Voting with One's Neighbors: Evidence from Migration within Mexico*

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Abstract

We study how proximate neighbors affect one's propensity to vote using data on 12 million registered voters in Mexico. To identify this effect, we exploit idiosyncratic variation at the neighborhood block level resulting from approximately one million relocation decisions. We find that when individuals move to blocks where people vote more (less) they themselves start voting more (less). We show that this finding is not the result of selection into neighborhoods or of place-based factors that determine turnout, but rather peer effects. Consistent with this claim, we find a contagion effect for non-movers and show that neighbors from the same block are much more likely to perform an electoral procedure on the same exact day as neighbors who live on different blocks within a neighborhood.

Keywords: neighborhood, voter registration and electoral procedures, turnout, peer effects, political behavior, developing countries.

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1 Introduction

The neighborhoods of Roma Sur and Doctores are located across the street from each other in Mexico City. In Roma Sur, turnout in the 2021 national elections was 60%, while in Doctores it was 37%. Such differences across neighborhoods in political behavior are observable wherever one looks.[1] But why they exist remains unclear. One possibility is that like-minded people, with similar voting propensity, want to live in the same neighborhoods. After all, Doctores' residents are less wealthy and less white than Roma Sur's. But an alternative explanation is that the neighborhood itself affects turnout choices directly either through interpersonal influence, its physical attributes, and/or other economic and political forces.[2]

This study is one of the first to systematically document neighborhood effects in voting behavior at the block level, and the first one to do so in a developing country. Our analysis relies on uniquely granular data that describe individual level turnout choices and place of residence across two recent elections for over 12 million Mexican citizens. Because of the fineness of these data, we are able to isolate the influence of neighbors who reside on the same *block*. This stands in contrast to a voluminous literature that has had to define a neighborhood using substantially larger geographical designations, such as the county, the commuting zone (Chetty and Hendren, 2018a), or the census tract (Kling et al., 2007). By focusing on the block, we not only mitigate the potential identification concerns associated with sorting, but we also provide valuable insights into one of the potential mechanisms for why neighborhoods matter. Our approach is consistent with the sociological understanding of "neighborhoods as ecological unit nested within successively larger communities" (Sampson et al., 2002; Park, 1916).

To estimate the effect of an individual's block neighborhood on her turnout, we focus on citizens who move from one place of residence to another. We find that moving to a block with higher (/lower) turnout is associated with a significant increase (/decrease) in the probability of turning out to vote. Specifically, a mover's probability of turning out to vote at destination changes by about half a percentage point for every 10 percentage point difference in average turnout between the origin and destination blocks.

In our analysis we zero in on block-level variation *within an electoral precinct or precinct-pair*, effectively controlling for the confounds associated with geographical sorting. Precincts

[1] An example in the US are the adjacent San Diego neighborhoods of Kensington and Teralta, with turnouts of 62% and 27%, respectively, in the 2014 general elections ("San Diego Neighborhoods Close in Distance, Miles Apart in Voter Turnout," Feb 10 2016, KPBS, Claire Trageser and Megan Burks, https://www.kpbs.org/news/2016/feb/10/san-diego-neighborhoods-close-distance-miles-apart/). For a turnout map of Chicago see: https://www.wbez.org/shows/wbez-news/chicago-elections-mapped-voter-turnout-high-but-low-in-minority-neighborhoods/38728dc7-85a8-41b6-849a-bf8888a715b2. Turnout for Mexico's 2021 election is available here: https://prep2021.ine.mx/diputaciones/nacional/votos-distrito/mapa. The corresponding electoral maps can be consulted here: https://cartografia.ife.org.mx/sige7/?cartografia=mapas.

[2] Throughout, we use 'interpersonal influence' and 'peer effects' indistinctly.

in Mexico encompass a median of only 19 blocks and are much smaller geographical units than various commonly-used definition of a neighborhood.[3] Our identification strategy assumes that, while people are generally able to pick a neighborhood to move to, the precise block within that neighborhood where they end up living is essentially the result of idiosyncratic factors such as the availability of housing units at a particular point in time.[4] Consistent with this identification assumption, we document that a mover's past voting behavior is not correlated with average turnout at her destination block once we control for origin-destination precinct pair fixed effects. We also show that the correlation of an individual's traits and the average traits of their neighbors is practically zero once we account for origin-destination precinct pair fixed effects.

To investigate the channels underlying our estimated effect, we classify potential mechanisms into three categories: physical and infrastructural factors that affect the costs of voting, such as distance from home to polling station; political campaigns and clientelistic mobilization; and interpersonal influence (peer effects). Because our measure of exposure to one's neighbors behaviors varies at the block level, our empirical strategy rules out any potential forces such as political campaigning, turnout buying, and clientelism, which by all accounts operate at geographical levels no smaller—and often much larger—than the precinct (Levitsky, 2003; Larreguy et al., 2016, 2017). In terms of physical layout, we are able to control for among other things, distance from home to precinct. We find that while distance to the precinct—presumably an important driver of the cost of turning out to vote—significantly influences a mover's turnout probability, its inclusion as a control does not affect our estimated effect.

Our results point to interpersonal influence as an important driver of neighborhood effects in voting. To further test for evidence of interpersonal influence, we implement two additional analyses. First, we study what happens to the turnout of residents *at the destination block* when others move into that block. In contrast with our main analysis, this strategy compares blocks that received a new neighbor, and uses variation in whether the arriving neighbor voted in the past to estimate the effect of movers' past turnout on the future turnout of non-movers at destination. We find that the arrivers' propensity to vote in the past influences the probability that their new neighbors at the destination block turn out, which is consistent with interpersonal influence.

Second, we test for interpersonal influence relating to election-related behavior that took place prior to Election Day. Specifically, we ask whether two citizens who live on the same

[3] Geographical units commonly used in studies of neighborhood effects in the U.S. include the census tract and the block group. A census tract is a set of block groups. On average, block groups contain about 39 blocks.

[4] Bayer et al. (2008) adopt a similar identification strategy to estimate effect of social interactions among neighbors on labor market outcomes.

block (but not in the same household) are more likely to update or renew their voter ID *on the same day* than two citizens who live on different blocks but in the same precinct. Using data on the universe of ID renewals and updates in Mexico, we find that this is indeed the case. We take this as a strong indication that people interact with their neighbors about election-related matters in daily life.

This paper's main contributions are, first, to furnish credible evidence of neighborhood effects in political participation in the developing world, where social norms, social networks, formal institutions, infrastructure, and political campaigns—ostensibly the main candidate factors underpinning neighborhood effects—often differ importantly in comparison with the United States and other wealthy Western nations. In the 2018 campaign season in Mexico, for example, close to one in three Mexicans talked to their neighbors about the elections sometimes or often, while only one in ten Brittons and fewer than one in five Americans, did.[5] Along these lines, we document a negative relationship between a country's level of development and the fraction of its citizens who report speaking to their neighbors about elections or electoral campaigns (Figure 6). One hypothesis consistent with this relationship is that, when formal institutions are weaker, people have incentives to rely on, and invest in, social ties more than in societies with stronger and more reliable formal institutions. Whatever the reason, the aforementioned empirical pattern suggests that interpersonal influence may matter more in the global South than in the global North, underscoring the importance of extending research on neighborhood effects to less-developed settings.

Second, our analysis speaks to the mechanisms responsible for neighborhood effects in political participation. We disentangle interpersonal influence from the effects of local infrastructure and services, while also ruling out campaign advertising, clientelism and other factors relevant to political participation that largely operate at levels of aggregation much greater than our geographical unit of analysis, the block.

Our analysis connects with a voluminous body of work on neighborhood effects that has focused on the United States and other developed countries. A lot of this literature studies non-political outcomes such as income, education, and health (Sampson et al., 2002). Meanwhile, the study of neighborhood effects on political behavior has largely concerned itself with sociodemographic determinants such as education and race, and on individual political preferences.(Gimpel et al., 2004; Huckfeldt and Sprague, 1987; Johnston et al., 2004; Baybeck and McClurg, 2005; Beck et al., 2002; Cohen and Dawson, 1993; Kenny, 1992; Huckfeldt et al., 1993; Rolfe, 2012). To our knowledge, only a handful of studies focus on the effect of neighborhoods on voter turnout. There is no standard definition of a

[5] Authors' calculations based on an identical question asked in the Comparative National Elections Project (CNEP) surveys for Mexico (2018), Great Britain (2017), and the United States (2012).

neighborhood, and operationalizations vary widely. On one end of the spectrum, Cantoni and Pons (2020) investigate the influence of geographical context on individual turnout in the US. In contrast with our focus on the very local, their geographical unit of analysis is the state.

There are advantages to basing the analysis on smaller geographical units. In our case, we gain causal traction by restricting comparisons to blocks within the same precinct. Barber and Imai (2014) study block-level influences on individual turnout in three US states, but they focus on different causes of turnout than us (racial and partisan neighborhood composition are their main independent variables). Relatedly, Bhatti et al. (2017) use individual level Danish data to estimate the effect of neighborhood-level ethnic diversity on turnout. Cutts and Fieldhouse (2009), also using individual level Danish data, estimate a hierarchical model to decompose the share of variance in voter turnout explained by the household, and to isolate it from the influence of post code (which they take to represent the "immediate neighborhood") and the ward. Their approach is not designed to establish causality.[6]

Our analysis also connects with the literature on interpersonal influence in voting. Both social networks (McClurg, 2003; Kenny, 1992; McClurg, 2006; Mutz, 2002) and social norms (Shulman and Levine, 2012; Gerber and Rogers, 2009) have been found to influence individual political participation. Sinclair (2012) sets out to distinguish between two mechanisms of interpersonal influence: information vs. social pressure to conform. Her findings are complementary to ours. Gerber et al. (2008) used randomly assigned mailings threatening social shaming upon failure to turn out to show that the threat increases turnout, while Nickerson (2008) uses randomization to document intra-household spillover effects on turnout. Relatedly, Bhatti et al. (2020) show that households are very important in turnout choices on the basis of Danish time-stamped data. Klofstad (2015) studied the influence of political discussion with randomly-assigned college roommates on turnout. Consistent with our findings, DellaVigna et al. (2017) experimentally demonstrate that interpersonal influence—specifically, the expectation of having to tell others whether one voted or did not do so—is an important driver of turnout. Collectively, the literature suggests, consistent with our findings on mechanism, that interpersonal influence is likely to account, at least partly, for neighborhood effects.

[6]They make an attempt to get at causality by focusing on a smaller sample and controlling for some observables, but a causal interpretation of their results must very strongly rely on selection-on-observables assumptions.

2 Context and Data

Mexico has had transparent and competitive national elections at least since 1997, following an important set of legal reforms that created an electoral authority independent of the executive branch (the *Instituto Federal Electoral* or IFE, now called *Instituto Nacional Electoral* or INE) and a transparent and reliable list of registered voters, among others improvements. INE—like IFE before it—is in charge of organizing elections for all national legislative and executive offices. INE's tasks include, among other things, continuously updating the voter registry, determining the locations of polling stations, assigning registered citizens to polling stations, and recruiting teams of citizen volunteers to staff the polling stations and count the votes. Elections for both houses of national congress take place every 3 years, and presidential elections take place every 6 years.

The basic unit of Mexico's electoral geography is the precinct. The number of precincts in the 2015 national elections was 68,362.[7] Every precinct contains one or more polling stations, depending on the number of voters registered in the precinct. The median number of blocks per precinct in 2012 was 19 blocks. Citizens are assigned to vote at a specific precinct according to their place of residence.[8] All citizens 18 years of age and over are eligible to vote if they have registered to do so. In order to cast a vote on Election Day, citizens must show a current INE ID at the polling station. As in most democracies, failing to turn out to vote on Election Day in Mexico does not result in any sort of penalty.

In this paper, we use data from the presidential and legislative elections of 2012, and the legislative elections of 2015. Our data set compiles information from the following sources:[9]

Voter list (*padrón electoral*). The voter registry is a cornerstone of Mexico's electoral system and INE devotes substantial resources to keeping it accurate and up to date. Every registered citizen is issued an INE ID card. Because the INE ID is, de facto, the main form of official identification in Mexico for both private-sector transactions and bureaucratic procedures, citizens have an incentive obtain it and to keep its information up to date. INE estimates that upwards of 97% of citizens 18 and over have a valid INE ID card. To obtain an INE ID, citizens have to present documentary evidence at an INE office, including proof of address, proof of birth, and photo ID. Citizens also report their educational attainment and occupation. This data source contains an up-to-date list of all citizens legally registered to vote in a particular election, recording, for every citizen, their gender, age, occupation,

[7]Based on the 2015 INE voter list.

