The Relationship between Voting and Crime: A Neighborhood-Level Analysis

By

Starr Moss

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Chapter 1. Introduction

1.1 Research Question

Why do people vote? Casting a ballot on election day is not just a way to show support for a particular candidate, it also embeds an individual into collective society. Knack (1992) argues that voting is a social norm, or a collectively understood rule that prescribes human behavior as defined by Cialdini (1998). Coleman (2002) theorizes that voting is an example of social conformity, which he defines as the alignment of people’s thinking or behavior with a societal or group norm. Coleman (2002) also discovered a parabolic relationship between voter turnout and crime rate at the state and county level. However, few studies have examined whether this relationship is true at the neighborhood level.

In order to see whether the patterns observed by Coleman (2002) might be reproduced at a much finer spatial scale, the interaction between voting and crime needs to be studied at the neighborhood level. Thus, my research focuses on how voter behavior influences crime rates at a neighborhood level. The question I seek to address is:

What is the relationship between voting behavior and crime at the neighborhood level, and what is the spatial structure of this relationship?

1.2 Background

1.2.1 Voting as a Measure of Conformity to Social Norms

In order to understand voting as a socially conforming behavior, it is important to understand what motivates people to vote. Appealing to common sense, Riker (1968) points out
that the act of voting is fundamentally irrational. A rational individual has little incentive to vote, knowing that the costs of voting – registering, researching candidates, travelling to the polls, and waiting in line – exceeds the benefits – the small chance that casting their ballot makes a difference. Yet, as Blais (2000) observes, the majority of people vote in major elections, even when they recognize that their ballot’s influence is inconsequential. This begs the question: why do people vote?

The answer – suggested by Wolfinger et al (1980), Knack (1992), Gerber (2004), and Coleman (2002) – is that voting is “norm-governed behavior”, and thus the decision to vote is strongly influenced by external social pressure. Here, for the sake of clarity, I will return to Cialdini’s (1998) concept of a social norm as a collectively understood rule that prescribes human behavior. As Riker (1968) and Blais (2000) have pointed out, voting is irrational at the individual level – a person has little intrinsic motivation to vote knowing that their vote will not likely decide the election. Knack (1992) explains this phenomenon by arguing that the social obligation and “duty” to vote is what provides the incentive to vote, rather than the prospect of determining an election’s outcome. In other words, voting appears irrational as an individual choice, but when seen as a social norm, an individual’s motivation to vote makes much more sense.

Knack (1992) characterizes voting as a social norm. He theorizes that voting is not only a civic institution but a societal institution, and people are more pulled by the act of voting itself rather than actually influencing the election. Knack (1992) cites a study by the National Election Board that show a majority of people in a Wisconsin poll believe it’s important to vote even if they know their party cannot win. Dennis (1970) explains this phenomenon, suggesting that "the average member of the public will more likely have internalized the norms of electoral participation than those of partisan competition...Voting and elections are 'us'; parties are 'them.'" Knack (1992) also argues that while voting may be motivated by a civic duty or ethical
obligation, the value placed on voting is still transferred and reinforced socially. He bolsters this case by presenting evidence that social sanctions provide strong voting incentives. As an example, he cites Alderman’s (1983) study that shows 41% of regular voters cited pressure from family and friends as a reason they voted. Knack (1992) also points to evidence that spousal enforcement of voting norms is a major contributor to voting turnout in marriages, which may account for the fact that married individuals vote more than non-married.

While Knack (1992) and Wolfinger (1980) present convincing evidence that voting is a salient social norm, Gerber’s (2004) work goes one step further by directly linking voting conformity to perceived social norms about voting. Asch (1956), Crutchfield (1955) and Deutsch et al (1955) argue that conformity is motivated by either the desire to make a factually correct decision, or is motivated by *normative influence* – the desire to go along with the group and its prescriptive norms. Gerber (2004) supports the latter explanation, showing in his study that individuals’ tendency to vote can be highly motivated by a desire to conform with the majority and avoid derision. He finds that people are 7% more likely to vote when they perceive that voter turnout was high, compared to low. Furthermore, Gerber (2008) finds that voter turnout is directly influenced by social pressure. Applying different levels of social pressure by threatening to expose an individual to their neighbors if they do not vote, Gerber (2008) finds that voter turnout increases proportionally to increased levels of social pressure.

