Dwelling on Turnout:

A GIS-based study on the neighborhood effect and local election vote density in Brookline, MA

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Abstract: Considerable scholarly attention is paid to the issue of the neighborhood effect. There is disagreement about the mechanism that causes the neighborhood effect. The goal of this study is to show that consistent voter turnout is geographically clustered at the local level. Despite the lack of a sharp political or racial divide in the town of Brookline, MA, which is the subject of similar studies on the topic, there is a relatively even divide between house-dwelling and apartment-dwelling registered voters. Using voter data projected onto GIS-based maps, I will show that if we rank voters by participation in recent elections, in some neighborhoods of houses there is a correlation between the regularity with which someone votes in local elections, and their relative proximity to other people, both neighbors and cohabitants, who have a similar voting record.

Introduction:

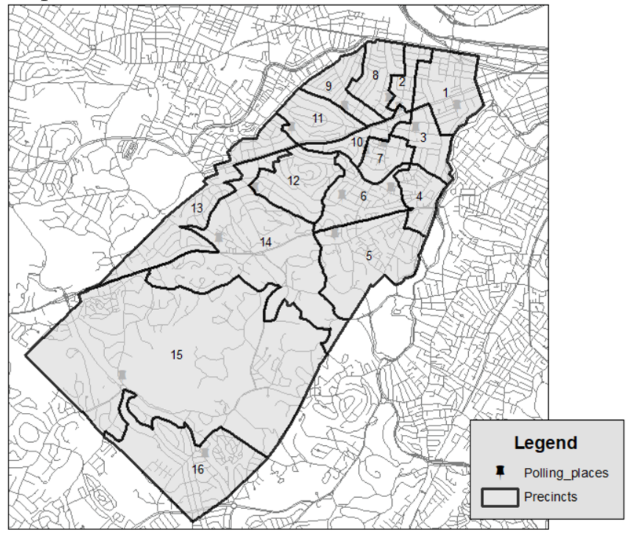
Political participation is critical to American democracy. It is the only way citizens can communicate their interests, preferences, and needs to the government. For this reason, scholars have paid attention to why some people vote more often than others. Literature points to a set of individual-level characteristics, like race and socioeconomic status, that are associated with higher levels of participation as well as work by party elites meant to mobilize members of certain groups as potential mechanisms for a neighborhood effect. Other research on the topic points to more subtle, contextual factors about neighborhoods that affect the likelihood of participation among its residents. This paper explores a relatively non-political trait by which to divide neighborhoods, choice of dwelling (house or apartment). Despite the lack of a large political or racial divide in Brookline, there is a pretty even mix of house-dwelling and apartment-dwelling registered voters. I will show how, in certain neighborhoods of houses, the more often someone votes, the closer they live to other people who always vote as often. In order to substantiate this claim, I calculated the average distance between groups of houses whose residents share a similar voting record in local elections over the last five years. I will show how house-dwellers make up a majority share of turnout in local elections and that within that group the highest turnout is concentrated in different parts of the town in different years. Using data from the Brookline voter file, public tax assessment data, and open source GIS maps, I hope to find for certain neighborhoods that the regularity of house-dwelling voters' participation in local elections is correlated with the average proximity between all houses with a similar voting record.

Definitions:

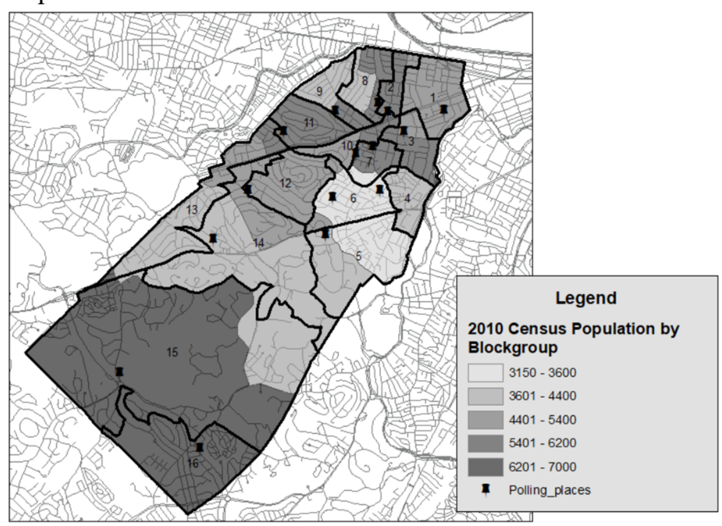
This section helps the reader better understand the town of Brookline and relevant terminology used in the paper. Included are maps generated using geographic information system (GIS) software.

- Neighborhood: A neighborhood is a residential group within a voting precinct. The average distance from every house in a neighborhood to all other houses in the neighborhood is less than that of the precinct as a whole. In terms of geographic spread, if a line is drawn connecting every house to every other house in the neighborhood, the average of the length those lines will be much less than that of the precinct as a whole
- House: A dwelling with three or fewer housing units
- Apartment: A dwelling with 4 or more housing units
- Street-level address: A street-level address corresponds to a unique set of latitude and longitude coordinates. That is, any registered voters in the same dwelling will share a set of coordinates. There is only one street address for all registered voters who reside in the same building.

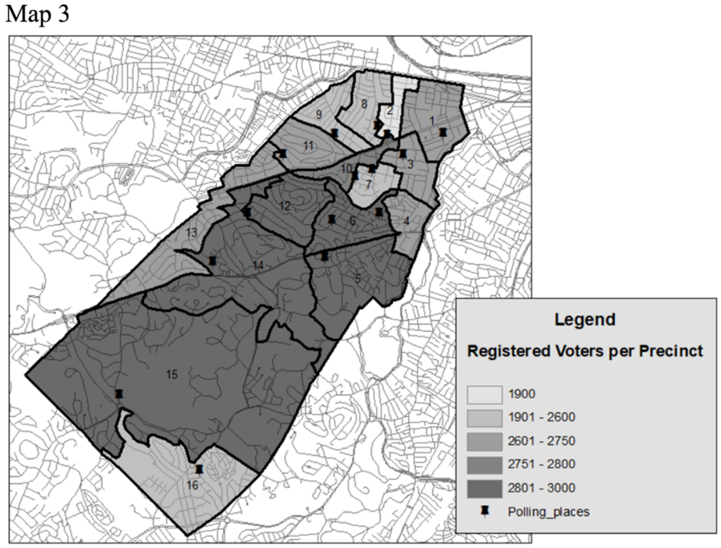
Map 1



Map 2



Map 3



Literature:

Research on the neighborhood effect investigates if a voter's residential area influences *whether* they vote and *how* they vote. In regards to the former, this study investigates participation rates in local elections by neighborhood, specifically within neighborhoods of houses in Brookline, Massachusetts. Despite the lack of an ideological split amongst its residents, clues still exist within the individual voting precincts that neighborhood-specific voting behavior occurs in local elections. This paper analyzes geo-coded voting data for local elections to see if registered voters who vote more often tend to live in denser clusters than those who never vote. This section will analyze existing theoretical literature on the neighborhood effect and explore how technology like GIS can be used to investigate a question like mine. Literature on the neighborhood effect varies in both focus and method. Just as this variation leaves room for disagreement between researchers, so too does it leave room for increasingly specific research questions on the topic. The first major scholarly disagreement about the neighborhood effect is whether the neighborhood effect exists independent of voters' individual-level characteristics. Many studies point to the fact that individual-level factors, like race, socioeconomic status, etc., help people make residential choices, and that people who share traits and behaviors tend to self-select into communities that look and act like them (Rosenstone and Hansen, 2003). Among those who support the notion of a neighborhood effect, there is further disagreement about the mechanism that causes it. Below are four explanations for the neighborhood effect; the first two theoretical mechanisms reject the neighborhood effect, while the second two support the neighborhood effect.

1) <u>Self-selection</u>:

The self-selection thesis posits that contextual effects arise from a self-sorting in which people's residential and political decisions are based on individual-level criteria (Rosenstone & Hansen, 2003). People determine the voting behavior of a neighborhood by choosing to live near other people who look and act like them. This almost rejects the idea of a neighborhood effect because it says that the *individuals* who choose to live in a neighborhood, just because they choose to live with like others, set the participation rate. While other theoretical mechanisms for the effect show how a neighborhood has an effects on residents' decision to vote the self-sorting mechanism works in opposite direction, where voters' collective self-sorting defines the frequency of electoral participation for the neighborhood. Although evidence suggests that self-sorting occurs, it cannot explain the neighborhood effect alone.