[8]There are some exceptions (for example, citizens who are traveling can vote in special precincts), but in practice these only apply to a small fraction of citizens.

[9]We never had access to personally identifiable information. The data belong to INE and we are not at liberty to post or share them.

educational attainment, home address, and assigned precinct. The 2012 voter list contains information on 84,464,713 citizens, and the 2015 list contains 87,243,321 citizens.

Place of residence. We do not observe the exact home address of citizens. However, we do have data on the coordinates for the centroid of the block of their home residence, as well as the coordinates for the location of their assigned polling station. On the basis of these data, we are able to construct the linear distance between home and polling station. The mean distance is 0.4 km with a standard deviation of 0.56. In addition, we have a household identifier variable that takes the same value for all citizens who reside at the same address. We use this variable as a proxy for "family." The average "family" size is 4.7 adults, compared to 3.7 adults in the 2015 *Encuesta Intercensal*.[10]

Turnout census. INE compiles a list of all registered voters who turned out to vote in each federal election. These data come from the precinct-specific booklet listing those citizens registered to vote at that precinct. When a citizen shows up at the polling station, poll workers mark that citizen in the booklet. INE then digitizes the booklets for all polling stations. We had access to the full turnout census for the 2015 elections, as well as to a random sample of about 13,554,266 citizens for the 2012 elections.[11]

ID registration, replacement, renewal, and updating procedures. Citizens can replace a lost card, renew an expired one, or update their home address, at any INE office at any time. In the year leading to the 2015 national elections (June 2014 to May 2015), citizens performed more than 11,895,125 procedures relating to their INE IDs at INE offices. We have transaction-level data describing the date of a procedure, the type of procedure, and the (anonymized) identity of the citizen who performed it.

Socio-demographic information. The national statistical agency, INEGI, together with INE provide a version of the 2010 Population Census where the data are presented at the precinct level. These data cover over 66 thousand precincts. We use the following variables to check for balance and/or as control variables: percentage of the population constituted by men, employment status, age categories, educational attainment categories, and occupation categories.

[10] INEGI, `https://tinyurl.com/pcncwuyr`.

[11] This is before merging with the other data sources.

2.1 Analysis sample

Our main analysis studies the voting behavior of registered citizens who move across blocks between the 2012 and the 2015 elections. We refer to such citizens as "movers." To create our analysis sample, we first merge the different data sources, and then drop observations with missing data for any of the regressors in the main analysis. Our merged dataset consists of all observations for citizens that meet the following criteria: (i) they are present in both the 2012 and 2015 voter lists, (ii) the data contain their block of residence in 2012 and 2015, (iii) there is information on their turnout behavior from the turnout census of 2015 and the 2012 turnout census sample, and (iv) the 2010 Population Census covers both their origin and destination precincts.[12] These data encompass 11,540,922 registered voters. Of these, approximately 1.2 million citizens are movers as previously defined. By using an anonymous individual identifier, we are able to construct a two-period panel of citizens.

For the main analysis, we work with a subsample of the analysis sample that contains information for all the variables in the regression with the largest subset of controls (subsequently the "estimation sample"). Thus, the estimation sample is consistent across our different econometric specifications. In the end, our estimation sample consists of 515,362 movers, each of whom we observe both in 2012 and 2015.[13] In the Appendix, we present results with maximal samples for each of the specifications in our main analysis.

2.2 Descriptive statistics

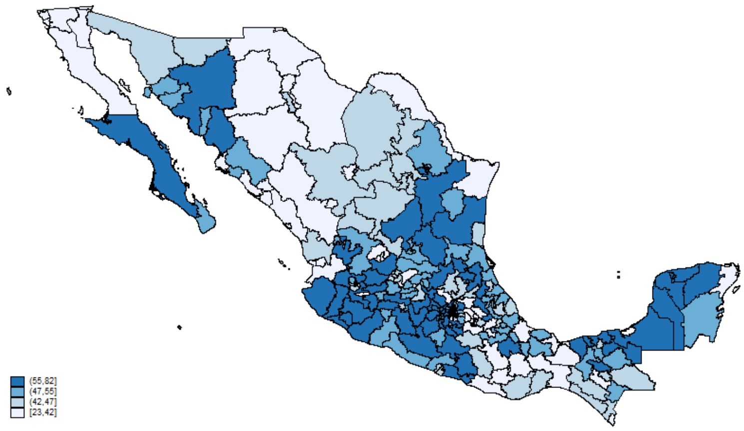
Variation in turnout. Turnout rates in Mexico exhibit substantial geographical variation. Figure 1(a) illustrates variation in turnout across electoral districts in the 2015 national legislative elections, with shading denoting quartiles of district-level turnout. Figure 1(b) zooms in on the state of Veracruz as an example, now displaying turnout rates at the precinct level. The shading indicates quartiles of precinct-level turnout rates. Note that turnout can vary substantially even across adjacent precincts. The standard deviation of turnout across all precincts in the 2015 election was 13.4 and the inter-quartile range was 17.2.

We also see a lot variation in turnout rates across blocks *within* a precinct, which is our main source of identifying variation. The average standard deviation of block-level turnout across blocks within a precinct is 0.30. Appendix Figure OA-7 displays the distribution of the standard deviations of block-level turnout within precincts for the 2015 elections. As we

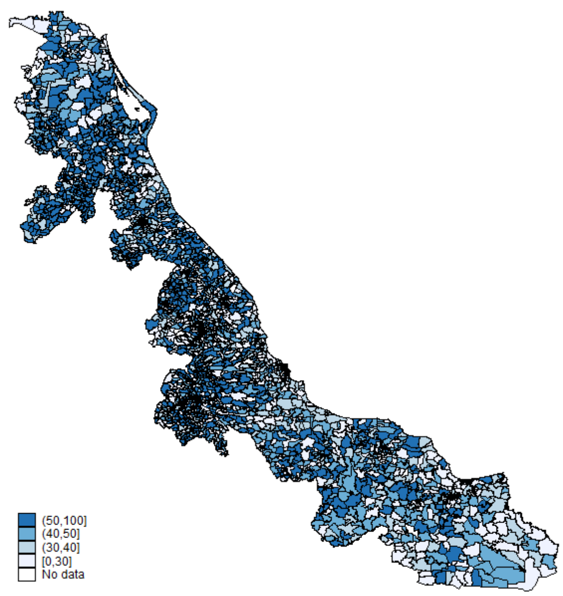
[12]For simplicity, we exclude from our sample the small subset of precincts that were reshaped or partitioned as part of INE's ongoing process of *reseccionamiento* between the 2012 and 2015 elections.

[13]We lose a total of 680,420 observations due to list-wise deletion of missing data. Of these, about 54 thousand are due to missing turnout either at origin or destination; about 191 thousand are due to missing data on educational attainment; about 181 thousand have missing data on household size, about 196 thousand lack distance to polling station, and about 67 thousand are missing block-level controls.

Figure 1: Variation in turnout across Mexico



(a) 2015 District turnout



(b) 2015 Precinct turnout

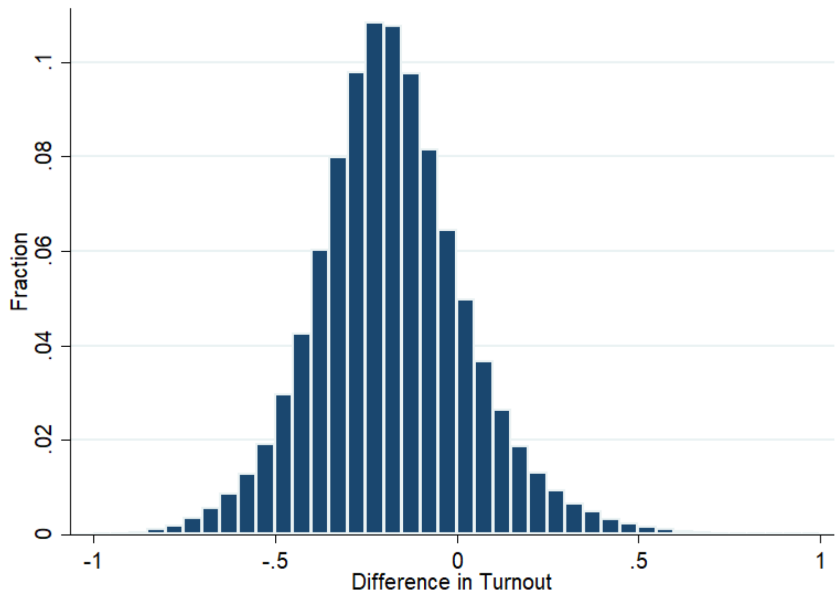
This figure shows the extent of variation in 2015 turnout. Panel (a) does this for the entire 300 Electoral Districts in Mexico. Panel (b) takes the state of Veracruz as an example and plots turnout at the precinct level. Each color represents a different quartile of the empirical distribution of turnout.

can see, the level of variation is considerable. In fact, the inter-quartile range of block level turnout within a precinct is on average 38 percentage points.

In cross-national perspective, the geographical variation in Mexican turnout appears to be quite typical. Table 1 provides information on cross-sectional variation in turnout across localities in all the countries for which we were able to obtain such information.

Our main explanatory variable is the difference in average turnout between the destination block in 2015 and origin block in 2012, for an individual mover. This is a measure of individual exposure to differences in the turnout environment of their block neighborhoods at origin vs. destination.

Figure 2: Distribution of exposure to destination-origin block turnout differences



This figure plots the differential exposure of movers, defined as the difference in block-average turnout for an individual mover at the destination block in 2015 minus that at the origin block in 2012. This variable is bounded in [-1,1]. Because turnout is greater in presidential elections (such as the 2012 one) than in legislative ones (such as the 2015 election), the differences variable is negative in most cases.

Table 1: **Variation in turnout across countries**

Country	Geographic Unit	Turnout	% of Elec./Unit	SD	IQR	N	Year	Type of Election
USA	Precinct	66.1	0.00%	12.6	14.3	84441	2012	Presidential
Chile	Comuna	41.1	0.29%	12.0	10.1	346	2013	Presidential
France	Departament	78.9	0.93%	10.0	3.8	107	2012	Presidential
Mexico	**Poll Station**	62.8	**0.00%**	9.6	12.1	**136128**	**2012**	**Presidential**
Costa Rica	Electoral District	66.5	0.21%	8.3	10.9	478	2014	Presidential
Panama	Electoral Circuit	77.9	2.56%	6.6	12.1	39	2014	Presidential
USA	State	61.3	2.38%	6.4	8.9	42	2012	Presidential
Mexico	**Electoral District**	62.7	**0.33%**	6.0	7.1	**300**	**2012**	**Presidential**
Canada	Federal Electoral Distrits	61.2	0.07%	5.7	7.2	302	2011	Parliamentary
South Africa	Province	71.7	0.43%	5.4	6.8	234	2014	Presidential
United Kingdom	Constituency	66.1	0.15%	0.5	7.8	650	2015	Parliamentary

This table shows various summary statistics of voter turnout. The statistics are computed across geographical units for different countries and elections and sorted by the standard deviation. Data for France obtained from The Guardian's France election results 2012 datablog <https://www.theguardian.com/news/datablog/2012/may/07/france-election-results-list#data>. Data for Panama obtained from the country's Electoral Tribune's 2014 elections results web page <https://www.tribunal-electoral.gob.pa/eventos-electorales/elecciones-generales-1994-2019/elecciones-2014/resultados-electorales-2014/>. Data for Chile obtained from Chile's Electoral Service's 2013 presidential elections results from their historical records website <https://historico.servel.cl/servel/app/index.php?r=EleccionesGenerico/Default/MesasElectores&id=2&n=2&v2=30&v3=0&v4=0&v5=0&v6=0&v7=0&v8=0>. Data for the United Kingdom obtained from the UK's Electoral Commissions electoral data <https://www.electoralcommission.org.uk/our-work/our-research/electoral-data/electoral-data-files-and-reports>. Data for Costa Rica obtained form CR's Supreme Electoral Tribune's statistics of election processes <http://www.tse.go.cr/estadisticas_elecciones.htm>. Data for Canada obtained from Elections Canada's 2011 general election official voting results raw data <http://www.elections.ca/content.aspx?section=res&dir=rep/off/41gedata&document=byed&lang=e>. Data for the United States obtained from United States Elections Project's 2012 General Election turnout rates data at the state level <http://www.electproject.org/2012g>and Harvard Election Data Archive's 2014 election data at the precinct level <https://projects.iq.harvard.edu/eda/data>. Data for South Africa was obtained from the Electoral Comission of South Africa's national and provincial election results <http://www.elections.org.za/content/Elections/National-and-provincial-elections-results/>.