### 1.2.2 Voting and Crime Rates

Having established that voting is a viable measure of conformity to a social norm, I will turn next to whether voting, as a potentially norm-governed behavior, has an effect on crime. If voting demonstrates a willingness to adopt the voting norm, does it show willingness to adhere to other norms, such as not breaking the law? In order to justify this question, I address whether
conformity to voting might be indicative of broader conformity to social and civic-minded norms that may influence crime rate. While there is no clear answer to this question, there is evidence (albeit limited) that conformity in voting may lead to conformity to other social norms. Knack (1992) links individual voting behavior to larger-scale “socially cooperative behavior” in terms of social and civic engagement. He finds that those who vote are more likely to be involved in various neighborhood institutions like Parent Teacher Associations (PTA), charitable organizations, and other political groups. He also finds that voters, compared to non-voters, are more likely to respond to the U.S. census. Finally, Knack cites a District of Columbia study by Tyler (1990) that shows the correlation coefficient between turnout and crime is -0.43 at the state level, and -0.30 at the neighborhood level. With this evidence, Knack (1992) suggests that voting may fall under a broad category of “norm-governed” behavior.

Uggen et al. (2004) echoes the idea that voting may be linked to broader social norms, offering evidence that voting may be a mechanism for civic and social integration. Uggen et al (2004) hypothesizes that voting creates “reciprocal obligations” between an individual and society, and that these bonds deter antisocial criminal behavior. He notes that voting is negatively correlated with criminal recidivism – an individual’s repeating of criminal behavior. Using 757 respondents who self-reported past arrests, Uggen et al (2004) found that compared to people who voted in the 1996 presidential election, those who abstained had higher rates of criminal recidivism. However, Uggen et al. (2004) only uses voting in the 1996 election as a basis for the study, and employs a limited sample population. While he presents a convincing case that voting is indeed linked to lower rates of criminal recidivism in individuals, it remains unclear whether this pattern would hold true at the macro-level. A geographic analysis, employing a larger sample population over a longer period of time, is needed to provide insight into how patterns between electoral participation and criminal behavior changes over time and space.
Coleman (2002) gets closer to this question. He pinpoints a clear relationship between voter turnout and crime rates over a period of time, though his research is generalized to the county and state level and therefore may miss nuances in how the relationship between voting and crime changes at the community level. Coleman (2002) uses voter turnout as a measure of social conformity in order to assess conformity’s effect on crime rates. In a study of state-wide voter turnout for presidential elections, Coleman (2002) finds that the relationship between voter turnout and crime is parabolic; high voting conformity is negatively correlated to crime, as is low voting conformity. Crime rate peaks at voter turnout “entropy”, where voter turnout is roughly 50%. Coleman (2002) argues at roughly 50% voter turnout, social conformity to the voting norm is absent.

The existing studies referenced above show that voting may likely be a measure of social conformity, and suggest that at least in some instances, there is an inverse relationship between voting and crime. The relationship between voting and crime has been examined at the individual level by Uggen (2004), and at the county and state level by Coleman (2002), yet few studies have examined how voting and crime interact at the neighborhood level.

The need for neighborhood-level research on the relationship between voting and crime is twofold. First, the county and state — the units of analysis used by Coleman (2002) — might not be as effective as transmitting social norms and enforcing social conformity compared to the neighborhood. It is likely that some people identify more as citizens of the particular neighborhood they live in rather than the state or county they reside in. Because the neighborhood might better encapsulate notions of social norms and conformity, it may be a more appropriate unit of analysis. Second, it is possible that the patterns observed by Uggen (2004) and Coleman (2002) are subject to the scale effect of Openshaw’s (1983) modifiable unit area problem (MAUP) — which states that observable patterns vary based on the geographic scale of
analysis. In other words, results obtained at one geographic scale might not hold true for a different geographic scale. In order to determine whether or not the results observed by Knack (1992), Uggen et al (2004) and Coleman (2002) would be replicated at the neighborhood level, my research will focus how voter behavior and crime rate interact at the neighborhood scale.