2) <u>Elite-driven Processes:</u>

In some political contests, party elites target populations to drive turnout amongst those who they think will vote in their favor. People who are contacted by a party or campaign are far more likely to vote (Huckfeldt & Sprague, 1995). When campaigns or parties try to target specific voting groups, they are often constrained by advertising budgets or number of volunteers, so people are targeted within the confines of a neighborhood boundary (Rosenstone & Hansen, 2003). Highly targeted races, like those in battleground areas, are geographically clustered, so any mobilization efforts in those areas is clustered as well. If vote clustering were solely a product of mobilization it would be easy to see where and why votes are clustered. In this case the locus of competition changes year to year and local elections do not usually see as much media or monetary attention, so the elite-driven processes thesis does not carry much weight here.

3) <u>Social Interaction:</u>

The social interaction thesis is framed in economic terms. At its center is the supply and demand of political information among members of a social network. On the demand side, people want political information quickly and cheaply. On the supply side, a social network is positioned to offer this information at the least possible cost (Huckfeldt, 1979). These networks, however, are assumed to have an informational bias (Huckfeldt & Sprague, 1995). This kind of interaction, or transaction, triggers a social learning process in which individuals are exposed to the ideas of their peers; the beliefs they share are positively reinforced (Huckfeldt & Sprague, 1995). Over time, the participatory tendencies of an individual within the group will start to resemble that of the group. This thesis has considerable empirical support at both the macro and micro level. Studies have found that the likelihood of participation among residents of a neighborhood is influenced by the neighborhood's social, economic, and racial composition (Huckfeldt, 1979; Oliver, 2001). Others have shown the importance of an individual's discussion network in shaping their political participation (Kenny, 1992). People are aware of their surroundings, to the extent that the prevailing attitudes of a neighborhood are strong enough to change voters minds (Johnson, et al., 2002). Moreover, social network involvement gives people with inherently limited understanding, information, and resources the opportunity to learn how their votes impact their lives and lower any perceived boundaries to voting (McClurg, 2003).

4) Casual Observation:

Unlike most of the literature about social interaction, which focuses on how influences on participation are mediated through explicit forms of socialization such as involvement in clubs and organizations, the casual observation thesis posits that a neighborhood may facilitate contextual influence through indirect, or even involuntary, social interaction (Baybeck & McClurg, 2005). This mechanism still involves exposure to meaningful information. In this case it is through low-intensity neighborhood cues like lawn signs, bumper stickers, or even just simple observations of a neighbor's public behavior like how they dress, the car they drive, or the condition of their front yard. This kind of cue communicates prevailing norms and attitudes of a neighborhood and may provide signals about the community's political culture. The distinction between social network cues and casual observation cues, although conspicuous, is important; casual observations are independent of any kind of intimacy a social network has (Huckfeldt & Sprague, 1995). You do not need to know someone to figure out their political stance if their car is plastered with political bumper stickers. Research indicates that people are politically aware of their neighbors' political and economic standing independent of their explicit involvement in any group (Huckfeldt & Sprague, 1995). Ultimately, the casual observation thesis creates a connection between a potential voter's geographic context and their likelihood to participate. Research on the casual observation thesis found the influence of neighborhood cues persisted after taking other potential contextual information into account (Cho & Rudolph, 2008).

Although all have theoretical merit, evidence using geocoded voter information points to the third and fourth explanations. Psychologically-speaking, results from Cho and Rudolph's study imply that the genesis and spread of ideas in a community is not wholly dependent on explicit communication with others (Cho & Rudolph 2008).

Data:

The first major hurdle in this project was forming a detailed research question that could be addressed with the data I had available. My first dataset was the Brookline voter file, which contained information on voters' age, address, and voting record in recent local and state elections, among other things. The first clue in the data that helped me narrow my question was found in a visual comparison of state and local election turnout. Of the elections included in the voter file there were three years where local and state elections occured in the same year, 2012, 2014, 2016. State elections are held every other year on Election Day in November, while local elections in Brookline are held in May. The comparison of two elections in the same year, despite being on different days, highlighted patterns in voting behavior at the local level that were distinguishable from changes in neighborhood composition or the political climate year to year. Finding differences in voter turnout over the 3 election years shared by local and state elections, both in terms of number votes and where the votes were located, was my first step toward a hypothesis.

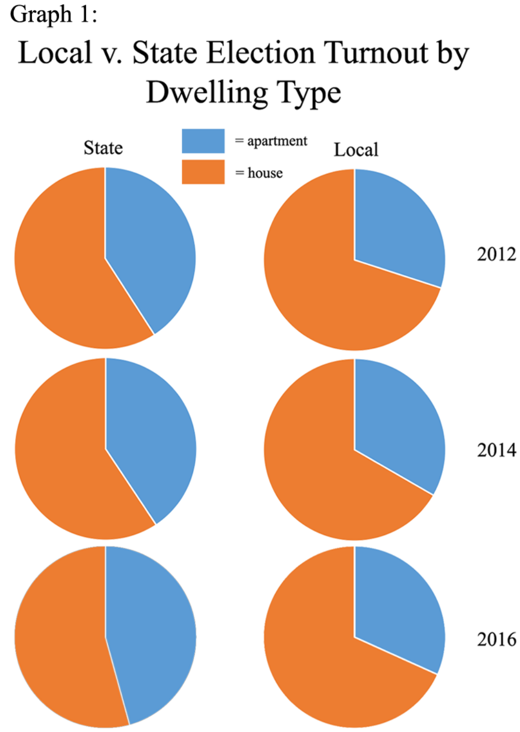
The next dataset I acquired was from a publicly accessible tax assessment database from the City of Brookline's online document service. I was able to download information for all properties assessed for sale in Brookline for a given year. The data includes addresses, value, condition, and amenities for all properties listed. As I will discuss in the methods section, this information was used to determine if a voter lives in a house or an apartment. Despite the dataset being incomplete, not every property in Brookline is listed, trends appeared that could be coded to fill in the gaps with conditional statements like: "If the value of the largest apartment number for a building is greater than three, all units in that building are apartments." This will be discussed in further detail in the methods section.

Finally, the last dataset I used was a series of GIS map layer files from the Town of Brookline, MassGIS, and MassDOT, all obtained through the program ArcGIS. Brookline's online web service has a dedicated page for GIS information ranging from parcels, to precincts, to the location and species of trees around the town. This map data was used for calculations based on precinct as well for census population data. The MassGIS and MassDOT layers were used to provide context for the Brookline map in the form of town boundaries and roads. All three parts of the data were put together to plot voters by dwelling-type in order to find patterns of voting behavior indicative of a neighborhood effect.

Theory/Hypothesis:

Other studies answering similar questions about voter turnout have employed similar GIS-based methods. In College Station, Texas, Sui and Hugill were able to show that when voting was random at a low level, but clustered at the intermediate and high level, local elections tended to be more polarized and show a strong neighborhood effect (Sui and Hugill, 2002). While this study was more concerned with election results than turnout, the researchers were still able to make connections between turnout and density at different levels. In this case, it is less applicable than a similar study by Barber and Imai which analyzed neighborhood-level voting patterns across the country. The study tracked voting participation in neighborhoods across the country based on individual-level characteristics like race and party affiliation, finding that the makeup of a neighborhood affected vote turnout (Barber and Imai, 2014). The researchers found that a ten percent increase in outgroup representation in a neighborhood, that is, a ten percent increase of members from a minority party or race in a neighborhood, leads to an approximate .5 to 2.5 percent decrease in turnout probability. The method employed to test their hypothesis involved a more comparable calculation at the neighborhood level. The Barber and Imai study tracked voting behavior along a binary like political party or ingroup/outgroup for majority race. As mentioned, the divide in Brookline is by dwelling type. Any marked difference in voting behavior along this binary may imply that the theoretical mechanism(s) used to explain the neighborhood effect might apply differently for each. Inherently there are different individual-level factors, like socioeconomics, that might make one more likely to live in an apartment or a house. Additionally forces of party mobilization might express themselves differently in neighborhoods of houses or apartments. Even though the first two mechanisms seem to have different implications for the different kinds of neighborhoods described here, I became more interested in how opportunities for social interaction and casual observation are afforded to residents of each.

Graph 1:



Once voters were coded as either house- or apartment-dwellers, which will be discussed in further detail in the methods section, it was easy to see differences in local and state election turnout.