Internal Migration. As mentioned previously, we observe the block of residence for registered citizens in 2012 and in 2015. In the merged dataset, 10.4% of citizens changed their home address between 2012 and 2015. Of these, 21.2% moved out of state, 21.7% moved within a state across municipalities, 30.8% moved within municipalities across precincts, and 26.3% moved across blocks within their precinct.[14] These movers originated in 20,151 precincts and arrived in 61,950 precincts. The origin precincts with the most movers saw 403 individuals move out. The 2000^{th}-ranked precinct saw about 80 individuals move out. In terms of origin-destination precincts *pairs*, the pair with the highest flow contains 125 movers, while the 2000^{th}-ranked pair contains 8.

In Table 2, we compare the characteristics of non-movers (column 1) to those of movers in the estimation sample (column 2). While both movers and non-movers are about 47% male, movers are more schooled (8.3% have a bachelor's degree vs 5.8% of non-movers, and 17.5% claim to be studying vs 12.7% of non-movers). Movers are also younger on average (34 years of age vs. 41 for non-movers). Movers are also less likely to have voted in 2012.

Table 2: **Summary statistics for non-movers and movers**

	Non movers	Movers in estimation sample		
		All	Q1 to Q4	Q4 to Q1
	(1)	(2)	(3)	(4)
Voted in 2012 at origin (%)	65.88	54.40	45.25	52.57
Male (%)	47.91	47.45	50.17	49.91
Age (years)	40.82	34.37	33.82	33.04
High school (%)	16.49	22.53	28.35	26.87
Bachelor (%)	5.83	8.27	11.68	10.10
Domestic work (%)	31.26	24.51	19.98	21.36
Employee (%)	28.48	35.91	39.36	33.04
Student (%)	12.67	17.53	19.67	24.04
Household size at origin	4.58	4.07	3.98	4.47
Distance to polling station at origin (km)	0.40	0.38	0.45	0.37
Number of observations	10,333,006	515,362	6,285	10,130

Figures are means of 2012 variables for different subsamples of the analysis sample. Column 1 refers to all non-movers in the analysis sample. Column 2 contains all movers in the estimation sample for the main analysis (note that listwise deletion of missing data drops 629,567 movers from the analysis sample). Column 3 describes those movers in the estimation sample who moved from blocks located in precincts in the lowest precinct-turnout quartile in 2012 to blocks located in precincts in the highest precinct-turnout quartile in 2015, while column 4 describes those movers in the estimation sample who moved from blocks located in precincts in the highest precinct-turnout quartile in 2012 to blocks located in precincts in the lowest precinct-turnout quartile in 2015.

The rightmost two columns of Table 2 compare two subsets of movers in our main estimation sample: those who moved from the lowest quartile to the highest quartile of precinct-level

[14] Figures for the main estimation sample are similar.

turnout (column 3) vs. those who moved from the highest to the lowest quartile (column 4). These two groups are quite similar in age and gender, but those moving to higher-turnout precincts are more likely to be employees and less likely to be students. They also voted at somewhat lower rates in 2012 in comparison with those who moved from high- to low-turnout.

3 Empirical Approach

Our main analysis aims to identify the influence of one's close neighbors (i.e., those residing on the same block) on one's decision to turn out to vote. To estimate the causal effect of neighbors on voting, we exploit the granularity of our data to isolate *block-level* variation in turnout within precincts. Specifically, we estimate the following econometric model:

$$Vote_i^{2015} = \alpha + \beta \Delta Turnout_{o(b),d(b)} + \phi Vote_i^{2012} + \delta X_i + \eta Z_{d(b)} + \theta_{o(p),d(p)} + e_{iod}. \quad (1)$$

The dependent variable, $Vote_i^{2015}$, is an indicator for whether person i living in destination block b voted in 2015. Our key independent variable, $\Delta Turnout_{o(b),d(b)}$, is the difference in average turnout between the destination block $d(b)$ in 2015 minus the origin block $o(b)$ average turnout in 2012.[15] Equation 1 also includes an indicator, $Vote_i^{2012}$, for whether the mover i voted in 2012. This is an important control because one's propensity to vote tends to be stable across time. Our model also accounts for a set of individual controls, X_i – including the person's age, gender, household size, education level and occupation both in 2012 and 2015, distance to the polling station in 2012 and 2015, moving distance, the number of voter IDs the person has held, and an indicator for whether the move included crossing a state boundary. It also controls for 11 destination block variables $-Z_d(b)-$ described in Table 3 containing the average characteristics of block-level neighbors. The model also includes precinct fixed effects—in our most demanding specification, *precinct-pair* fixed effects $\theta_{o(p),d(p)}$. The fixed effects imply that we compare individuals who moved from and to the same precincts, but happen to live in different blocks. Our key identifying assumption is that, conditional on the precinct (and our rich set of controls), movers do not sort across blocks on the basis of their block neighbors' potential turnout.

[15] The fact that average turnout at the national level is different across these two elections is not an issue for our empirical strategy since identification relies on comparison across individuals, not across elections. Nevertheless, we construct an alternative measure of exposure based on relative turnout in each of the elections, which we describe later in the paper.

3.1 Identification strategy

The main concern with using movers as a source of identifying variation is that people do not choose where to live at random. It is possible, for example, that individuals who are more likely to vote also tend to move to places where turnout rates are higher. In order to deal with this concern, we only make use of variation in turnout across blocks *within* a given precinct, discarding all variation in turnout across precincts. Accordingly, our identifying assumption is that, within a given precinct, movers do not sort across blocks on the basis of their neighbors' turnout or factors correlated with turnout.

We believe this is a plausible assumption for at least two reasons. First, the housing market within a precinct is very thin—the median precinct is comprised of only 19 blocks — and thus limits an individual's ability to choose a specific block. During a 3-month period, on average only about 0.5% of houses/apartments in a block become available in Mexico.[16] This is less than half than what Bayer et al. (2008), which employs a similar research design, finds for Boston. Second, before they move, individuals are unlikely to know about turnout rates for specific blocks or about the characteristics of their future neighbors on a given block, as compared to other blocks *within* a neighborhood.

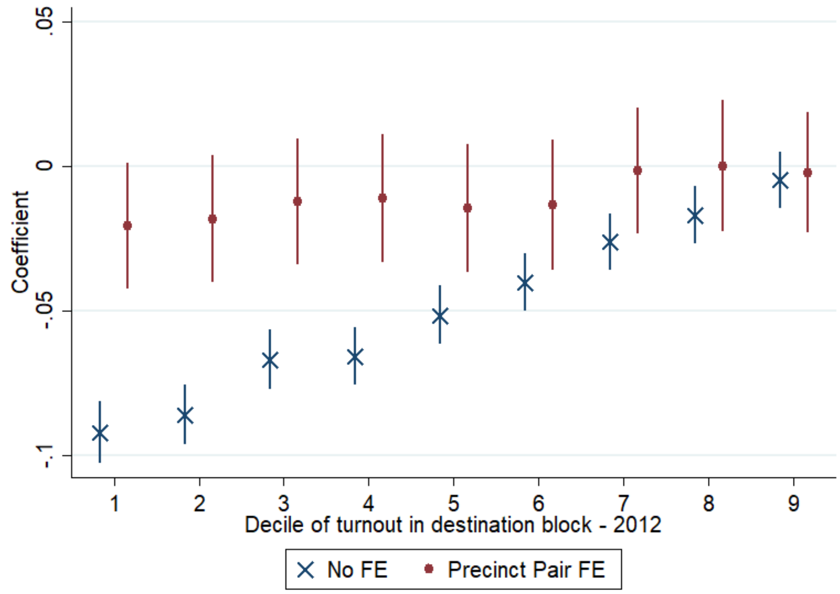
The data support our identification assumption. Figure 3 shows that, while people who voted in 2012 moved to blocks with higher average turnout than those who did not vote (star markers), that correlation disappears once the precinct pair fixed effects are controlled for (dot markers). To construct the graph, we first calculated deciles of block-level turnout for all destination blocks in 2012 and created dummy variables for each decile. We then regressed an indicator for whether a mover voted in 2012 on these dummies. Figure 3 plots the coefficients on each of the dummy variables (except for the reference category, which is the 10^{th} turnout decile), both with and without precinct pair fixed effects. We cannot reject the hypothesis that the coefficients on the dummies are equal to each other in the specification with precinct pair fixed effects. In other words, movers appear to sort according to precinct turnout, but they *do not* sort on turnout across blocks within a neighborhood.

We further test our identification assumption by studying whether individuals select into residential blocks populated by people with similar socio-demographic traits. Even if individuals do not care about turnout, they could potentially sort on factors correlated with turnout. Specifically, in Table 3 we compute correlations between the characteristics of an individual mover and the characteristics of his or her neighbors living in the destination block.[17] Column 1 reports the means of various socio-demographic traits for these movers.

[16] Authors' calculations based on INE data.

[17] If there are several movers arriving to one same block, we pick one of the movers at random. The random pick is for computational simplicity.

Figure 3: Selection of movers on turnout at the destination block



We estimate a regression where the dependent variable is an indicator for whether an individual mover voted in 2012 (before moving) and the explanatory variables are indicators for deciles of block-level 2012 turnout at the destination block (with the 10^{th} decile as the omitted reference category), plus the same controls as the model described in column 3 of Table 4. Standard errors are clustered at the destination precinct level. The analysis is run on the estimation sample (i.e., the same used in Table 4 further below). The figure plots the estimated coefficients on the destination-block turnout indicators, together with 95% confidence intervals. We estimate one specification without precinct fixed effects (cross markers) and one specification with origin-destination precinct pair fixed effects (dot markers). We test the hypothesis of equality of the coefficients on the decile indicator variables, and while we reject equality for the specification without precinct fixed effects (p-value = 0.00), we cannot reject equality for the specifications with precinct pair fixed effects (p-value=0.60).

Next, for each mover, we identify all registered voters on her destination block, excluding the movers's household members and other movers, and calculate their average characteristics: age, family size, gender, education level, propensity to vote, and self-reported occupation—student, employee, homemaker, or worker. We next compute the correlation between the individual mover's trait X and the average trait of her non-family and non-mover block neighbors, $\overline{X}$, by running the following regression: $X_{i,j} = \alpha + \beta \overline{X}_{i's\, block\, neighbors,j} + \epsilon_j$, where i is the randomly-picked mover living in block j. Column 2 reports β estimates from this regression equation. In column 3, we report the results of the same analysis adding origin-destination precinct pair fixed effects to the regression. Comparing column 3 with column 2, we see that the inclusion of the fixed effects causes most β estimates to decrease quite substantially (between 47 and 168 percent). Columns 4 and 5 display 95% confidence intervals of the β estimates of column 3.

Table 3: **Selection on block-level socio-demographic characteristics**

		Individual - block correlations		Precinct pair FE CI	
	Means for individuals (1)	Unconditional (2)	Precinct pair FE (3)	Lower bound (4)	Upper bound (5)
Age 45-59	0.150	0.032	-0.012	-0.056	0.033
Age 35-44	0.248	0.035	0.039	-0.010	0.089
Age 25-34	0.405	0.075	0.039	-0.013	0.092
Male	0.466	0.009	0.013	-0.040	0.066
Household size	4.088	0.101	-0.069	-0.086	-0.051
High-school graduate	0.381	0.486	0.166	0.124	0.207
College graduate	0.164	0.592	0.254	0.212	0.296
Housework	0.317	0.207	0.034	-0.016	0.085
Employee	0.338	0.337	0.022	-0.030	0.073
Student	0.042	0.062	0.016	-0.023	0.055
Self-employed	0.085	0.117	-0.011	-0.061	0.039
Predicted probability of voting	0.427	0.127	0.028	0.001	0.054

The table (specifically, columns 2 and 3) displays conditional correlations between the demographic characteristics for a randomly chosen mover for each block and those of her non-family and non-mover block neighbors. The socio-demographic variables are listed in the rows of the table. They include indicators for age group, an indicator for being male, the number of household family members (proxied by the number of registered voters with the same address), indicators for educational attainment, and indicators for the four occupations most commonly reported to INE (housework, employee, student, and self-employed). The last line displays the probability of voting as predicted by these demographic variables (details of the prediction method are provided in the text). Column 1 displays the mean of each variable for the set of randomly picked individuals. Column 2 reports the β estimates from the regression equation: $X_{i,j} = \alpha + \beta \overline{X}_{i's\, block\, neighbors,j} + \epsilon_j$, as described in the text. Column 3 adds origin-destination precinct fixed effects to this regression. Columns 4 and 5 provide the confidence interval lower and upper bounds associated with Column 3.