Chapter 2. Methodology

2.1 Study Area

Chicago, Illinois was selected as the study area. For a spatiotemporal assessment of the relationship between voting and crime at the neighborhood level, Chicago is ideal. Being one of the largest cities in the United States – both geographically and population-wise – Chicago has a large enough spatial extent to show meaningful variation in voter turnout and crime rate. Chicago also keeps a rich database of publicly available crime data dating back to 2001. These data are often hard to obtain. The availability of these data sets for Chicago makes it possible to conduct this research.

Chicago’s 77 community-areas (neighborhoods) will serve as enumeration units for aggregated voting and crime data and thus the community-area will be the basis for the analysis (Map 1).
The benefits of a community-area level analysis are two-fold. Though performing the analysis at the precinct level seems intuitive because voter turnout is reported by precinct, a precinct level analysis becomes problematic because block-group boundaries – the spatial units for which the American Community Survey (ACS) reports socioeconomic data – do not fall wholly precinct boundaries (Map 2). However, blocks and block-groups fall wholly within community-areas since community-areas are drawn at the block level (Map 3). Therefore, a major benefit to a community-area level analysis is that block-group level ACS data that is necessary for the analysis is easily aggregated up to the community-area level.
Second, community-areas are relatively large geographic units of analysis and have substantially greater populations than smaller units such as voting precincts, census tracts, or census block groups. Using units with greater populations may help avoid large variations in the dependent variables, a trend that Coleman (2002) observed when comparing the crime rates for sparsely populated counties and more heavily populated counties. If the unit of analysis has too small a population, the analysis may be overly sensitive to variations in the independent variables.
2.2 Key Data and Variables

2.2.1 Election data

Voter turnout will be the metric for assessing voting behavior. Voter turnout is defined as total votes cast divided by voting age population (VAP) in a given community-area. Using VAP will help avoid skewed voter turnout results, as certain community-areas have higher populations of young people who cannot vote. It is common, particularly in the political redistricting process, to define voter turnout as total votes cast divided by citizen voting age population (CVAP) in order to account for those who are not legally able to vote due to non-citizen status. However, CVAP data is based on estimates over 5-years, and thus may not be appropriate when making estimates for single years 2010 and 2012, respectively. Therefore, this analysis does not take CVAP data into consideration.

Turnout data will be gathered for years 2010 and 2014 in the form of aggregated totals of ballots cast per race, per precinct (Figure 1). Since voter turnout is reported at the precinct level, these voter turnout totals will be aggregated from roughly 2,000 precincts up to the community-area, ultimately giving each community-area a value for turnout. It is worth noting that due to the redistricting of Chicago precincts, precinct boundaries are not the same for 2010 and 2014. A Freedom of Information Act (FOIA) request was submitted to the Chicago Board of Elections Commissioners in order to secure shapefiles with accurate precinct boundaries for 2010 and 2014.

For each of the above years, the election for Cook County Clerk – a race in which all Chicago residents were able to vote in – will be used in order to assess turnout. Each precinct in Chicago will have a voter turnout value, thus the entire study area will be represented.
To assess crime rates, I primarily use violent crimes, which are crimes that involve "force or the threat of force" per the Federal Bureau of Investigation’s (FBI) Uniform Crime Reporting (UCR) program. Specifically, I focus on homicide, rape, robbery, and assault, which the UCR deems the most serious violent crimes. I also add burglary to the analysis, since Coleman (2002) used burglary in his model. Using the same five crime types that Coleman (2002) used makes it possible to compare my results against his. This process will be detailed further in the next section.