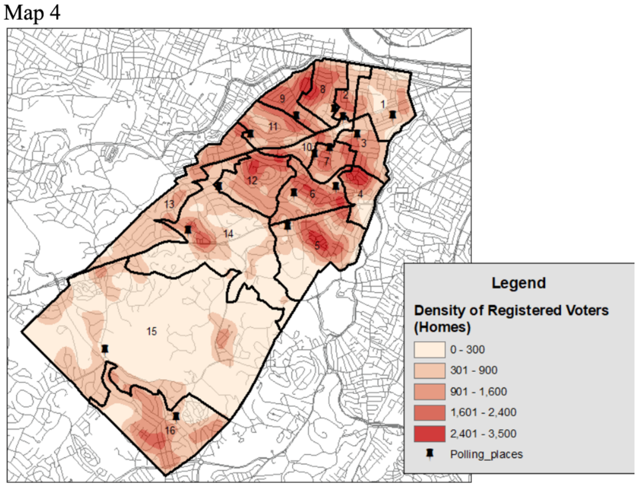
While house-dwellers hovered between 50-60% of the turnout in state elections, they consistently made up 65-70% of the turnout in local elections, indicating that a neighborhood effect, if it exists, would be found by looking at recent local election data and by limiting the search to neighborhoods of houses. The kernel density maps for those elections, located in the Appendix, show that while house-dwellers consistently cast 60 to 70% of the votes in local elections, the most dense areas change year to year. This tells us that even though not every neighborhood votes every time, yearly changes in the locus of density indicate that neighborhood specific voting effects may be at play, which leads me to my hypothesis. Within individual precincts, house-dwelling registered voters who have participated in nearly all of the most recent five local elections will be more geographically clustered than those who participated in none of the last five local elections.

Methods:

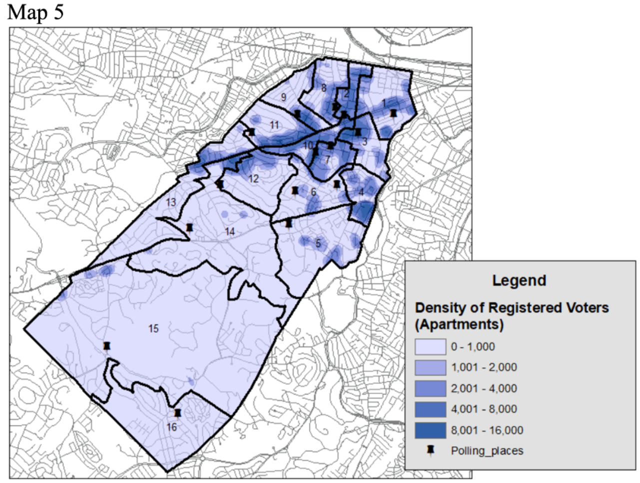
First, I geocoded all of the registered voters' addresses. I wrote a script that used the voter file as input and sent addresses to Google via the Google Maps API, which returned the coordinates that correspond to each address. Once that was complete, I could plot all of the registered voters on the map to start looking for trends in voting behavior. It was clear from the start that voting was concentrated in different areas. Based on a cursory search of the layout of Brookline, it was clear that some of the clusters were in areas of dense apartment buildings and others were in communities of houses. Here, I wrote another script that used the voter file and the tax assessment data to determine with relative certainty which voters are house-dwellers and which are apartment-dwellers. Despite the tax dataset being incomplete, the dwelling-type for every voter was determined or imputed using descriptions from the tax data, number of units at an address from the tax data, the number of voters at a given address in the voter file, and the type of abutting buildings. The script for dwelling type allowed me to code conditional statements to try and determine the dwelling type, which is inherently imperfect. The only way to ensure that every dwelling type is accurately coded would be to individually search each address on Google Street View to verify the dwelling type, which is too large a task for more that 40,000 registered voters and 10,000 addresses.

Next I used a tool in ArcGIS called kernel density to create a heatmap for vote turnout in a given election. Kernel density works by calculating the mean center of the input points, then calculating the distance from all points to that point. Once the weighted mean and median distances are calculated, it uses a bandwidth function to find clusters of points with similar distances to the mean. This function allowed me to generate heat maps for where voters live based on their dwelling type, as can be seen in Maps 4 and 5, as well as maps for overall voter turnout and turnout by dwelling type for a given election, which can be seen in the Appendix. Based on Map 5, it is clear that apartment-dwellers live and vote closer together solely because of how an apartment building is laid out: vertically. On the other hand, the kernel density for

Map 4



Map 5



house-dwelling registered voters in Brookline was more varied, which provides at least a place to look for neighborhood specific voting behavior. These findings led me to the mean distance calculations for house clusters that make up the classification scheme.

The crux of the research came with this house classification scheme. Looking at the three elections years in Graph 1, the vote share for house-dwellers was twice that for their apartment-dwelling counterparts. Yet, it was clear based on kernel density maps in the Appendix that the locus of the density changed year to year. Not every person in the densest areas votes every year. In order to see if those who did vote consistently live near other consistent voters, I created the classification scheme that follows:

1. First, I assigned voters a score from 0 to 5. A score of 0 means that they participated in none of the last five local elections whereas a score of 5 means that they participated in all of the last five local elections.
2. Next, all of the street-level addresses were given a score that corresponds to the average score of its vote-registered residents calculated in step 1. Since we are only concerned with vote turnout, not registration, the average score of a house is computed by dividing the sum of the scores of its vote-registered residents by the number of vote-registered residents at that address.
3. I then sorted each house by its average score and voting precinct. The 6 classifications are as follows: 0, >0 to 1, >1 to 2, >2 to 3, >3 to 4, and >4 to 5. Since the locus of density changes year to year, not everyone always votes, so attention is paid not only to voters who always vote, in the >4 to 5 class, but to the >3 to 4 class as well.

4. Once the houses were separated by class and precinct, another script calculated the distance between each house in a precinct/classification to every other house in the same group and divided it by the number of connections between houses in that group to get an average distance, as shown in the following formula:

$$\overline{d}_{\langle \text{ p,c } \rangle} = \frac{\sum d(p_i,p_j)}{\sum n-1,n-2,\ldots,1} \mid \text{for all } 0 < i < n \text{ and } i < j < n$$

Average distance, or "*d-bar,*" for a precinct, *p*, and a classification, *c*, is calculated by adding the result of the haversine distance function, d, for all points p_i and p_j. This formula can also be used to calculate the average distance between all houses in the precinct by leaving out c. The ranges for i and j are written as $0 < i < n$ and $i < j < n$ in order to eliminate any redundant calculations. If the ranges were $0 < i < n$ and $0 < j < n$, or between every point and every other point indiscriminately, the formula would calculate the same distance twice (because the distance from point A to point B is the same as the distance from point B to point A). An easy way to understand the ranges set for i and j would be to write out all of the points in a precinct and classification in some order as a list. Then as we traverse the list from left to right, we only have to calculate the distances between the current point in the list and all points to the right of the current point in the list. This minimizes the number of calculations required. Every time we move right in the list to the next point, we have to do one fewer calculation. If we do n-1 calculations for the first house, next we do n-2 calculations, and one less calculation for every house we meet as we traverse the list right. We repeat this until we get to the last two points, where there is only 1 calculation to get the distance between them. The denominator is the sum of all of the calculations, which equals $(n^2-n)/2$, but is more easily understood as the sum of the series described above.

My hypothesis is that house-dwelling registered voters who nearly always turn out for local elections live closer together than house-dwelling registered voters who never turn out. Ideally, this method show the inverse relationship between house score and average distance between houses in the same score classification. Results supporting the hypothesis for a specific precinct would show the greatest average distance for a classification between houses with a score of 0 and the least average distance for a classification between houses that nearly always vote, indicating a neighborhood-specific voting effect. An added layer is meant to normalize these results between precincts. As we will see in Table 3, if we divide every value for a classification/precinct combination by the value for the whole precinct, we can see how the geographic spread and clustering of the neighborhood compares to that of the precinct as a whole. If clustered pockets of high-voting or low-voting houses are concentrated within a neighborhood, the value for that classification should be much less than that of the precinct as a whole.