The coefficients reported in column 3 are quite small in magnitude and for 8 out of the 12 characteristics, we cannot reject that they are statistically zero. Nevertheless, one might still be concerned that these correlations, although small, might be sufficiently large to induce spurious (i.e., non-causal) correlation in voting behavior between an individual and her block neighbors. To test whether this is the case, we isolate the part of individual voting behavior that is due to the aforementioned characteristics. We then compute the correlation between the individual and her neighbors in voting as explained by these characteristics. Operationally, we regress an indicator variable for having voted in 2012 (Y_k) on the set of characteristics X_k (i.e., those listed on the first eleven lines of the table) and calculate predicted values $\widehat{Y_k}$, for all individuals k in the data.[18] We then regress the predicted values $\widehat{Y}_{ij}$ for individuals i who reside on block j on their non-household block neighbors' average predicted values: $\widehat{Y}_{ij} = \gamma + \delta \overline{\widehat{Y}}_{i's\, block\, neighbors,j} + \nu_j$, with and without precinct fixed effects. A large coefficient δ would indicate that the residual correlations in the first 11 lines of column 3 are large enough that selection is likely to remain a problem for identification.

The estimated δ coefficients are shown in the last line of columns 2 and 3. Loosely speaking, these estimates represent the degree to which the traits on the first 11 lines of

[18] We use a logit regression to maintain predicted values in the (0,1) range.

the table indirectly induce residential selection on turnout. Our estimate of 0.028 implies that an increase of 10 percentage points in the predicted turnout of the block neighbors is associated with an increase of a mere 0.28 percentage points in the mover's predicted likelihood of voting. This suggests that once precinct-pair fixed effects are accounted for, block-level sorting based on socio-demographic characteristics will only explain a tiny fraction of individual voting behavior.

3.2 Local nature of interactions

By discarding all variation at the precinct level through the inclusion of precinct-pair fixed effects, we are implicitly focusing on social interactions at a very local level. We believe we are on firm ground in supposing that those interactions matter for political behavior. Many studies have found that neighbors close by are important sources of information and constitute important contacts in an individual's social network. Lee and Campbell (1999) find that 31% of neighbors in the closest 10 housing units are judged as personally close or very close by Nashville survey respondents. Otani (1999) uses the US General Social Survey and finds that neighbors comprise about 1/5 of people listed as part of an individual's social network in the US and Japan. Huckfeldt (1980) argues that "neighbors are a potential powerful source of contextual influence on political behavior" (see also Rolfe and Chan (2017)). Survey evidence indicates that Mexican citizens speak quite often with their neighbors about electoral campaigns. In 2018, 31% of Mexicans reported doing so either sometimes or often. Mexicans also reported speaking about electoral campaigns sometimes or often to friends (44%) and family (56%).[19]

One of the most successful interventions to date to increase turnout is by Gerber et al. (2008), and it involved sending a letter about the turnout record of neighbors, showing that people do care about opinions of their neighbors regarding voting. Relatedly, DellaVigna et al. (2017) show that people vote in part to be able to tell others that they did so, since "it is common for neighbors, friends, and family to ask whether we voted." Overall, this literature suggests that localized interactions matter for voting. This is precisely what we test in the paper. To the extent that people on blocks other than one's block of residence influence voting, our design may provide a lower bound of the effect of immediate neighbors.

[19] All figures in this paragraph based on the 2018 CNEP Mexico survey.

4 Main Results

Our main analysis estimates the effect of exposure to different block neighborhoods for citizens who move from one block to another in the period 2012-2015. As mentioned previously, the exposure variable consists of the difference in average block turnout at destination minus at origin. The dependent variable is an indicator for whether the mover turned out to vote in the 2015 elections. In all specifications we control for whether the mover had voted in 2012.[20] Standard errors are clustered at the precinct level.

In column 1, we find that exposure to a higher turnout block neighborhood is positively correlated with one's propensity to vote. The coefficient of 0.048 implies that a one standard deviation increase in destination-origin exposure is associated with 1 percentage point increase in the likelihood of voting. We also find the common result that past turnout predicts future turnout (e.g., Green and Shachar (2000)). In column 2, we add individual controls. These controls are predictive of an individual's decision to turn out in the expected direction. Distance from the home block to the precinct, a driver of voting costs, is negatively associated with propensity to vote, while age is positively correlated with voting. The inclusion of these additional controls leaves our main coefficient of interest virtually unchanged at 0.043.

Column 3 augments the model with block level controls. These controls consist of the block average values of each of the 11 traits presented in Table 3. Consistent with the lack of sorting by block that we documented earlier, our coefficient of interest is unaffected by the inclusion of these block-level controls. We then add precinct-pair fixed effects (Column 4). In this specification, our most stringent, we are comparing individuals who both used to live in precinct A and both moved into precinct B, but happen to live in different blocks. The estimated effect of the exposure variable is even stronger, with a point estimate of 0.055, implying that a one standard deviation increase in destination-origin exposure is associated with a 1.2 percentage point increase in the mover's likelihood of voting.

[20] Thus, we are effectively estimating the dependent variable in changes.

Table 4: **Effect of destination-origin exposure on individual turnout of movers**

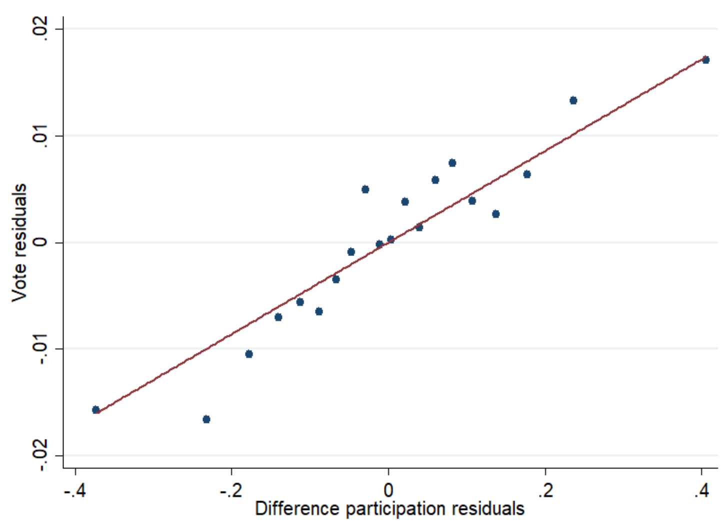
	Dependent variable: individual mover's turnout in 2015				
	(1)	(2)	(3)	(4)	(5)
Destination-origin block turnout difference	0.048***	0.043***	0.043***	0.055***	
	(0.004)	(0.004)	(0.004)	(0.011)	
Destination-origin block turnout percentile diff.					0.002***
					(0.000)
Individual mover's turnout in 2012	0.236***	0.209***	0.209***	0.253***	0.265***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
Male		-0.028***	-0.028***	-0.034***	-0.034***
		(0.002)	(0.002)	(0.005)	(0.005)
Age		0.004***	0.004***	0.004***	0.003***
		(0.000)	(0.000)	(0.000)	(0.000)
Household size 2015		0.004***	0.004***	0.003***	0.003***
		(0.000)	(0.000)	(0.001)	(0.001)
Distance to polling station in 2015 (km)		-0.015***	-0.014***	-0.015***	-0.013**
		(0.001)	(0.001)	(0.004)	(0.004)
N	515362	515362	515362	515362	515362
R^2	0.206	0.244	0.244	0.735	0.737
Mean of dependent variable	0.351	0.351	0.351	0.351	0.351
Mean of destination-origin block turnout diff.	-0.182	-0.182	-0.182	-0.182	-3.097
Effect per 1 SD chg. in block turnout diff.	0.00997	0.00905	0.00900	0.0115	0.0505
Individual level controls		✓	✓	✓	✓
Block-level controls			✓	✓	✓
Destination precinct fixed effects	✓	✓	✓		
Origin-destination precinct pair fixed effects				✓	✓

This table reports the estimated relationship between individual movers' turnout in 2015 (dependent variable) and the difference in average block turnout between the mover's destination block in 2015 and her origin block in 2012 (explanatory variable). Coefficients are estimates of: $Vote_i^{2015} = \alpha + \beta \Delta Turnout_{o(b),d(b)} + \phi Vote_i^{2012} + \delta X_i + \eta Z_{d(b)} + \theta_{o(p),d(p)} + e_{iod}$., further described in the text. Each column corresponds to a different regression model. All regressions are run on the same estimation sample. Standard errors, clustered at the level of origin precinct, are provided in parentheses below the regression coefficients. Column 1 only includes as controls the mover's past turnout (in 2012) and destination-precinct fixed effects. Column 2 adds controls for mover's age in 2012, gender, household size in 2015, distance from home block to polling station at origin in 2012 and at destination in 2015, the number of voter IDs the citizen has historically held, an indicator for whether the citizen performed any transactions related with her voter ID in the period covered by the data, an indicator for whether the citizen crossed a state boundary when moving, distance between previous (2012) and actual (2015) households, and education level and occupation in both 2012 and 2015. Column 3 adds as control variables the eleven destination block-level average neighbor characteristics described in the first eleven lines of Table 3, as well as the average block neighbors' distance to the polling station (in 2015). Columns 4 and 5 add origin-destination precinct *pair* fixed effects. Column 5 defines the exposure variable (destination-origin block turnout difference) in percentiles of block-level turnout. To construct this variable, we calculate the 2015 percentile of block-level turnout for the destination block, and subtract the 2012 percentile of block-level turnout for the origin block (thus this variable potentially ranges in -100 to 100).
Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Relative differences in turnout In addition to measuring exposure as an "absolute" difference in destination (2015) minus origin (2012) turnout, we also create a "relative" measure of exposure, based on turnout percentiles in each of the two elections in our data. Specifically, we compute for each block its percentile in the turnout distribution in a given election. We then calculate the difference in percentiles between movers' destination and original blocks. This measure washes out level differences in national turnout across election years. The results, presented in column 5, are qualitatively similar. A standard deviation (31 point) increase in the destination-origin turnout percentile is associated with around 5 percentage points increase in the likelihood that the mover votes in the 2015 elections.

Positive vs. negative exposures The estimated coefficient on the destination-origin turnout difference variable in Equation 1 corresponds to an average effect. It is possible, however, that the effect of moving to a higher-turnout block could differ from the effect of moving to a lower-turnout block. We examine the linearity of the effect in Figure 4, where we plot a bin scatter of the relationship between our explanatory and dependent variables after partialling out our controls (a specification similar to the one presented in column 4). We do not find evidence that the relationship is non-linear. Moreover, moving to higher turnout blocks increases the mover's likelihood of voting, while moving to lower turnout blocks lowers it.

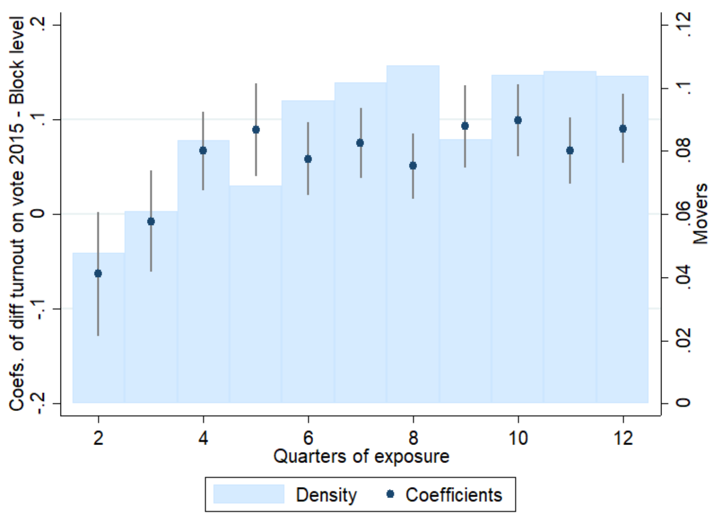
Figure 4: Symmetry and linearity of effects



This figure explores whether the effect estimated in column 3 of Table 4 shows symmetry and linearity, i.e. whether increases in exposure to voting in destination blocks has effects that are similar but of the opposite sign as decreases in exposure to voting. To this end it shows a residuals-residuals partial-out plot for the main estimating equation 1 (using the Frisch–Waugh–Lovell theorem). The first regression estimates equation 1 without the main explanatory variable $\Delta Turnout_{o(b),d(b)}$ and predicts residuals $\hat{e}_{1i}$; the second regression uses $\Delta Turnout_{o(b),d(b)}$ as the dependent variable on the same covariates and predicts residuals $\hat{e}_{2i}$. It then plots a bin scatter of $\hat{e}_{1i}$ against 20-percentile bins of $\hat{e}_{2i}$, along with a linear regression line.