This research operates under the assumption that social conformity influences violent crime to some degree. Though Glaeser et al (1996) have found evidence that social conformity – at least in a state-level analysis – has less of an influence on murder and rape than other types of crimes, Coleman (2002) points to research that suggests social conformity does have an effect on
certain violent crimes. With this in mind, it would be expected that if voter turnout is indeed a barometer of social conformity, a community-area’s crime rate would vary depending on its level of voter turnout.

Fortunately, geo-referenced Chicago crime data dating back to 2000 is publicly available from the City of Chicago (Figure 2). Police reports for each crime type (homicide, rape, robbery, assault, and burglary) with latitude/longitude coordinates referencing where the crime occurred allows for easy importation of crime data into a GIS, where it is converted to point-data and aggregated up to the community-area level. For each crime type, the crime rate is defined as the number of incidents of a particular crime type in a given community-area, divided by the total population of a given community-area. This number is then multiplied by 10,000 to obtain a per-capita rate. Chicago crime data for years 2010 and 2014 will be used to correspond to voter turnout for years 2010 and 2014.

Figure 2: Geo-referenced raw crime data from City of Chicago web portal.
2.2.3 Other Violent Crime Covariates

There is a need to control for other common predictors or “explanatory variables” of crime. Land, McCall, and Cohen (1990) present other variables that are used as common crime predictors, including: socioeconomic status, racial composition, population density, median family income, % families under the poverty line, and % families unemployed, all of which are obtained from the U.S. census and American Community Survey (ACS). The variables listed above form the basis for the explanatory variables used in this research, but the particular explanatory variables chosen will vary depending on the analysis used. This will be further detailed in section 2.4. The complete list of candidate explanatory variables used in this research is (with variable name indicated in parenthesis): percentage black (%_Black), percentage white (%_White), percentage Asian (%_Asian), percentage Latino (%_Latino), households with no male present (%_NoMaleHH), single-parent households (%_SingleHH), percentage of population aged 15-34 (%_Age15to34), percentage of divorced males (%_DivorcedMales), percentage of population under 25 with a high-school degree or less (%_HSorLess), percentage of labor force unemployed (%_Unemployment), percentage of households in poverty (%_HHPoverty), percentage of families in poverty (%_FamilyPoverty), percentage of population renting (%_Renter), % of population who pay $600 or less in monthly rent, (%_Rent600Less,) log of total population (Log_Pop), log of population density (Log_PopDensity), and log of income (Log_Inc).

2.3 Data disaggregation and aggregation

With the exception of voter turnout, data for all independent variables come from either block or block-group level geography. Since every block and block-groups’ centroid falls within a
community area, each block and block-group can be assigned to a community-area. Then, data coming from either block or block-group levels can simply be aggregated up to the community-area level.

Raw turnout counts, on the other hand, are reported by precinct. While all block and block-groups fall wholly within community-area boundaries, there are many precincts that do not fall wholly within community-area boundaries (Map 4). Thus, the process of aggregating turnout data up to community-areas becomes more complicated and some method must be devised in order to split precincts that are divided by community-areas. If a single precinct falls within multiple community-areas, the precinct must be subdivided into precinct fragments so that the entire precincts’ voter data can be distributed among community-areas. This means that raw voter turnout counts must be estimated for each precinct fragment before being aggregated back up to the community-area level. This requires the disaggregation of voter turnout data, or in other words, a process to estimate voter turnout at a smaller spatial unit (precinct fragments) than it was originally reported (precinct). This process is detailed below.

First, the raw voter turnout from precincts that fell wholly within community-areas were simply aggregated up to the community-area level. The precincts that did not fall evenly within community-areas were identified (Maps 4 – 5). Since precincts are drawn at the block-level, the voting-age population (VAP) for each precinct can be calculated (Map 6). Precincts are then split into fragments amongst community-areas so that fragments fall wholly within community-area boundaries (Map 7). The VAP is calculated for each precinct fragment (Maps 8 – 9), and the VAP for each precinct fragment is divided by its parent precinct’s (the precinct from which the fragment originated) VAP to produce a weight for each precinct fragment (Map 10). These weights determine the proportion of voter turnout each precinct fragment receives from the whole precinct (Map 11). With each precinct fragment having an estimate for voter turnout and
falling wholly within community-area boundaries, each community-area can aggregate voter turnout estimates from the precinct fragments that lie within its boundaries (Map 12). Finally, for each community-area, the aggregated voter turnout estimates from precinct fragments is added to the aggregated voter turnout from precincts falling wholly within that community-area to produce a final voter turnout value.