Results:

In order to conduct the *d-bar* calculations, I sorted the houses in each precinct into their respective classification and tallied them up. The number of houses in each classification for each precinct is seen in Table 1:

Table 1 Number of Houses in each Classification by Precinct

Precinct	0	>0-1	>1-2	>2-3	>3-4	>4-5	Avg Score for Precinct	Number of Houses in Precinct
1	84	62	45	16	19	10	1.16	236
2	48	38	12	5	2	2	0.62	107
3	69	89	44	17	17	5	1.07	241
4	74	90	42	25	19	9	1.19	259
5	204	182	117	64	31	20	1.14	618
6	138	167	103	60	40	25	1.33	533
7	123	73	32	8	8	4	0.84	202
8	123	120	66	46	21	10	1.15	386
9	182	124	63	25	15	4	0.78	413
10	37	36	20	7	2	2	0.87	104
11	133	112	73	41	16	7	1.05	382
12	182	196	123	65	24	11	1.09	601
13	205	203	110	45	21	12	0.98	596
14	230	225	83	42	17	7	0.81	604
15	392	243	122	53	24	17	0.81	851
16	473	236	149	99	54	50	1.08	1061

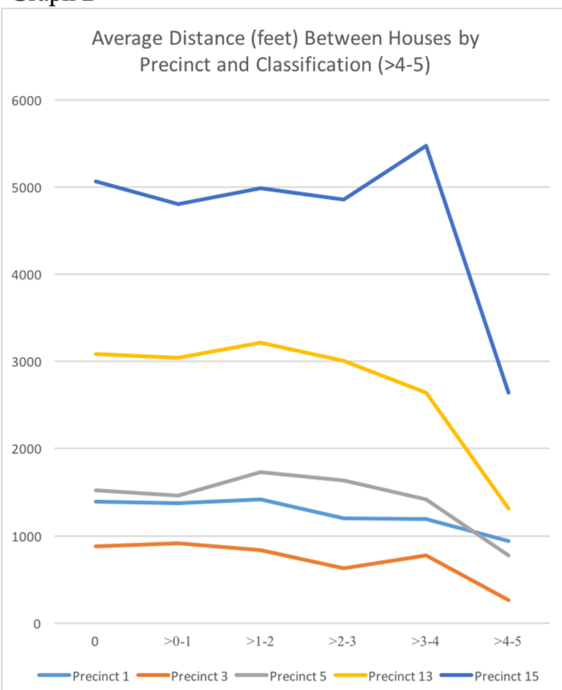
Table 1 includes the average house score for the precinct. There is one main finding and two potential issues from this first sort. As the classification within a precinct increases, moving right along a row, the number of houses in each decreases. For example, Precinct 1 has 84 houses where the registered-voters at that address have not voted in any of the last five elections, and only 10 houses where the registered-voter residents have voted, on average, in more than four of the last five local elections. This trend for all precincts can be seen in Graph 6 in the Appendix. There are two potential issues. First, it is clear that most residents never vote in local elections. This is shown twice; the average score for most precincts is a little above or below a 1, indicating that registered residents of houses in those precincts voted, on average, in one of the last five elections and most houses are in the 0 classification. A second potential issue is that some precincts have as few as 2 houses in the top two classifications. Although neither is exceptional, both have implications that will be expanded upon in the discussion section.

Once I sorted houses by classification and precinct, I could do the individual *d-bar* calculations for houses in each precinct/class combination. The results are seen in Table 2:

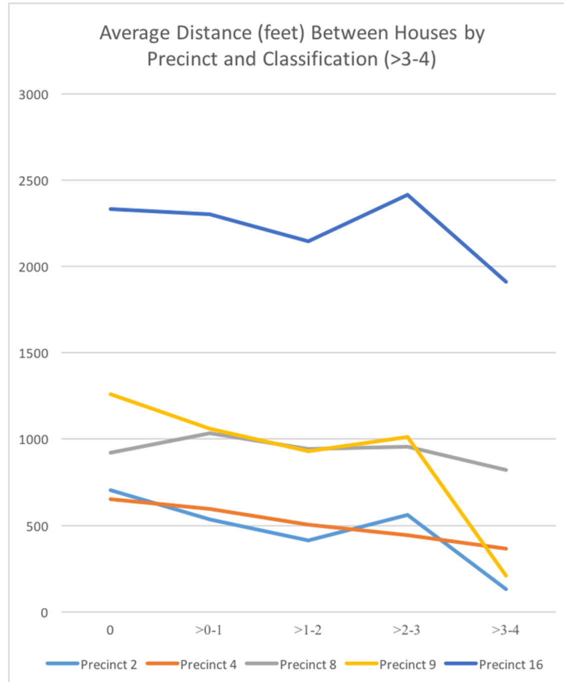
Table 2	Average Distance Between all Points in a Classification by Precinct (Feet)						
Precinct	0	>0-1	>1-2	>2-3	>3-4	>4-5	Avg Distance for Precinct
1	1391	1374	1420	1197	1196	941	1347
2	704	536	413	563	130	1162	605
3	876	912	836	625	771	266	863
4	654	598	506	442	364	520	599
5	1526	1462	1726	1632	1417	776	1803
6	1590	1510	1312	1760	1346	1511	1715
7	954	1329	877	898	928	1708	1633
8	921	1036	944	955	820	1001	1200
9	1260	1061	931	1013	209	969	1675
10	1284	928	4247	723	1150	1188	1420
11	1274	1393	1456	1322	1562	1714	1518
12	1354	1485	1501	1428	1570	1425	1615
13	3083	3037	3211	3003	2640	1316	3872
14	2612	2830	2418	1873	3111	3180	3014
15	5061	4804	4983	4854	5472	2640	5448
16	2333	2302	2144	2416	1911	4913	3831

As stated, the function finds the average distance from every house to every other house in a specific precinct/classification bin by tallying up the lengths of the individual lines and dividing by the number of lines. The smallest result of the function for a precinct is highlighted in each row. For 10 of the 16 precincts (highlighted in the leftmost column) the smallest result of the *d-bar* function (highlighted in every row) was in the highest or second-highest classification for that precinct. As stated, some of the precincts only had two houses in the highest classification, which might not be indicative of a cluster, and the kernel density maps show that not every neighborhood votes at the same density every year, which is why attention is paid to the top two classifications as opposed to just the highest one.

Graph 2



Graph 3

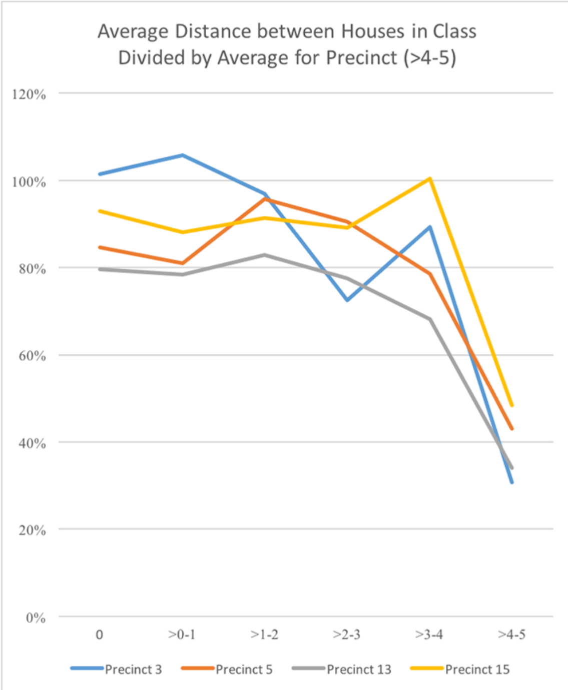


If we plot the rows for the precincts where the smallest *d-bar* was in the >4-5 and >3-4 column separately, as in graphs 2 and 3, a trend becomes clear. In both, there is a general downward slope in the average distance between houses from same classification as we move up classifications. What is is not clear, however, is how each precinct compares with the others in the same graph, as the population density and the extent of their geographic spread differs. This makes it difficult to compare clustering relative to the precinct as a whole. To accommodate for this, Table 2 includes a precinct-level value for *d-bar*. When results for each classification are divided by the results for the precinct as a whole, the result is the what percent of the precinct, both in terms of clustering and spread, the neighborhood makes up. This value easier to compare between precincts. Table 3 tabulates the result for every value from Table 2:

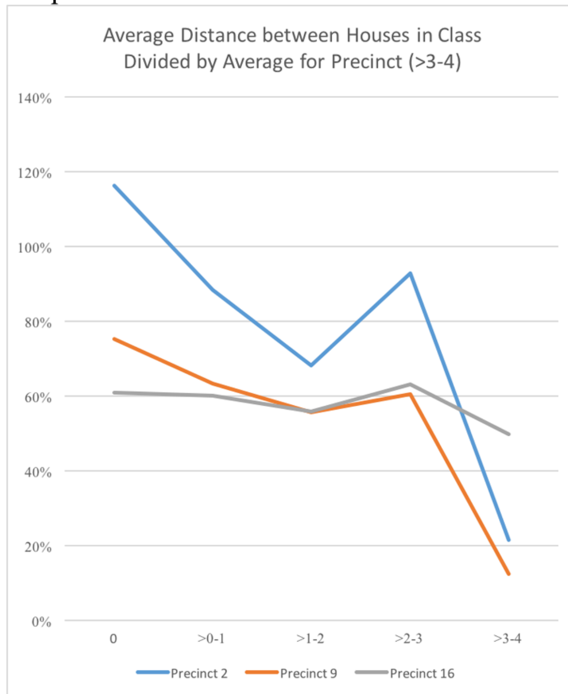
Table 3	Average Distance Between Houses in a Classification by Precinct (as a Percentage of Precinct Average)						
Precinct	0	>0-1	>1-2	>2-3	>3-4	>4-5	Avg Distance for Precinct
1	103%	102%	105%	89%	89%	70%	1347
2	116%	89%	68%	93%	21%	192%	605
3	102%	106%	97%	72%	89%	31%	863
4	109%	100%	84%	74%	61%	87%	599
5	85%	81%	96%	90%	79%	43%	1803
6	93%	88%	77%	103%	78%	88%	1715
7	58%	81%	54%	55%	57%	105%	1633
8	77%	86%	79%	80%	68%	83%	1200
9	75%	63%	56%	60%	12%	58%	1675
10	90%	65%	299%	51%	81%	84%	1420
11	84%	92%	96%	87%	103%	113%	1518
12	84%	92%	93%	88%	97%	88%	1615
13	80%	78%	83%	78%	68%	34%	3872
14	87%	94%	80%	62%	103%	105%	3014
15	93%	88%	91%	89%	100%	48%	5448
16	61%	60%	56%	63%	50%	128%	3831

Table 3 shows us that for seven of the ten precincts previously highlighted in Table 2, the average distance between houses in that class is 50% or less than that of the precinct as a whole. This is indicative of a neighborhood-level clustering of houses where vote-registered residents regularly participate in local elections. If we plot these seven precincts by the column highlighted in Table 3, as we did for Graphs 2 and 3, an even clearer comparison is drawn. After the values for average distances are normalized by average distances for the precinct, the general downward trend of the y-values as we move up classification is clear. Three of the seven precincts see an uptick in the average distance in the classification to the left of the one with the lowest percentage, but that is a matter for discussion. Ultimately, the results support my hypothesis. In certain precincts and neighborhoods, the more often a person votes, the more likely it is that both their cohabitants and neighbors do as well.

Graph 4



Graph 5



<u>Discussion:</u>

Understanding mechanisms behind political participation at all levels is important. Without participation there is no representation in government. For reasons that are still being explored, people are barred from voting, think they are barred from it, disinterested in it, or forget to altogether en masse. This paper explores a new avenue in research on local-level election participation. While similar studies have been employed in this realm, many have focused on individual level characteristics like party affiliation and race to determine the makeup of neighborhoods. While worth analyzing, these kinds of studies say less about the effect a neighborhood has on its people than it does about the effect introduction of an outgroup has on a neighborhood. The goal of this study was to hone in on one relatively non-political individual characteristic, the apartment/house split. To some, the word neighborhood may evoke the image of a tree lined street of houses, but that is not what all neighborhoods look like. I hope to contextualize the results by considering the applicability of the different theoretical mechanisms for the neighborhood effect to those of houses and apartments.

The self-selection model might apply to a potential voter's choice to live in a house or an apartment. A residential choice is influenced by individual-level factors that are already correlated with rates of electoral participation (Rosenstone & Hansen, 2003). Ultimately, the choice might boil down to a socioeconomic question. Homeowners tend to be more well off and earn more in the long-term than their renting peers, but I make no distinction between owning and renting for either dwelling-type in this study, as it was infeasible with the data available (Di, et al., 2007). In terms of elite driven processes, the means by which parties and campaigns get in touch with voters, like phone banking, mailing, and canvassing, work differently in different neighborhoods. Merits of different kinds of voter targeting aside, based on neighborhood layout alone, campaigns must operate differently to get out the vote. For example blind canvassing is effective in high-registration areas, but less effective in areas of low-registration, like large apartment complexes (Green & Gerber, 2008). Ultimately, local elections receive less financial and media support than state elections, and are less likely to be affected by party mobilization efforts. In terms of social interaction and casual observation, way these mechanisms are described in the literature evokes the image of a tree-lined suburban Massachusetts street with lawn signs, chatty neighbors, and a bumper sticker for every Prius. The mechanisms, as discussed in the literature review, are based on the explicit and implicit cues that neighbors give each other. On the social interaction side, networks of people who live close together and participate in explicit social groups, like church or golf, give and receive information that impacts people's political decisions. On the casual observation side, subtle cues like lawn signs and a neighbor's car are indicative of political attitudes. Both of these models presuppose that residents of different neighborhoods have equal access to such cues. This is a limited view, as apartment buildings with rows of anonymous doors create an environment that is less conducive to the transmission of cues both explicit and implicit. My results, that house-dwellers who vote more often tend to live closer together, support the idea that social interaction and casual observation are at play for local-level elections in neighborhoods of houses.

As mentioned in the results section, Table 1 showed that even among house-dwellers, people almost never vote in local elections. The classification with the most houses was the 0 classification for most precincts, indicating that most house-dwelling registered voters never vote in local elections. Additionally, the average voting participation score for houses in every precinct fell between .5 and 1.5, indicating that while there is still variation in the average participation precinct to precinct, the difference is not very large. The second finding from Table 1, however, was more tricky. It was clear that as we moved right in a row, the number of houses in each column went down. In some precincts, there were only two houses in the column for the highest 2 classifications, which means when *d-bar* is calculated for that classification, the result is only the distance between two points, not a cluster of points. That being said if the *d-bar* result met the criteria for 50% or less of the calculation of the precinct as a whole, it was included in the graphs, as the trend across classifications was still noteworthy. Keeping Table 1 in mind, the downward trend in Graphs 4 and 5 is consistent irrespective of the number of houses in each classification.

Finally, it would be unlikely that the average distance would be between groups of houses that never vote, if the smallest for a classification in a precinct, would be dramatically less than that of the precinct as a whole. It is unlikely because, as we can see in Table 1, most people do not vote and due to the high number of houses in that group, they are more likely to be spread out around the precinct. If it were true though, could there be an anti-neighborhood effect? One where people self-select to live with other apolitical people or individual-level characteristics of people in the neighborhood, like affluence, make people complacent. Precincts 11 and 12, which are split by the main thoroughfare of the town and have neighborhoods of houses that border areas of apartment buildings along Beacon Street, both have the smallest *d-bar* in the 0 classification. The average distance did not go up as dramatically as it went down for some of the other precincts, indicative of an anti-neighborhood effect, and the *d-bar* value for each classification was similar to that of the precinct as a whole, which can be seen in Table 3. Still, I was curious as to why the smallest average distance would be between houses with residents who never vote for those precincts. Looking back to Maps 4 and 5, it is clear that these precincts border large pockets of apartment complexes in a busier part of town. Could the presence of dense populations of both houses and apartments in a precinct negate any neighborhood effect we would see among similar houses in an apartment-free precinct? This would be a good avenue of future research.