Intensity of exposure. In Figure 5, we investigate whether the estimated effect varies according to how long the mover has resided in their destination block before the 2015 elections. To estimate these differential effects, we classify voters by the number of quarters that they have lived in their destination block. We then re-estimate Equation 1 separately for each group of voters. The figure displays these coefficient estimates, along with confidence intervals, by time of exposure. The effect becomes stronger with the time that the mover has spent at the destination block up until the 4^{th} quarter. After that, the effect remains fairly constant.

Figure 5: Exposure time at destination block



This figure estimates regression of column 3 of Table 4, splitting the sample according to the number of quarters that movers have resided at the destination block at the time of the 2015 election. Regressions are estimated separately for each subsample. The dots correspond to the regression coefficients for the destination minus origin turnout variable. We also plot in the background a histogram that displays the fraction of movers in each subsample.

Homophily. We now check whether socio-demographic similarity with one's neighbors at destination enhances the effect of exposure. Specifically, we allow the effect of destination-origin turnout exposure to vary according to the similarity of the mover and her block neighbors at destination. We implement this by adding to Equation 1 an interaction term between the explanatory variable, $\Delta Turnout_{o(b),d(b)}$, and the absolute value of the difference between the mover's trait and the average of the same trait for the block neighbor's (excluding members of the mover's household). We run a single regression including the main effects and interaction terms for gender, age, years of education, occupation, and household size. The results, presented in Table OA-2, show that even though the differential effects all go in the expected direction (i.e., similarity strengthens the effect of the exposure), the effect sizes are small in magnitude. For example, a one standard deviation in the difference between the age of the mover and that of her neighbors results in an increase of 0.2 percentage points in the effect of the main explanatory variable.

Clientelism. Could clientelism explain the block-level neighborhood effects on turnout that we have documented? There is, in fact, little question that clientelistic exchanges are common in present-day Mexico. Nevertheless, all the available evidence suggests that clientelism in Mexico (as virtually everywhere else) operates on geographical units much larger than the block—our geographical unit of analysis. Shefner (2001), for example, documents a squatter community near Mexico City where clientelism operates at the level of "colonia," which is much larger than precinct (and in some cases larger than a zip code). Hagene and González-Fuente (2016) similarly find clientelism at the level of community in Xico, Veracruz (population over 35,000) and in San Lorenzo Acopilco in Mexico City (population 24,000). In Xico, brokers "went to all the houses, including the remote settlements, and those of opposition" and gave "live animals, goats and chickens" (p.14). These ethnographies suggest that clientelism does not vary at the block level because blocks are only small subsets of any relevant electorate and because people share a community-wide sense of belonging, which could even make it counterproductive to treat blocks differently within one same community. Larreguy et al. (2016) and Larreguy et al. (2017) argue that brokers employed by political parties in Mexico are responsible for at least a full precinct, not a block. In this case, the argument is about the possibility of monitoring the brokers' effort: precinct level electoral results are readily available (while block level results are not). Organizational brokers, as Holland and Palmer-Rubin (2015) refer to leaders who can deliver the full set of votes of their organization's members, operate on an even larger scale than run-of-the mill party brokers. In cross-national perspective, Mexico appears quite typical in this sense.[21]

Clientelism, as an alternative explanation, would also stand at odds with our empirical findings. The fact that the treatment effects become stronger, the longer a mover has spent at destination, is inconsistent with common forms of contemporary clientelism, whereby money or goods are distributed just prior to the elections in anonymous, one-off exchanges.[22] Moreover, clientelism could also not account for the finding that non-movers' turnout is influenced by the past turnout of those who move into their block (presented in the next section).[23]

[21] Levitsky (2003), for example, relates that clientelism in Argentina operates at the level of a "base unit" (*Unidad Básica*), which on average encompasses 1750 citizens in La Matanza and 2400 citizens in San Miguel Tucuman (p.60), and Stokes et al. (2013) exemplify the lowest-level broker in Venezuela (*jefe zonal*) as someone who was responsible for 13 blocks.

[22] Recipients of gift cards given out by the PRI in the 2012 elections, for example, recounted that they received the cards from "people they met at random" Cantú (2019) (see also (Szwarcberg, 2012; Muñoz, 2014)).

[23] We thank the Editor for these two helpful insights.

5 Additional Analyses

In this section, we present additional analyses aimed at probing the mechanism at work. Specifically, we test for two kinds of empirical implications of peer effects. First, if peer effects are at play, then block-level turnout should not only affect the voting behavior of movers, but also of the people in the blocks that received movers—although we do not expect the effect to be as large as for a mover, whose whole environment changes. Second, peer effects require that neighbors interact with each other regarding matters related to the election. We test whether block neighbors are more likely to attend an INE office to obtain or replace their voter ID on the same day than people who live in different blocks within the same precinct.

Peer effects of movers on non-movers

In this analysis, the mover's past voting behavior is the treatment variable. The dependent variable is the voting behavior of residents at the mover's destination block (who themselves are not movers). We henceforth refer to movers as "arrivers." This provides a separate test for peer effects that complements our main analysis. In this case, the only variable that changes for non-movers (whose voting behavior is the dependent variable) is the past voting behavior of the arrivers. The notional comparison is between two blocks that both received a mover, but one of the movers had voted in the past while the other had not. Also in contrast with our main analysis, this test uses data for both movers and non-movers.

We estimate the following econometric specification for "stayer" (i.e., non-mover) individuals in our sample:

$$V_{ib(d),2015} = \alpha + \beta T_{b(d),2012} + \theta X_i + \mu A_{b(o)} + \delta_d + e_{ib(d)}, \tag{2}$$

where $V_{ib(d),2015}$ is an indicator for whether individual non-mover i in block $b(d)$ voted in the 2015 elections. Our main independent variable, $T_{b(d),2012}$, measures the average 2012 turnout of all those movers who arrived in block $b(d)$.[24] The regression includes the same set of individual controls X_i that we used in the main analysis, as well as a set of controls $A_{b(o)}$ based on arrivers' traits, including census information about the arrivers' precinct of origin as well as average individual characteristics of arrivers. Finally, the regression includes destination-precinct fixed effect δ_d.

[24] For example, if 3 movers arrived in block $b(d)$, of which 2 had voted in 2012 and 1 had not, then $T_{b(d),2012} = 2/3$.

Table 5: **Effect of arrivers' past turnout on the turnout of non-movers at destination**

	Dependent variable Individual non-mover's turnout in 2015		
	(1)	(2)	(3)
Average past (2012) turnout of arrivers to the block	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
Individual non-mover's turnout in 2012	0.311***	0.311***	0.310***
	(0.001)	(0.001)	(0.001)
Male	-0.036***	-0.036***	-0.036***
	(0.002)	(0.002)	(0.002)
Age	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
Household size 2015	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)
Distance to polling station in 2015 (km)	-0.024***	-0.024***	-0.024***
	(0.003)	(0.003)	(0.003)
N	562241	562241	529028
R^2	0.229	0.229	0.231
Mean of dependent variable	0.410	0.410	0.410
Mean of avg. past (2012) turnout of arrivers to the block	0.510	0.510	0.510
Effect per one SD chg. in avg. past arriver turnout	0.00201	0.00193	0.00192
Destination precinct fixed effects	✓	✓	✓
Non-mover individual and block level controls	✓	✓	✓
Arriver individual-level controls		✓	✓
Dropping citizens in arrivers' households			✓

This table reports regression estimates of the association between the average past (2012) turnout of movers arriving at a given block ("arrivers") and the individual 2015 turnout of non-movers at that block. We estimate OLS regressions as described by equation 2 in the text. The main explanatory variable is the average 2012 turnout of the set of arrivers to block $b(d)$ where non-mover i lives. Thus, the dataset on which these regressions are estimated contains one row per non-mover. The dependent variable is individual level turnout for the non-mover in 2015. The equation includes destination precinct fixed effects. The set of control variables in X_i is the same as the individual and block-level controls in column 3 of Table 4, excluding distance between address in 2012 and address in 2015, and the indicator for whether a mover crossed state lines, since the analysis here focuses on non-movers. We exclude from the sample blocks where the proportion of arrivers constitutes either less than 10% or more than 90% of the population of the block. The specification in column 2 additionally includes controls for the average individual characteristics of arrivers (age and gender), the number of movers arriving to the block, and indices for the average economic, demographic, household, and education census variables corresponding to the arrivers' precincts of origin (these indices were constructed via principal-components analysis of census variables; see Appendix for details). The specification in column 3 excludes from the sample citizens residing in the same households as the arrivers. Standard errors, displayed in parentheses below the coefficient estimates, are clustered at the block level.
Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

We present the estimation results of Equation 2 in Table 5. In column 1, we see that the average 2012 turnout of arrivers positively correlates with the turnout decisions of non-movers in 2015. The point estimate of 0.005 (clustered standard error = 0.002; clusters are 2015 destination blocks) implies that a one standard deviation increase in the average 2012 turnout of the arrivers is associated with an increase in a non-mover's propensity to vote of 0.2 percentage points.[25] As in our main analysis, the inclusion of precinct fixed effects strongly controls for selection of movers into destinations. Nevertheless, as additional checks we control for the number of arrivers and their average characteristics (column 2). The inclusion of these controls does not affect the point estimate. Column 3 further excludes all individuals who reside in the same household as the arriver at destination from the analysis. Again, the point estimate remains unchanged. Overall, we take these results as further evidence for peer effects.[26]

Beyond voting: Peer effects in bureaucratic electoral procedures

We now use our data on procedures relating to voter registration and the voter ID in order to further test for peer effects. Insofar as people interact with their neighbors about voting-related matters in daily life, peer effects should be apparent not just in turnout behavior. They should also influence a person's decision of when to register to vote, renew one's voter ID, or any other related bureaucratic procedures that precede an election and are required to turn out and cast a vote.

Specifically, we test whether citizens who live on the same block (but, crucially, not in the same household) are more likely to perform such procedures on the same day than citizens who live on different blocks within the same precinct. As explained in Section 2, to conduct any of these procedures, citizens attend an INE office in person. INE offices are open throughout the year, and both appointments and walk-ins are accepted. If citizens decided independently when to go to an INE office to update or renew their voter IDs, one would not expect to observe any difference between block neighbors and neighbors who live on different blocks within the same precinct in the likelihood of performing a procedure on the same day. Conversely, if citizens were more likely to discuss election-related matters with their block neighbors, then one would expect block neighbors to be more likely to conduct electoral procedures on the same day than neighbors on different blocks. We view this as a strong test for peer effects, as we are hard-pressed to find an alternative explanation for why, within a precinct, block neighbors are more likely to go to an INE office *on the same day* than neighbors on different blocks, other than peer effects.[27]

We construct our estimation sample on the basis of the universe of electoral procedures in

[25] One way to think about this estimate is as a reduced form effect, where the first stage would be the effect of having voted in 2012 on voting in 2015 for the arriver (which is approximately 0.2-0.25 on the basis of Table 4). Under this interpretation, the treatment on the treated would be approximately five times as large as the reduced form, that is, about 1 to 1.25 pp for a one standard deviation change in the 2012 turnout of arrivers.

[26] We have also estimated Table 5 weighting by the number of arrivers in the block. Results are unchanged to 3 decimal points. We also have experimented with clustering standard errors at the origin-precinct level and at the origin-destination precinct level. Again, the standard errors are the same up to 3 decimal points.

