instead, education is the only variable showing a significant correlation with average voter effects.

The fact that our sample covers the vast majority of voting-age individuals in the U.S. from 2008 to 2014 (a total of about one billion observations) makes these results unusually precise and their external validity maximal. Overall, our findings demonstrate that context matters at least as much as individual drivers of voter turnout.

The next iterations of the paper will build on the results discussed in the present version and explore moves across counties within states in addition to moves across states, to disentangle the influence of contextual factors varying at the county vs. state level; test for heterogeneity in the relative role of individual vs. place factors by gender, age, and race; include the 2016 and 2018 election results; and decompose the role of individual vs. contextual drivers of two additional
behaviors: voter registration and partisanship (measured by the decision to register as a Democrat, Republican, or independent).
Figure 1: Average Voter Turnout by State, 2008–2014

Notes: The map plots average state turnout in the Catalist data in six bins, each comprising 6 or 7 states. Lower and upper limits of voter turnout in each bin are displayed in the legend. For each state, we take the simple average of turnout across the four elections (2008–2014) in the Catalist data. The sample is all movers and non-movers. The histogram reports average turnout rates separately for each state.
Figure 2: Distribution of Destination-Origin Difference in Voter Turnout

Notes: The figure shows the distribution of the difference in average turnout across states of origin and destination ($\hat{\delta}_i$) in the movers sample. The sample is all mover-years.
Figure 3: Change in Movers’ Turnout Against Destination-Origin Difference in Voter Turnout

Notes: the figure shows how voter turnout changes before and after move in relation to differences in average participation across states of origin and destination. The $x$-axis displays the average $\delta_i$ for movers in each ventile. For each ventile, the $y$-axis shows average turnout in all post-move elections minus average turnout in all pre-move elections. The line represents the best linear fit from a simple OLS regression using the 20 data points, and its slope is reported on the graph. For comparison, we also compute the change in turnout for a sample of matched non-movers and denote it with an $\times$ in the graph. Details on the matching procedure are described in the text.
Figure 4: Change in Matched Voters’ Turnout Against Destination-Origin Difference in Voter Turnout

Notes: The figure replicates Figure 3 replacing the mover sample with the matched sample. That is, we replace changes in movers’ turnout on the y-axis with changes in voter turnout from the matched sample by assigning matched observations the value of $\hat{\delta}_i$ of the corresponding mover (instead of $\hat{\delta}_i = 0$, as in Figure 3).
Notes: The figure plots estimates of $\theta_{r(i,t)}$ and 95-percent confidence intervals (robust to two-way clustering by states and individuals) from event-study specification [6]. The dependent variable $y_{it}$ is a dummy equal to 1 if voter $i$ voted in election $t$, and 0 otherwise. For each mover, $\hat{\delta}_i$ is constructed using the difference in average turnout in the state of destination across all elections in our sample minus average turnout in the state of origin. The sample is all mover-years ($N = 35,188,709$).
Notes: The figure replicates Figure 5 using $\hat{\delta}_t$’s based on McDonald (2018)’s turnout data instead of the Catalist data.
Figure 7: Correlates of State Effects

Notes: The left panel reports estimates and 95-percent confidence intervals from bivariate OLS regressions of state fixed effects $\hat{\gamma}_j$’s on state and average voter characteristics. The right panel shows results of a post-Lasso multivariate regression. All covariates are standardized to have mean 0 and unitary standard deviation. To obtain post-Lasso estimates, we first run a Lasso regression using all covariates, choosing the penalty with a 10-fold cross-validation to minimize the mean squared error. We then run a single multivariate OLS regression on the covariates selected by the Lasso regression. The sample in both panels consists of the 50 states plus the District of Columbia. Population density comes from 2010 decennial census data. Electoral competitiveness is defined as the average margin of victory of the presidential candidate who carried the state in the 2008 and 2012 presidential elections. The share of 2008-2014 general elections covered by strict voter ID laws, as well as the share of elections in which same-day voter registration, no-excuse absentee voting, and early voting were available to voters in each state come from the National Conference of State Legislatures. Information on median age and on the share of non-white or Hispanic population come from 2010 decennial census data. Average education is the share of the state population 25 or older with a high-school degree as computed from 2016 5-year ACS data. Median household income and the percentage of foreign-born population also come from 2016 5-year ACS data. Information on the incarceration rate (per 100,000 adults) comes from the Bureau of Justice Statistics, 2013 correctional population figures. The Republican two-party vote share is the average vote share of the Republican presidential candidate in the state in the 2008 and 2012 elections divided by the sum of his vote share and that of the Democratic presidential candidate.
Figure 8: Correlates of Average Voter Effects

Notes: The Figure shows results from bivariate OLS regressions (left panel) and from a post-Lasso multivariate regression (right panel) of state-level averages of voter effects ($\hat{y}_{i,j}^{vot}$) on state and voter characteristics. Other notes as in Figure 7.
Table 1: Linearly Additive Decomposition

<table>
<thead>
<tr>
<th></th>
<th>Outcome: 1(Voted)</th>
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<tbody>
<tr>
<td></td>
<td>Top 25/</td>
</tr>
<tr>
<td>Bottom 26</td>
<td>(1)</td>
</tr>
<tr>
<td>Difference in Average Turnout</td>
<td></td>
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<tr>
<td>Overall</td>
<td>.074</td>
</tr>
<tr>
<td>Due to Voters</td>
<td>.036</td>
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<tr>
<td>Due to States</td>
<td>.039</td>
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<tr>
<td>Share of difference due to</td>
<td></td>
</tr>
<tr>
<td>Voters</td>
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</tr>
<tr>
<td>States</td>
<td>.518</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
</tr>
</tbody>
</table>

Notes: Each column reports the results of our main decomposition of voter turnout using a different set of areas $R$ and $R’$. Standard errors (in parentheses) are calculated using a voter-level bootstrap with 50 repetitions. The sample used to run the underlying regression [1] consists of all movers and non-movers ($N=1,021,935,784$ voter-years).
Table 2: Variance Decomposition

<table>
<thead>
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<th>(1)</th>
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<tr>
<td>Cross-State Variance of Average</td>
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<td>Voter Turnout</td>
<td>.00226</td>
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<tr>
<td>Voter Effects</td>
<td>.00109</td>
</tr>
<tr>
<td>State Effects</td>
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<tr>
<td>Correlation of Average Voter and State Effects</td>
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<tr>
<td></td>
<td>(.00591)</td>
</tr>
<tr>
<td>Share variance would be reduced if:</td>
<td></td>
</tr>
<tr>
<td>Voter effects were made equal</td>
<td>.448</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
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<tr>
<td>State effects were made equal</td>
<td>.518</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
</tr>
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</table>

Notes: The table reports results of the variance decomposition described in Section 4.2. Cross-state variances of average voter and state effects, as well as their correlation, are estimated using the split-sample approach described in the text. Standard errors, reported in parentheses, are computed using a voter-level bootstrap with 50 repetitions. The sample used to run the underlying regression [1] consists of all movers and non-movers (N=1,021,935,784 voter-years).
References