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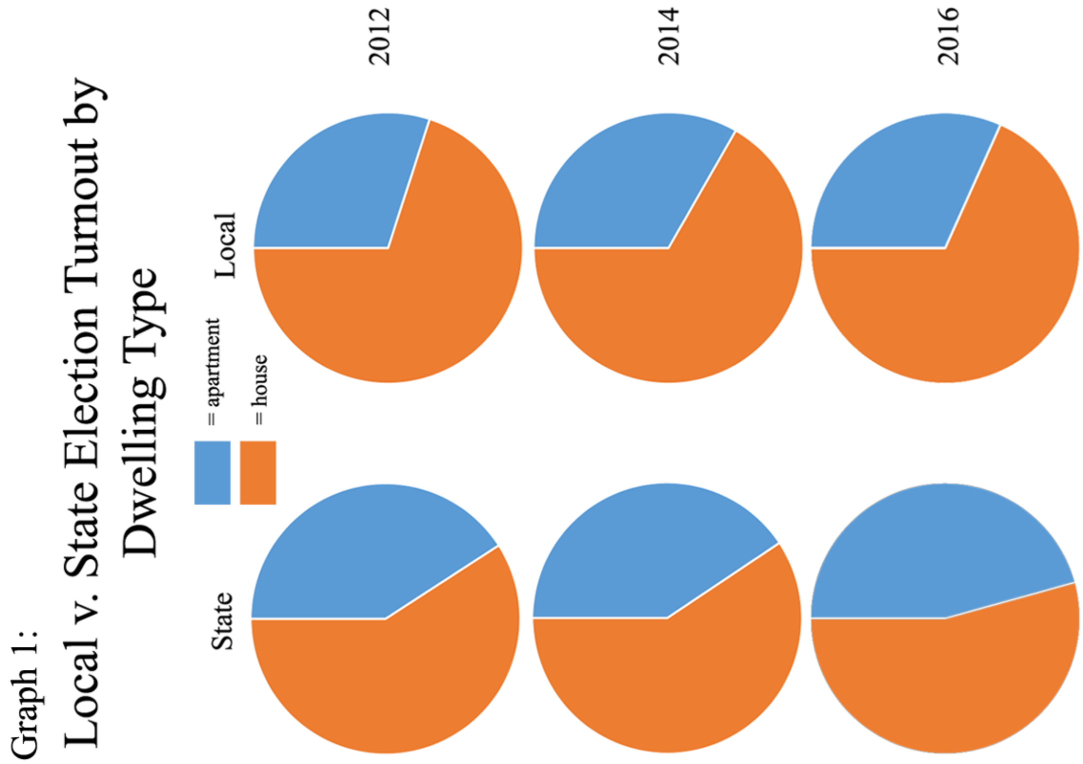
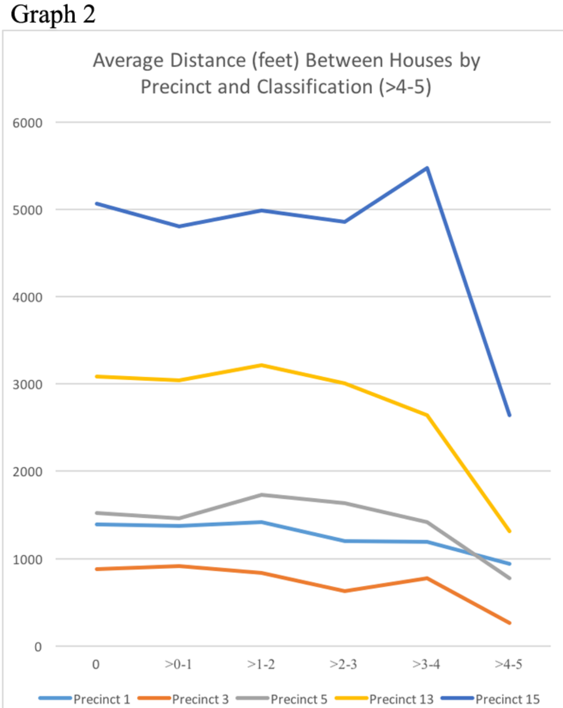
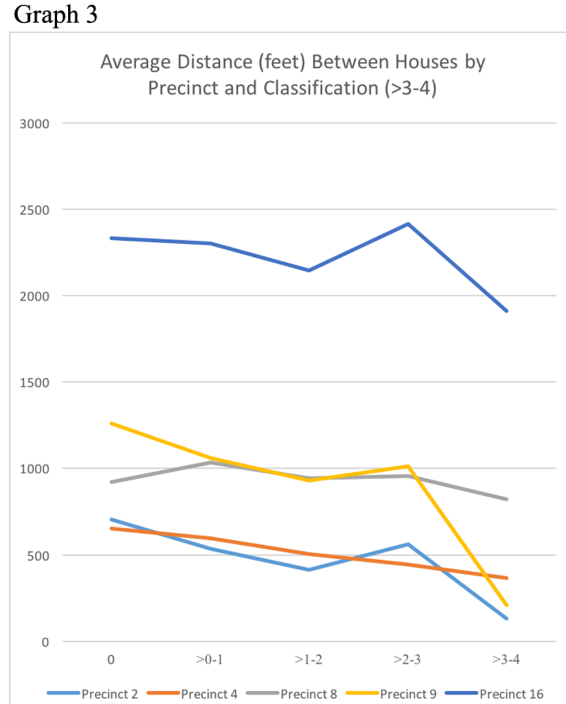
Appendix:



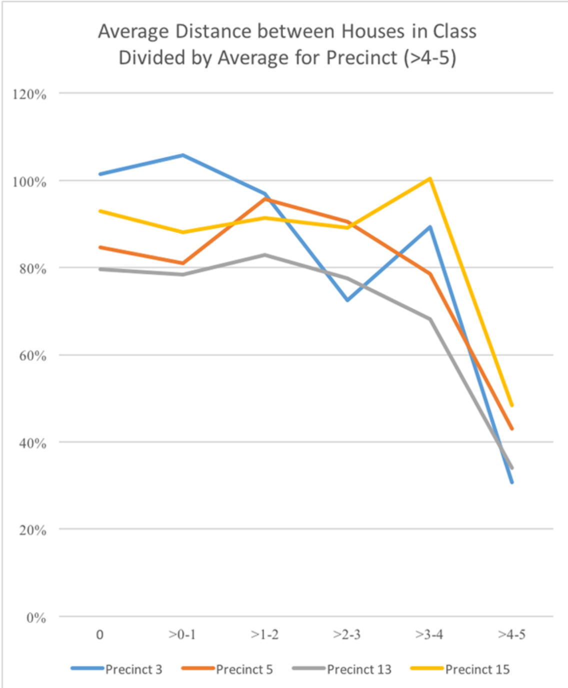
Graph 2



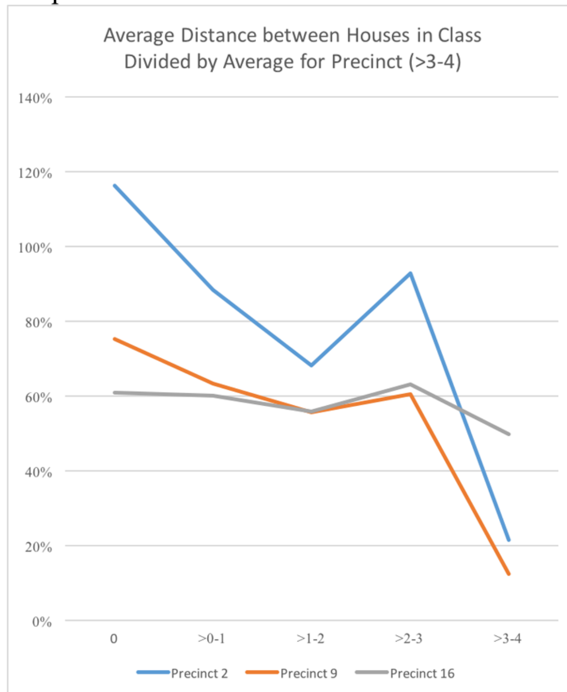
Graph 3



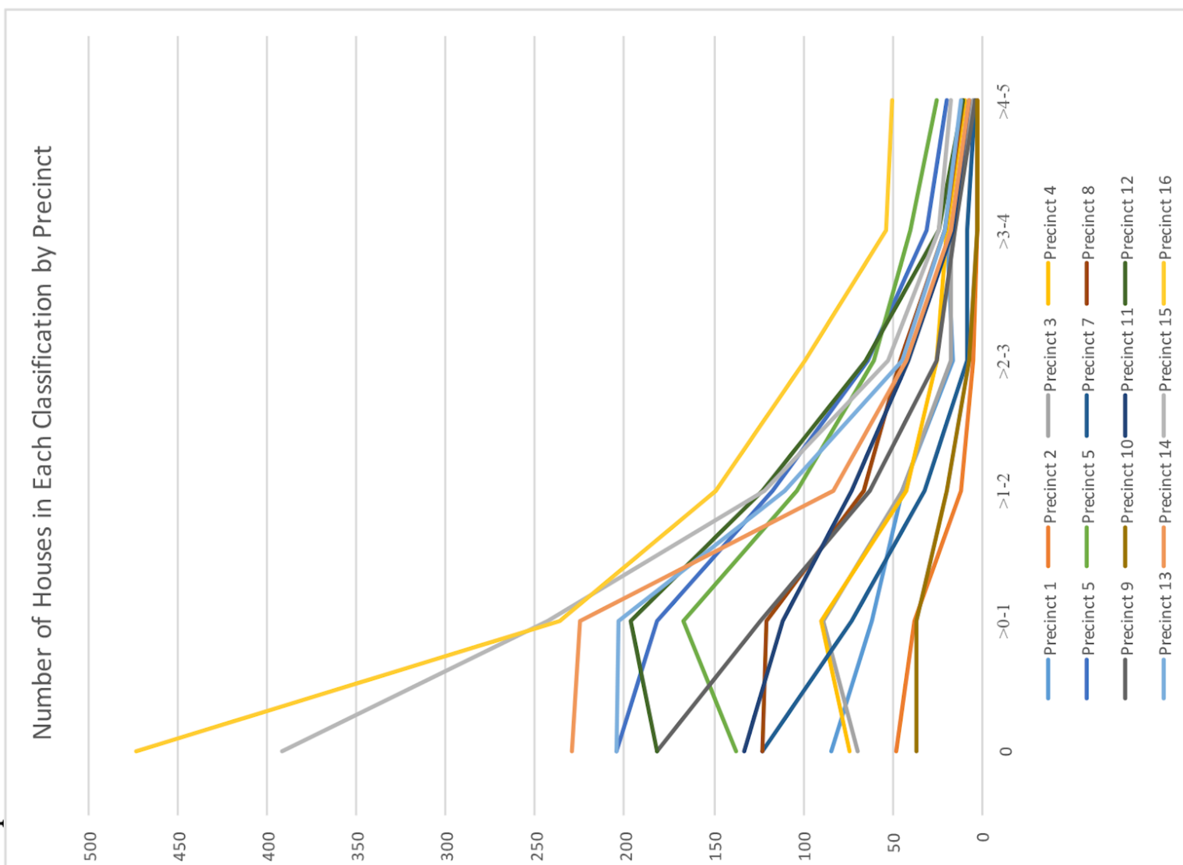
Graph 4



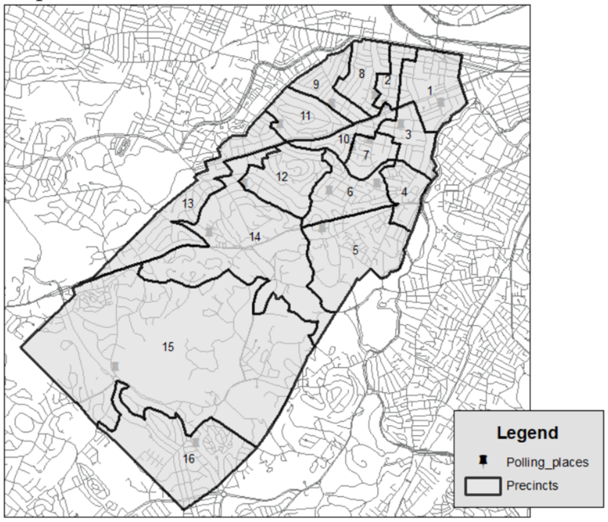
Graph 5



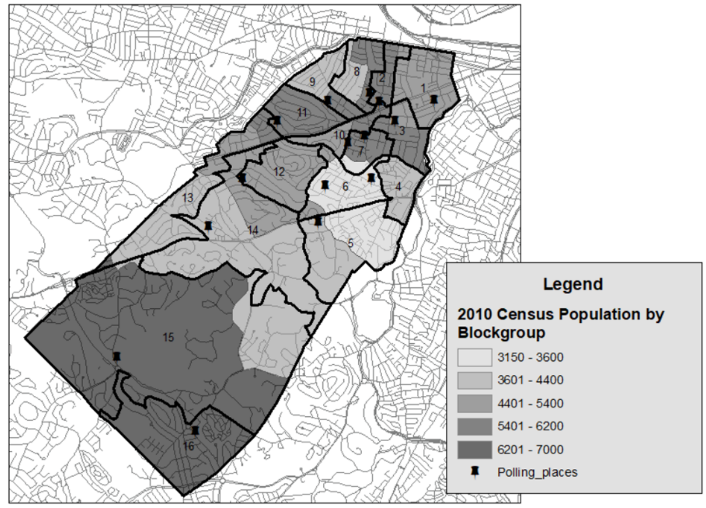
Graph 6



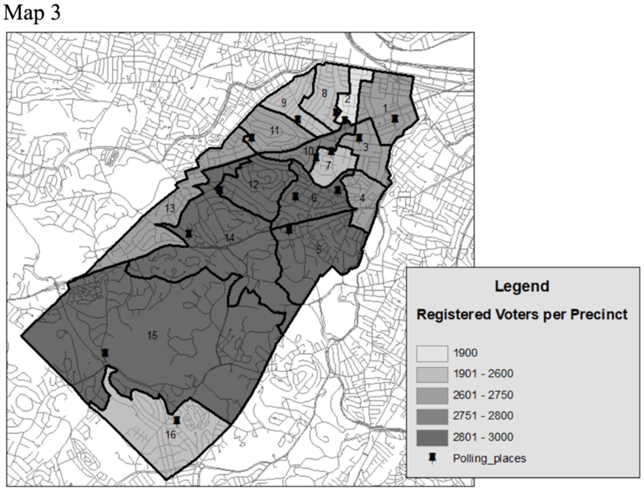
Map 1



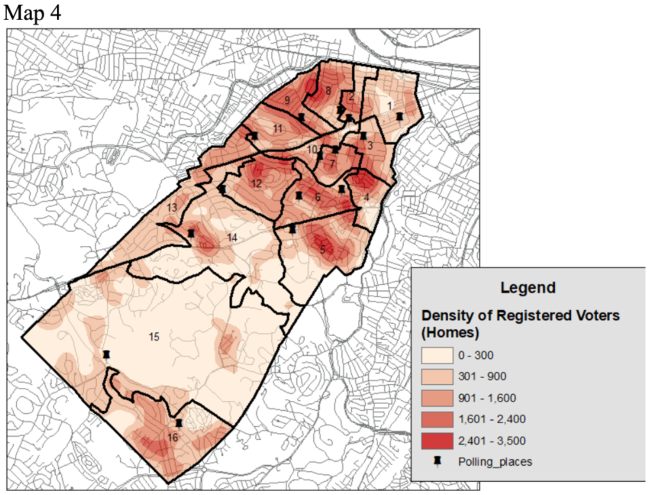
Map 2



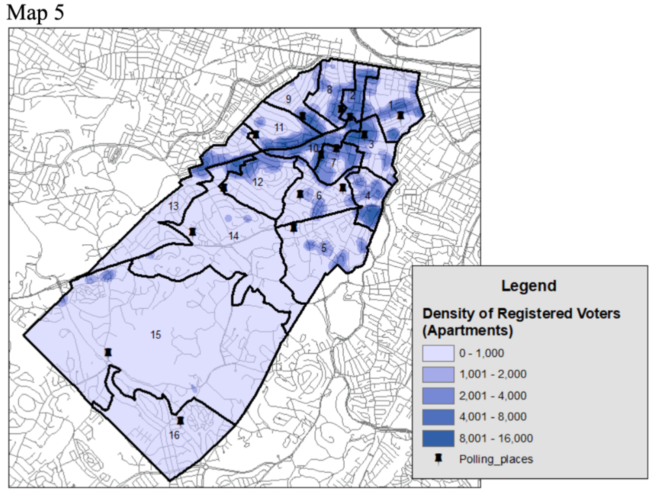
Map 3



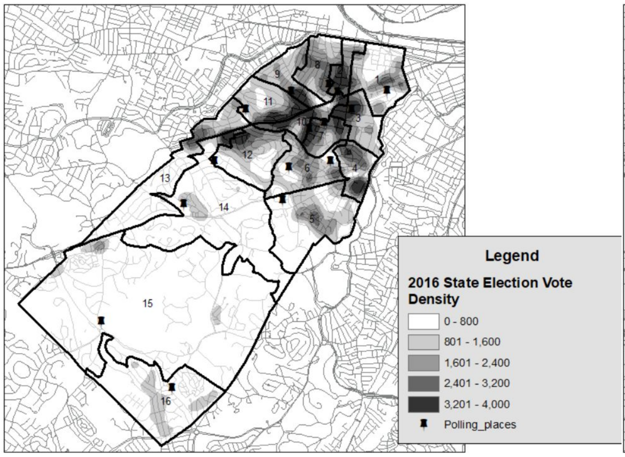
Map 4