[27] Bhatti et al. (2020) show that *household members* are more likely to attend the polls together.

the year-or-so preceding the 2015 elections (June 2014 to May 2015).[28] We restrict the sample to registered voters who performed a procedure in this time window. We further restrict the sample to precincts that have at least 40 such voters, living on at least two blocks, with at least two voters on each block. Within every precinct in this sample, we randomly draw 10 pairs of citizens who live on the same block and an additional 10 pairs of citizens who live on different blocks within the same precinct.[29] As constructed, our estimation sample contains approximately 970,000 pairs of citizens. We estimate the following regression:

$$Procedure_{ij} = \theta_p + \beta I(Same\ Block)_{ij} + \beta' \mathbf{X}_{ij} + e_{ijp}, \tag{3}$$

where $Procedure_{i,j}$ is an indicator that takes the value of 1 when citizens i and j, $i \neq j$, (who by construction live in the same precinct) performed an electoral procedure on the same day, and 0 otherwise. The indicator $I(Same\,Block)_{ij}$ equals 1 if citizens i and j lives on the same block according to the 2015 voter list. We include precinct fixed effects θ_p, which absorb all cross-precinct variation.

Table 6: **Neighbor influence in electoral procedures**

	All procedures	Enrollment	Replacement
	(1)	(2)	(3)
Same block	0.012***	0.007***	0.013***
	(0.000)	(0.001)	(0.001)
Precinct fixed effects	✓	✓	✓
With controls	✓	✓	✓
Observations	972619	214072	530010
R^2	0.109	0.094	0.144
Mean number of same-day procedures for non-block neighbors	0.018	0.016	0.020

This table reports estimates of equation 3. We cluster standard errors at the precinct level. Column 1 reports results using all procedures performed, while columns 2 and 3 focus on enrollment and INE ID replacement procedures, respectively. The number of observations is highest in column 1 as the sampling of pairs draws from the larger population of those doing any procedure. The last row of the table displays the mean probability that a pair of randomly chosen registered voters living in different blocks within the same precinct perform a procedure at the INE office on exactly the same day.
Significance: * p<0.05; ** p<0.01; *** p<0.001

The evidence that we presented earlier in the paper shows that there is virtually no selection into blocks once precinct fixed effects are considered. Nevertheless, one might hypothesize that people of similar age, education, or occupation, or of the same gender, might be both more likely to live on the same block and to attend an INE office on the same

[28] Not all electoral procedures can be performed right up to Election Day; INE sets specific deadlines for registration, renewal, and correction of voter IDs much before the election takes place.

[29] A given citizen may appear in more than one pair, but we dropped identical pairs.

day. To guard against this possibility, we control for a set of indicators $\mathbf{X}_{ij}$, each taking the value of 1 when citizens i and j are of the same gender or are in the same category of age, gender, occupation, schooling level, or quartile of distance from home to polling booth. Note also that the control group (precinct neighbors living on different blocks) is extremely similar to the treatment group (precinct neighbors living on the same block) in terms of socio-demographic traits, local infrastructure, exposure to political information, and exposure to mobilization efforts, importantly limiting the scope for selection in the first place.

The first column in Table 6 presents the results for a dependent variable that pools across all different types of procedures.[30] The coefficient on the indicator for living on the same block implies that block neighbors are 1 percentage point more likely to conduct a procedure on the same day vis-a-vis a pair of precinct neighbors living on different blocks. Given a sample mean of 0.018, this implies a 66 percent increase in the probability of conducting a procedure on the same day. In columns 2 and 3, we respectively focus on registering to vote and on replacing one's voter ID—the two most common procedures. In both cases, block neighbors are significantly more likely to perform these procedures on the same day compared to neighbors who live on different blocks. The marginal effects are similar in magnitude as that in column 1. We take these results as evidence consistent with a peer effects mechanism for our main findings.

6 Conclusions

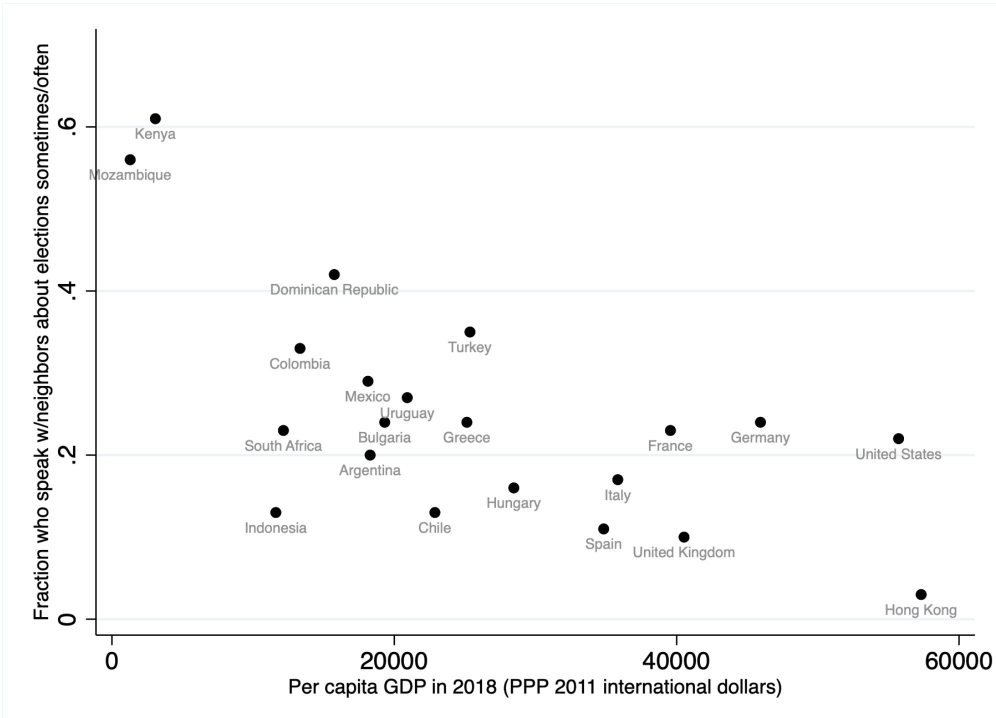
Explaining variation in turnout is a challenge that has long vexed political scientists. In this study, we suggest that neighborhoods may play an important role in explaining part of this puzzle. In particular, we show that the actions of one's neighbors affect not only one's propensity to vote, but also to register and perform other electoral procedures. Our emphasis on proximate neighbors—which we operationalize as neighbors on one's same block—connects with recent work on intergenerational mobility that underscores the importance of context at the very local, sub-neighborhood level (Chetty and Hendren, 2018b; Pinsker, 2019). Our findings show that what is true for intergenerational mobility is also true for voter turnout. While our results point to peer effects as a key channel of influence, it remains unclear what the sources of these effects might be. Whether they come from social conformity or from neighbors learning from one another remains an open question for future research.

We believe our general findings are likely to extend beyond the Mexican case, for two reasons. First, cross-locality variation in voter turnout is very large in many countries, as

[30] That is, the dependent variable takes the value of 1 if citizens i and j attended an INE office on the same day to perform a procedure *of any type*. The set of procedures includes: change of address, data corrections, enrollment, and replacement of voter ID.

Table 1 shows. Second, cross-national survey evidence suggests that the fraction of citizens who talk to their neighbors frequently about elections is substantial, particularly in middle to low income countries (Figure 6).

Figure 6: Fraction of people who talk to neighbors about elections by country



Source: Authors' calculations based on Comparative National Election Project data for the question: "How frequently did you speak to your neighbors about electoral campaigns: very frequently, sometimes, rarely, never." Income is per-capita GDP in 2018, expressed in 2011 purchasing power parity international dollars, taken from the World Development Indicators.

Finally, to the best of our knowledge this is the first systematic evidence on peer effects in turnout outside the global North. Most electoral systems today, and most democracies, are in the global South. As such, the evidence from Mexico is perhaps more representative of the modal case than most of the existing literature, which has focused largely on the United States. Figure 6, for example, shows that the fraction of voters who speak to their neighbors about elections is strongly and inversely associated with a country's per-capita GDP. This suggests that peer effects could matter even more in middle- and low-income democracies than in high-income countries.

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Voting with One's Neighbors: Evidence from Migration within Mexico

Appendix – For Online Publication

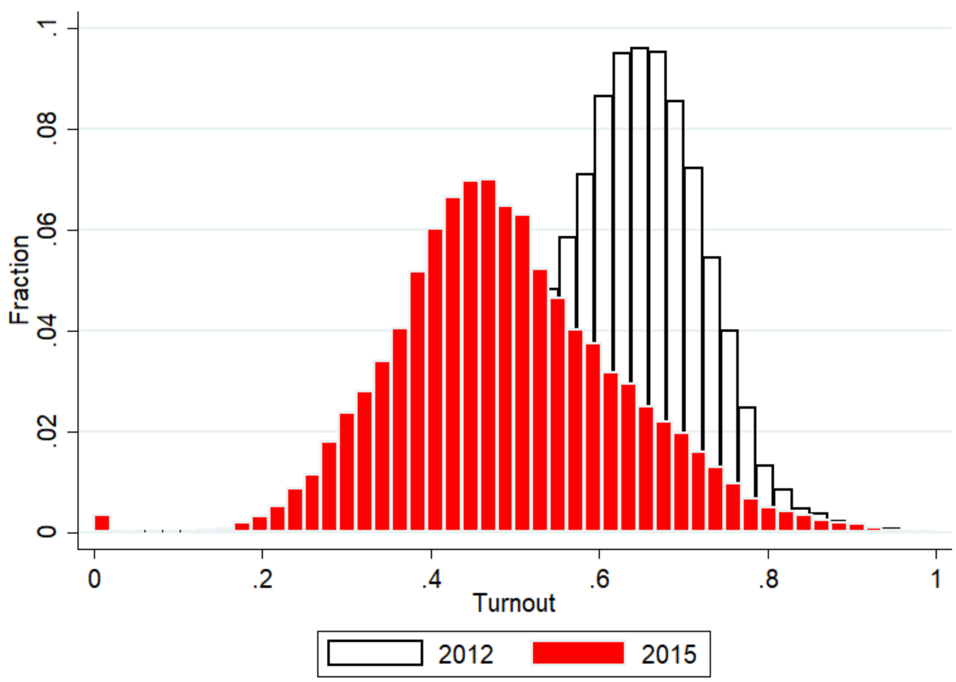
Frederico Finan, Enrique Seira, and Alberto Simpser

Appendix A. Further results

Figure OA-1: Blocks in a precinct

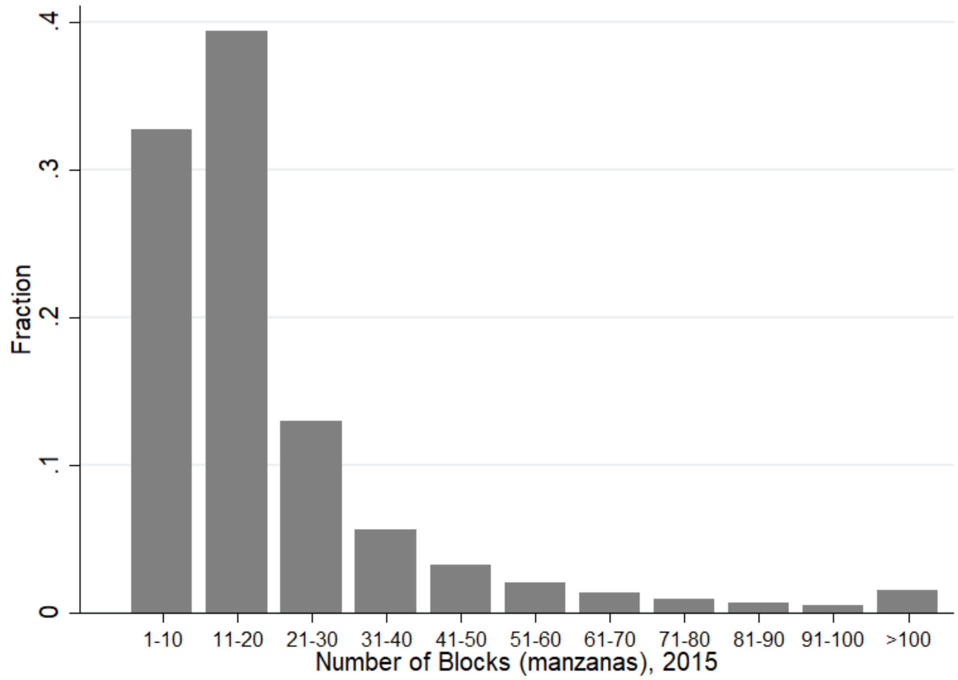
Panel A shows an example of blocks within a precinct in Mexico City. The black lines delimit one precinct and the grey lines delimit blocks.