Map 4: Precincts falling entirely within community-areas and precincts split by community-areas
Map 5: Close-up of precincts split by multiple community areas

Map 6: VAP is computed for each precinct split by community areas
Map 7: Precincts are split by community-areas to form precinct fragments that evenly fall within community-areas.

Map 8: Since precincts are drawn at the block level, VAP can be computed for each precinct fragment. The 2010 census block layer is joined to each precinct fragment in order to calculate VAP for each fragment.
Map 9: VAP is calculated for each precinct fragment.

Map 10: The VAP for each precinct fragment is divided by the VAP of the entire precinct to obtain weights.
Map 11: The turnout for each whole precinct is multiplied by the precinct fragment’s weight to obtain each precinct fragment’s share of turnout.

Map 12: For each precinct fragment that falls within Lincoln Square, the turnout values from the prior step are aggregated.
2.4 Analytical Methods

2.4.1 Overview

In order to evaluate the relationship between voting and crime at the community-area level and the spatial pattern of this relationship, the analysis and methodological approach is informed by two questions:

1. Can Coleman’s (2002) results can be replicated at the community-area level? In other words, will the same results emerge even though the scale of analysis changes?

2. Might another model better explain the data in this research, and in such a model,
   2.1 What is the relationship between voter turnout and crime?
   2.2 What is the spatial pattern of this relationship?

2.4.2 Replicating Coleman’s (2002) study

In order to answer question #1 – whether Coleman’s (2002) results at the state and county level could be reproduced at the community-area level – I used the same independent and dependent variables utilized in his study. Following Coleman’s (2002) model, I took the log of the per-capita rate of each crime type. Log homicide, log rape, log assault, log robbery, and log burglary were used as dependent variables. The independent variables used were also repeated from Coleman’s (2002) model: %_Turnout, turnout^2, % single parent households, log income, log population density, % males divorced, % population aged 15-19, and % population in poverty. In order to determine the impact of the %_Turnout variable, two Ordinary Least Squares (OLS) regression models were run for each crime type. The first OLS model regressed a
particular crime type on all independent variables listed above, but omitted the %_Turnout variable. The second OLS model was exactly the same as the first OLS model, but added the %_Turnout variable as an independent variable.

### 2.4.3 Developing an Optimal Model

This section deals with question #2 in section 2.4. Though repeating Coleman’s (2002) study at the community-area scale might not reveal a strong relationship between voter turnout and crime rate, it is possible that a different scale of analysis requires a different set of explanatory variables. To address this issue, stepwise regression was used to regress each crime type on all possible independent variable combinations and select an independent variable subset that produced the highest quality model according to the Akaike Information Criterion (AIC). Each crime type was regressed on the same 17 candidate variables: %_Black, %_White, %_Asian, %_Latino, %_NoMaleHH, %_SingleHH, %_Age15to34, %_DivorcedMales, %_HSorLess, %_Unemployment, %_HHPoverty, %_FamilyPoverty, %_Renter, %_Rent600Less, Log_Pop, Log_PopDensity, and Log_Inc. The optimal model for each crime type varied (Figure 3).
Once an optimal model was identified for each crime type, OLS regression was performed twice for each crime type. Using the same approach detailed in the previous section, the first OLS model used the optimal variable subsets identified by stepwise regression as independent variables for each crime type (Figure 3). The second OLS model was exactly the same as the first OLS model, but added the %_Turnout variable as an independent variable. This made it possible to assess the impact of the %_Turnout variable on the optimal model for each crime type.