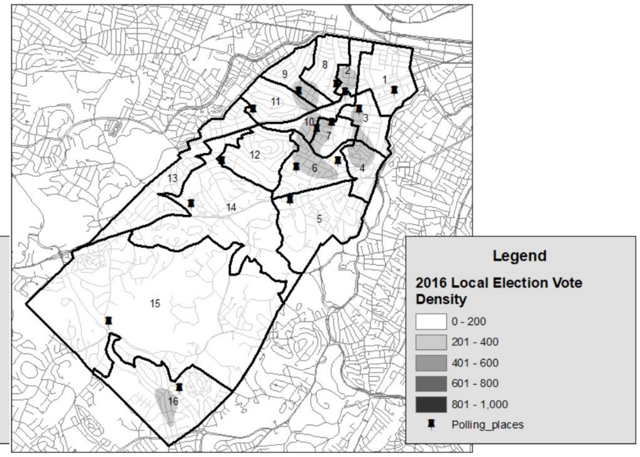


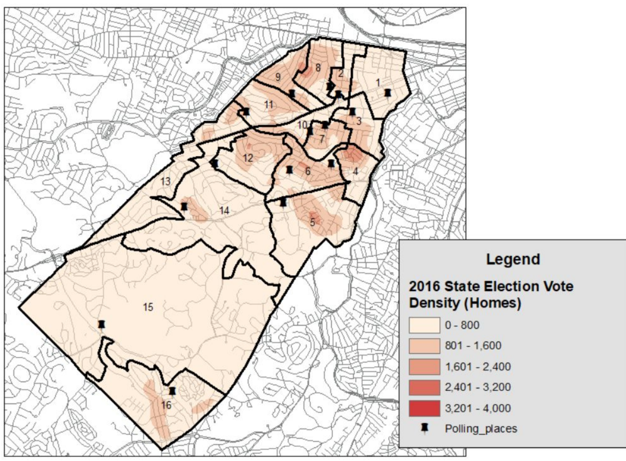
Map 5

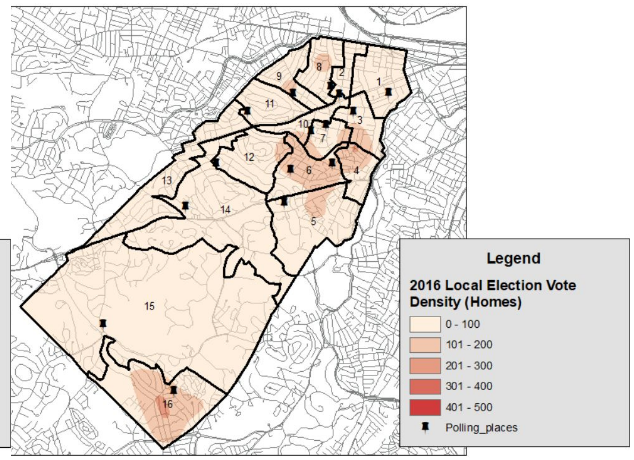


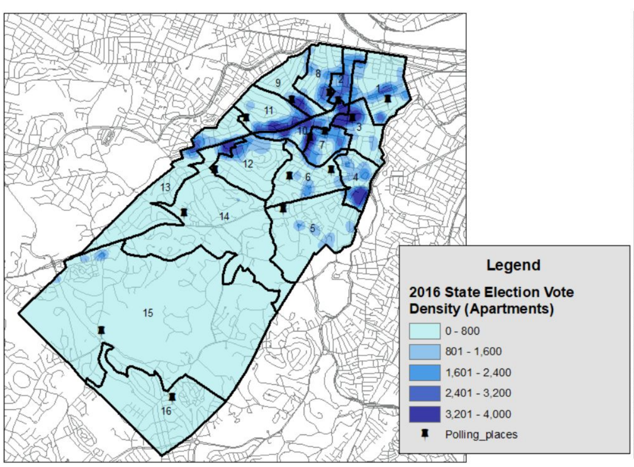
Maps 6-11: 2016 Local and State Election Vote Density by Dwelling Type

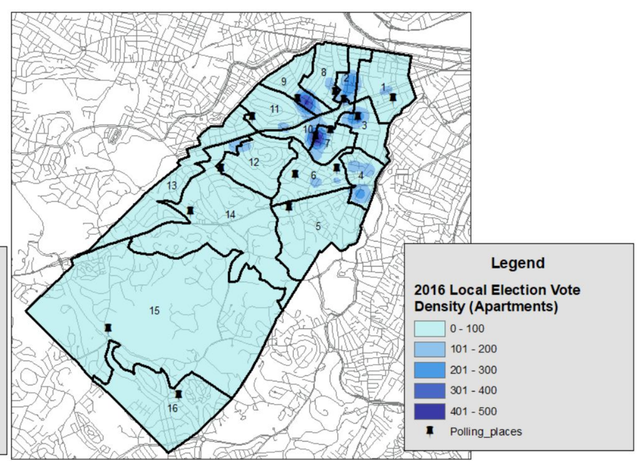




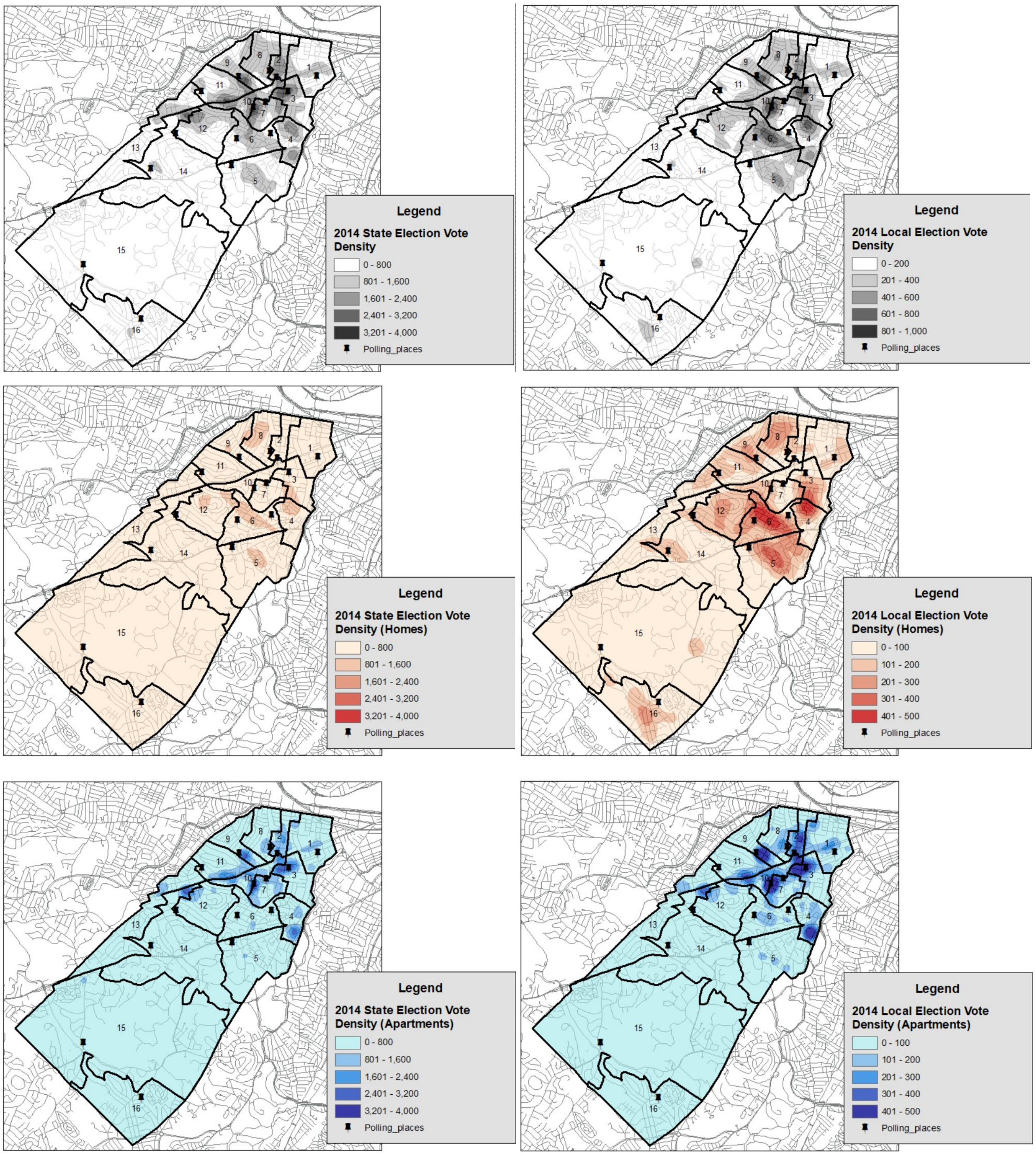








Maps 12-17: 2014 Local and State Election Vote Density by Dwelling Type



Maps 18-23: 2012 Local and State Election Vote Density by Dwelling Type