Figure OA-2: Precinct level turnout



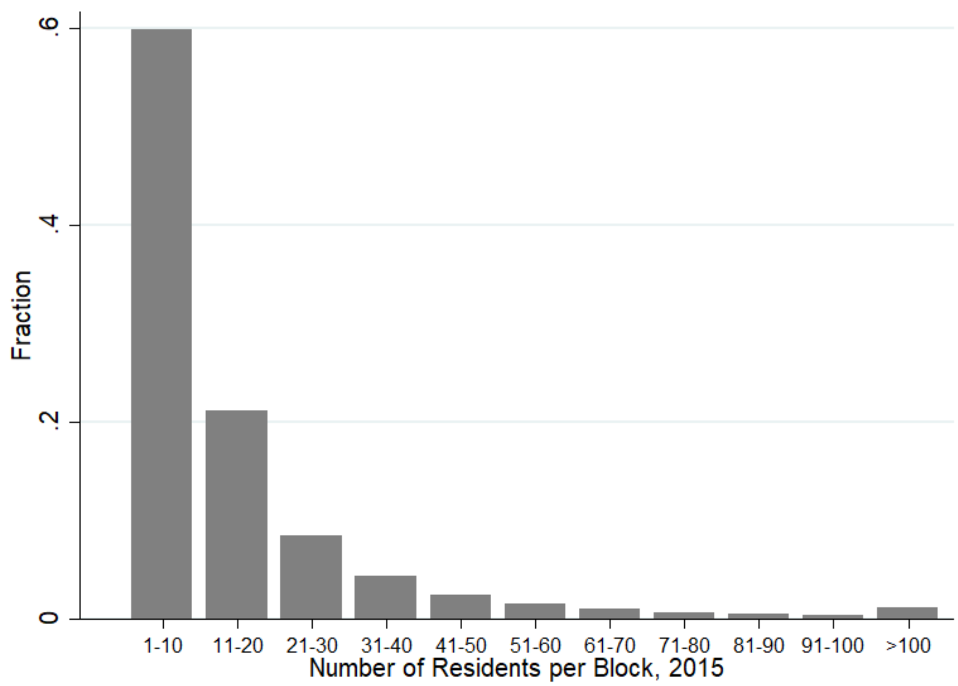
This figure shows the distribution of voter turnout at the precinct level for the 2012 and 2015 elections in the analysis sample.

Figure OA-3: Number of blocks per precinct



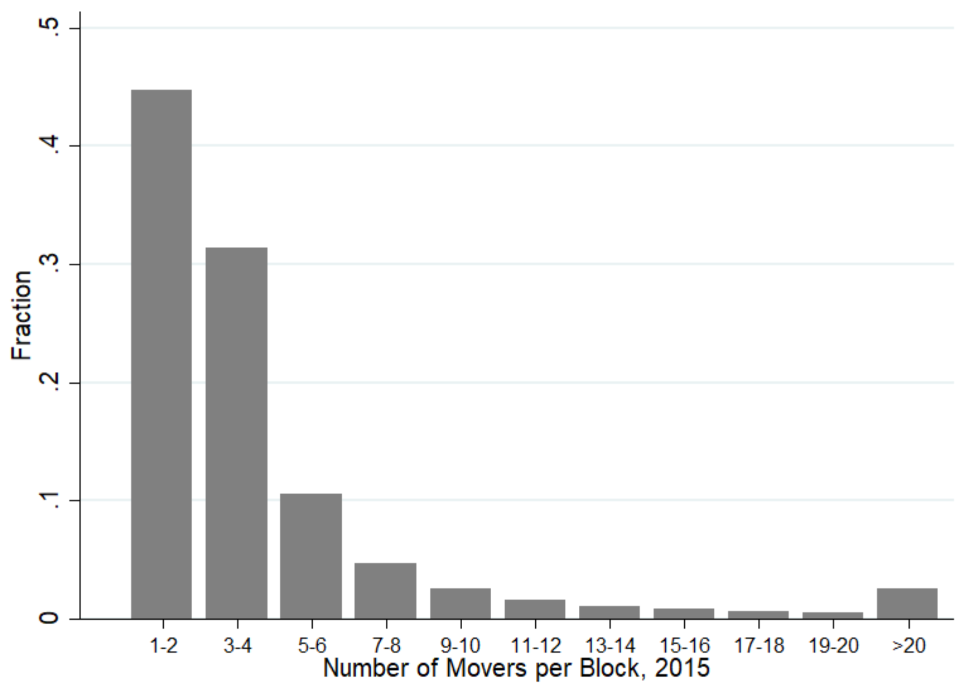
Histogram of the fraction of blocks per precinct in 2015 where an observation is a precinct.

Figure OA-4: Number of residents per block



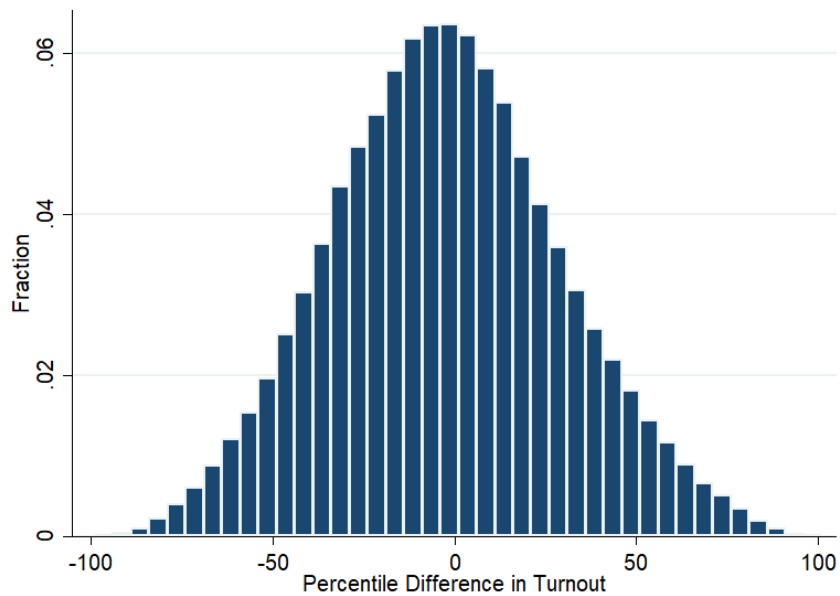
Histogram of the fraction of residents per block in 2015 where an observation is a block.

Figure OA-5: Number of movers per block



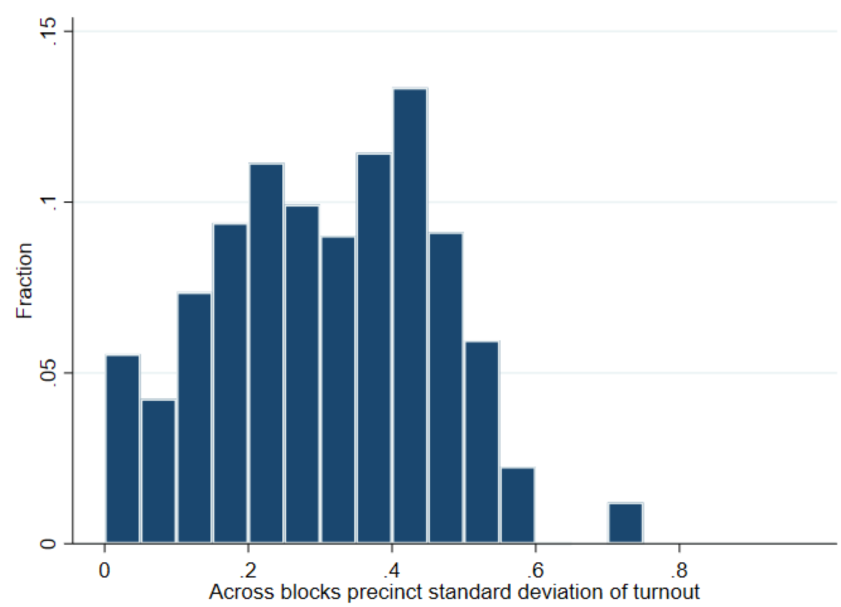
Histogram of the number of movers per destination block where an observation is a block.

Figure OA-6: Percentile turnout differential exposure (block level)



This figure plots the differential exposure of movers to percentile differences in their block turnouts. An observation is a mover. For each mover we first assign a percentile to average turnout of registered voters in the destination block in 2015 as well as a percentile for the average turnout of registered voters in the origin block in 2012, and take the difference of percentiles (2015 destination block percentile minus 2012 origin block percentile). The variable is bounded in [-100,100].

Figure OA-7: Distribution of standard deviation of block-level turnout within precincts



An observation in this figure is a precinct in the 2015 data. For each precinct we compute the standard deviation of (average block) turnout across blocks within that precinct. We then plot a histogram of those standard deviations. The average standard deviation is 0.30.

Table OA-1: **Main results with maximal sample**

	Dependent variable: individual mover's turnout in 2015					
	(1a)	(1b)	(2)	(3)	(4)	(5)
Destination-origin block turnout difference	0.0687***	0.0662***	0.0767***	0.0426***	0.0550***	
	(0.003)	(0.003)	(0.003)	(0.004)	(0.011)	
Destination-origin block turnout percentile diff.						0.00163***
						(0.000)
Individual mover's turnout in 2012	0.241***	0.244***	0.207***	0.209***	0.253***	0.271***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)
Male			-0.0293***	-0.0285***	-0.0342***	-0.0338***
			(0.002)	(0.002)	(0.005)	(0.005)
Age			0.00362***	0.00364***	0.00350***	0.00342***
			(0.000)	(0.000)	(0.000)	(0.000)
Household size 2015			0.00419***	0.00398***	0.00261***	0.00239**
			(0.000)	(0.000)	(0.001)	(0.001)
Distance to polling station in 2015 (km)			-0.0133***	-0.0134***	-0.0132**	-0.0130**
			(0.001)	(0.001)	(0.004)	(0.004)
N	1153091	1206229	583474	516335	516335	528698
R^2	0.199	0.200	0.243	0.244	0.735	0.727
Mean of dependent variable	0.379	0.380	0.350	0.351	0.351	0.353
Mean of destination-origin block turnout diff.	-0.166	-0.158	-0.179	-0.182	-0.182	-3.080
Effect per 1 SD chg. in block turnout diff.	0.0148	0.0141	0.0165	0.00895	0.0115	0.0484
Individual-level controls			✓	✓	✓	✓
Block-level controls				✓	✓	✓
Destination precinct fixed effects	✓	✓	✓	✓		
Origin-destination precinct pair fixed effects					✓	✓

This table is analogous to Table 4 in the main paper, except that instead of keeping the same sample across columns, we try to maximize sample size in each columns. The different sample sizes arise because the control variables change across columns and these controls have missing values. Results are very similar nonetheless.
Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table OA-2: **Heterogeneity of exposure to neighbors**

	Block (baseline)		Block pair FE	
Variable	Coefficient (1)	1 sd change (2)	Coefficient (3)	1 sd change (4)
$\Delta Turnout_{o(b),d(b)}$*blockdiff_gender	-0.0584***	-0.0010	-0.0616	-0.0010
	(0.017)		(0.053)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_age	-0.0018***	-0.0009	-0.0024	-0.0012
	(0.000)		(0.001)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_years_education	0.0007	0.0001	0.0039	0.0006
	(0.002)		(0.005)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_housekeeper	0.0146	0.0002	0.0597	0.0009
	(0.016)		(0.047)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_employee	-0.0358*	-0.0006	-0.0051	-0.0001
	(0.015)		(0.047)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_student	-0.0092	-0.0001	0.0423	0.0005
	(0.018)		(0.055)	
$\Delta Turnout_{o(b),d(b)}$*blockdiff_household_size	-0.0029	-0.0004	-0.0028	’0.0004
	(0.002)		(0.005)	
N	512394		512394	
R^2	0.244		0.735	
$\lvert Avg.\ \Delta Turnout_{o(b),d(b)}\rvert$	0.183		0.183	