<table>
<thead>
<tr>
<th>Log Homicide</th>
<th>Log Rape</th>
<th>Log Assault</th>
<th>Log Robbery</th>
<th>Log Burglary</th>
</tr>
</thead>
<tbody>
<tr>
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<td>%_Black</td>
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</tr>
<tr>
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</tbody>
</table>

Figure 3: Optimal variable subsets determined by stepwise regression, for year 2010
2.4.4 Geographically Weighted Regression: An Overview

Though OLS regression can provide insights about the relationship between voter turnout and crime, there are limitations to the OLS approach. Linear regression models such as OLS produce one estimate for each variable, assuming that the relationship between dependent variables and independent variables is constant over space. A relationship that does not change over space is referred to by Fotheringham (2002) as “stationary”. In this sense, linear regression techniques such as OLS are referred to as “global models”, with an estimate being the same at every location.

Geographically Weighted Regression (GWR) is an extension of the basic linear regression model with one fundamental difference: it assumes that the relationship being modeled varies over space. According to Fotheringham (2002), GWR is best suited to model relationships that exhibit non-stationarity, which means that they change over space. Fotheringham (2002) argues that while many physical processes are fixed over space, social processes often vary, and GWR can be a valuable tool to explore the spatial variation of these processes. Voting and crime, both of which are social processes, thus are ideal candidates for GWR analysis. The basic equation for GWR is:

\[ y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \epsilon_i \]

Where \((u_i, v_i)\) are the geographic coordinates of point \(i\) and \(\beta_k(u_i, v_i)\) represents “the realization of the continuous function \(\beta_k(u_i, v_i)\) at any point \(i\)” according to Fotheringham (2002). In essence, GWR model can estimate parameter values at all points in space. This is done by a weighting function that weights points closer to the point of estimation more heavily than points further away. This weighting function will be discussed in more detail in section 2.4.5.
To illustrate the basic concept of GWR practice, consider the following example of house-size and selling price across the city of Pittsburg. If this relationship is analyzed using linear regression, a single value would be produced for the house-size variable. If a positive relationship is found, one might assume that an increase in square footage of the house leads to a higher selling price at every location in Pittsburg.

GWR, on the other hand, can offer insight into the local relationship between house-size and selling price across Pittsburg. If the GWR model is used to analyze house-size vs. selling price, it may reveal that the relationship between house-size and its selling price is not constant, but variable over space. For example, an increase in house-size in an area of downtown Pittsburg may have a greater impact on selling price than the same increase in size has on a house in a Pittsburg suburb. It may be that in cramped downtown Pittsburg, the additional spaciousness is seen as very valuable, whereas in suburban Pittsburg, the extra spaciousness is not as valuable and thus does not command a significantly higher selling price. GWR could even reveal that house-size and selling price might be positively associated in some areas, but negatively associated in other areas.

2.4.5 GWR Analysis of Voter Turnout and Crime

As mentioned previously, the OLS results can offer limited insight into the relationship between voter turnout and crime rate at the community-area level. However, in order to understand the significance of voter turnout across space and the spatial structure and variation of voter turnout’s relationship to crime rate, GWR will be used.

Fotheringham (2002) identifies two main issues associated with GWR: the selection of a weighting scheme and bandwidth. Weighting schemes can be either fixed or adaptive, though the basic idea behind either weighting scheme is to use data points surrounding the point of
regression in order to estimate a value at the point of regression. For this analysis, the centroid of each community-area is used as the point of regression. In a fixed scheme, a region with a particular distance or \textit{bandwidth} is prescribed around the point of regression. Data points falling within this specified distance will be used to estimate the value at the point of regression. The weight of a data point is larger when it is closer to the point of regression, and smaller when it is further away. In an adaptive scheme, the bandwidth prescribed around the point of regression changes based on fluctuations in the data. In areas with fewer data, the bandwidth will be greater to include more data, and in areas with more data, the bandwidth will be smaller.