To explore heterogeneity of the effect of exposure to neighbors, this table uses the main specification in equation 1 and adds covariates (z^k) of "similarity" between the mover and her neighbors, and their interactions with our main explanatory variable $\Delta Turnout_{o(b),d(b)}$. These covariates are the absolute value of the difference between the mover's k=gender, age, years of education in 2015, household size in 2015, and dummies of the three main occupations in the dataset (housekeeper, employee, student) and the same variables averaged across her (non-family $f(i)$ member) neighbors: $z^k = |x_i^k - Avg(x_j^k)|_{j\neq f(i)}$. The table reports only the interaction coefficients on $z^k \times \Delta Turnout_{o(b),d(b)}$ along with their standard errors (columns 1 and 3). Column 1 uses the baseline specification corresponding to column 2 in Table 4, including destination precinct fixed effects, while column 3 corresponds to the same specification as in column 2 with added pair precinct fixed effects. A negative value indicates that the more different they are the smaller the effect of living in the same block on turnout. Even columns correspond to the implied magnitude of the effect on 2015 vote of the mover from a 1 standard deviation change in z^k, multiplied by the absolute value of the average of $\Delta Turnout_{o(b),d(b)}$ (0.182). For instance, a 1 standard deviation in the difference between the age of the mover and that of their neighbors results in a decrease of 0.1 percentage points of the effect of $\Delta Turnout_{o(b),d(b)}$.
Significance: * p<0.05; ** p<0.01; *** p<0.001

Table OA-3: **Neighbor influence in electoral procedures - Restricted time period**

	All procedures	Enrollment	Replacement
	(1)	(2)	(3)
Same block	0.012***	0.009***	0.014***
	(0.000)	(0.001)	(0.001)
Precinct fixed effects	✓	✓	✓
With controls	✓	✓	✓
Observations	970846	213084	516229
R^2	0.111	0.091	0.144
Mean same-day procedure for non-block neighbors	0.018	0.017	0.020

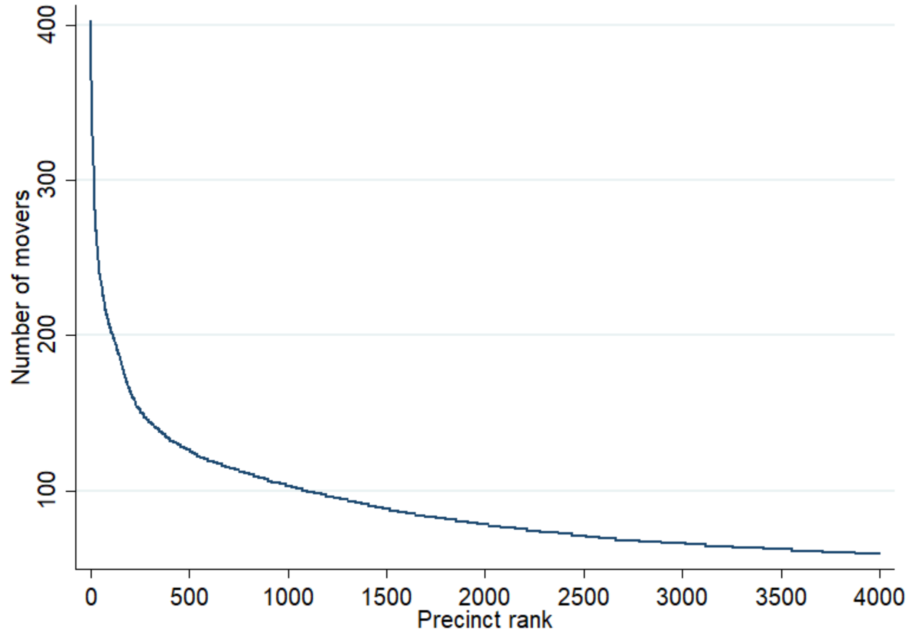
This table is analogous to Table 6, but we restrict the sample period from June 2014 to February 2015.
Significance: * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Table OA-4: **Variable list**

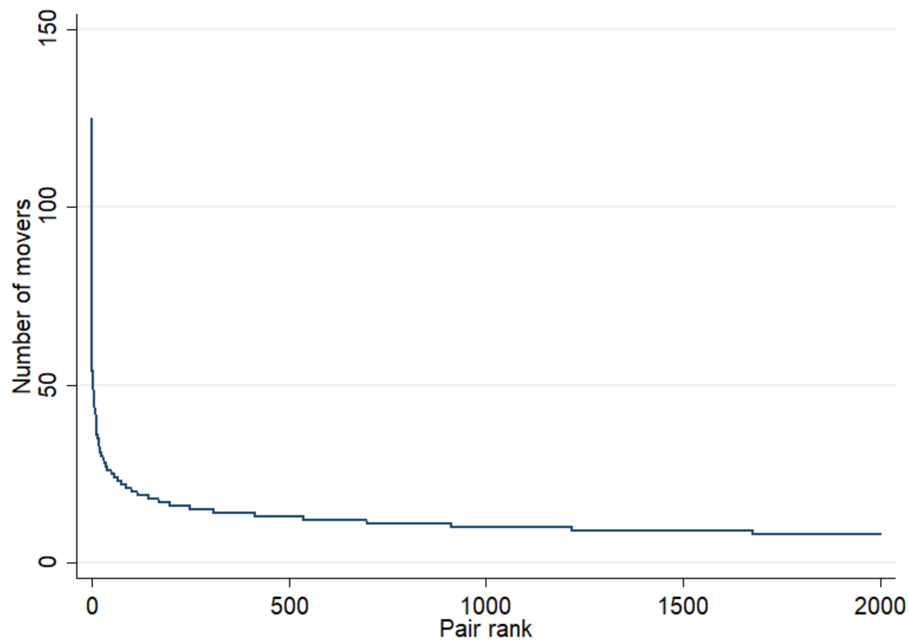
Variable	Source	Notes
Precinct code/identifier	Census 2010 at precinct level	
PCA of demographics variables	Census 2010 at precinct level	Total population, male population, female population, population by gender and age intervals, number of houses, population by religious beliefs, population by marital status.
PCA of education variables	Census 2010 at precinct level	Children who do not attend school by age interval and gender, children who attend school by age interval and gender, population with illiteracy by age interval and gender, population by educational attainment by age interval and gender.
PCA of economic variables	Census 2010 at precinct level	Employed population, unemployed population, economically activate population, inactive population.
PCA of household variables	Census 2010 at precinct level	Number of occupied houses, number of unoccupied houses, average number of occupants per house, number of houses by type of floor, number of houses by number of rooms, number of houses with various goods (refrigerator, radio, television, car, etc.), number of houses by access to public services (water, electricity, sewage, etc.).
Unique citizen code/identifier	Padron Electoral 2012, 2015, 2018	
Socio-demographic variables	Padron Electoral 2012, 2015, 2018	Gender, Age, Occupation (housework, student, employee, etc.) and education level attainment (no education, high school, undergraduate, etc.)
Citizen location	Padron Electoral 2012, 2015, 2018	State, Locality, Precinct and Block of residence
Polling station	Padron Electoral 2012, 2015, 2018	
Unique citizen code/identifier	Individual vote 2012, 2015	
Dummy citizen voted	Individual vote 2012, 2015	
Unique citizen code/identifier	Voter ID Procedures 2015, 2018	
Type of procedure	Voter ID Procedures 2015, 2018	Registration, change of address, etc.
Date of procedure	Voter ID Procedures 2015, 2018	
Numbers of voter id had	Voter ID Procedures 2015, 2018	
Unique citizen code/identifier	Households 2012, 2015	
Household code/identifier	Households 2012, 2015	
Number of household members	Households 2012, 2015	
Block code/identifier	Blocks shapefile	
Block centroid coordinates (latitude and longitude)	Blocks shapefile	
Polling station code/identifier	Polling Station Coordinates	
Coordinates (latitude and longitude)	Polling Station Coordinates	
Precinct code/identifier	Electoral results 2012, 2015	
Total votes at the precinct level	Electoral results 2012, 2015	

Number of registered voters at the precinct level	Electoral results 2012, 2015	
Turnout at the precinct level	Electoral results 2012, 2015	

Figure OA-8: Flow of movers



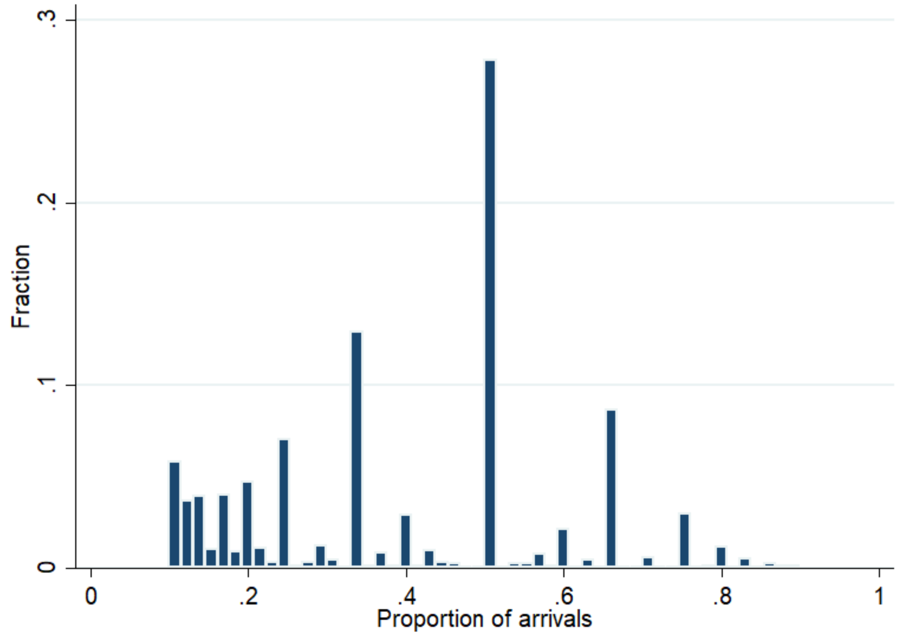
(a) Movers by origin precinct



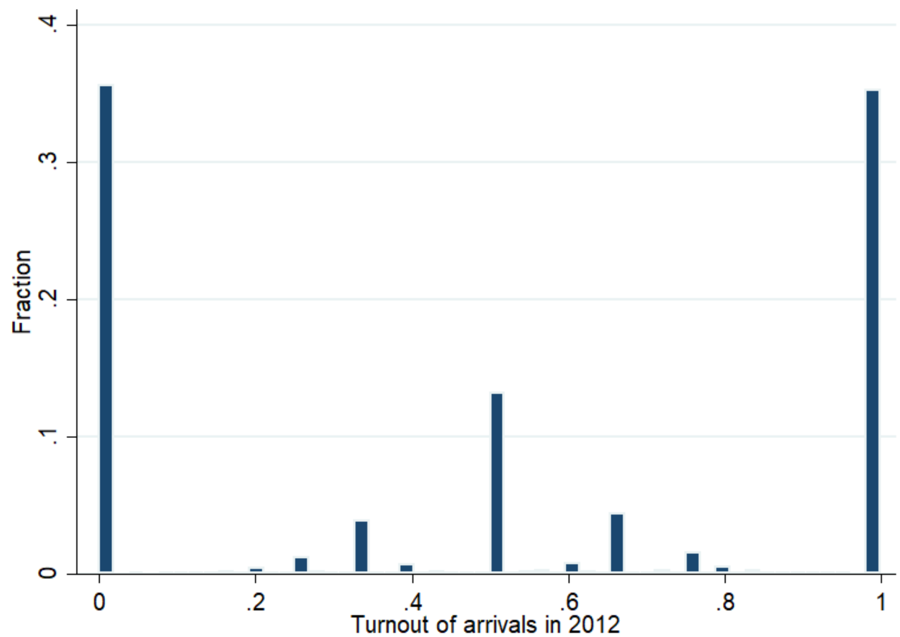
(b) Movers by origin-destination precinct pair

Panel (a) shows the number of movers by precinct of origin. For each of the precincts we counted the number of voters that were registered there in 2012 and moved to another precinct by 2015. Panel (a) plots this count ordered by precincts with the largest the number of such movers. We truncate the figure at the top 10,000 origin precincts. Panel (b) shows the number of movers across precincts between 2012 and 2015 for all origin-destination precinct *pairs*. The figure plots the 2,000 precincts with the highest flow, ordered from highest (left) to lowest (right).

Figure OA-9: Arrivers to a block



(a) Arrivers as fraction of block's registered voter



(b) Average 2012 turnout of block' arrivers

Panel (a) shows the proportion of arrivers in 2015 in a block as a proportion of that block's registered voters in 2015. Panel (b) shows the distribution of turnout in 2012 of the arrivers at the block level, which is our measure of "influence". Only blocks with at least 10% and no more than 90% of its residents being arrivers are included in the figures.