GWR 4.0, a software package for geographically-weighted modelling, was used to perform a GWR analysis of voter turnout at the community-area level. An adaptive Gaussian weighting scheme was employed. Instead of allowing the bandwidth to vary (a measure of linear distance), the adaptive Gaussian scheme allows the amount of “nearest neighbors” – data points used in making an estimation at the point of regression – to vary. In this case, the adaptive Gaussian weighting scheme allows the number of community-areas taken into consideration when making an estimation to vary.

\textbf{Chapter 3. Results and Discussion}

\textit{3.1 Reproduction of Coleman’s Work}

By repeating Coleman’s (2002) analysis at the community-area level, two clear differences emerge. First, Coleman (2002) found that \%_Turnout was statistically significant variable for all crime types. At the community-area level, for the year 2010, \%_Turnout was only statistically
significant for assault and robbery. Second, while Coleman’s (2002) study found that the crime rate and %_Turnout exhibited a parabolic relationship, with crime rate peaking at roughly 50% turnout, the data in this research demonstrated a linear relationship rather than quadratic (Figures 4 – 8). The R² value suffered considerably when the data was fit to a quadratic model that regressed crime rate on %_Turnout and turnout squared.

Figure 4: %_Turnout vs. Log Homicide
Figure 5: %_Turnout vs. Log Rape
Figure 6: %_Turnout vs. Log Assault
Figure 7: %_Turnout vs. Log Robbery
For each crime type, the $R^2$ value increases slightly when %_Turnout is added to the model, with homicide seeing the largest increase (Table 1). However, the introduction of the %_Turnout variable clearly does not make a significant impact on the explanatory power of the model.

![Figure 8: %_Turnout vs. Log Burglary](image)

<table>
<thead>
<tr>
<th></th>
<th>Log Homicide</th>
<th>Log Homicide + Turnout</th>
<th>Log Rape</th>
<th>Log Rape + Turnout</th>
<th>Log Assault</th>
<th>Log Assault + Turnout</th>
<th>Log Robbery</th>
<th>Log Robbery + Turnout</th>
<th>Log Burglary</th>
<th>Log Burglary + Turnout</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>.698</td>
<td>.710</td>
<td>.666</td>
<td>.671</td>
<td>.734</td>
<td>.748</td>
<td>.719</td>
<td>.740</td>
<td>.725</td>
<td>.727</td>
</tr>
</tbody>
</table>

Table 1: $R^2$ for Log Crime Types, using Coleman’s (2002) variables, 2010
3.2 Results from Optimal Model

While each crime type’s optimal model yielded a higher $R^2$ compared to Coleman’s model, indicating an improvement in the explanatory power of the optimal models identified by stepwise regression, the effect of the %_Turnout variable was still negligible across all crime types (Table 2). Interestingly, homicide saw the largest increase in $R^2$ with the addition of the %_Turnout variable, while rape showed zero increase in $R^2$ with the addition of the %_Turnout variable.

<table>
<thead>
<tr>
<th></th>
<th>Log Homicide</th>
<th>Log Homicide +Turnout</th>
<th>Log Rape</th>
<th>Log Rape +Turnout</th>
<th>Log Assault</th>
<th>Log Assault +Turnout</th>
<th>Log Robbery</th>
<th>Log Robbery +Turnout</th>
<th>Log Burglary</th>
<th>Log Burglary +Turnout</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>.767</td>
<td>.772</td>
<td>.720</td>
<td>.720</td>
<td>.910</td>
<td>.917</td>
<td>.909</td>
<td>.912</td>
<td>.633</td>
<td>.638</td>
</tr>
</tbody>
</table>

Table 2: $R^2$ for Log Crime Types, using optimal model from stepwise regression

3.3 Observed Spatial Patterns

One of the most obvious questions raised with GWR analysis is whether the observed patterns between voter turnout and crime are random. In order to answer this question, the GWR analysis was performed for the year 2010 and 2014 in order verify whether the pattern observed in 2010 was also observed in 2014 (Maps 13 – 42).
3.3.1 Homicide

For homicide, an interesting spatial pattern emerges. In 2010 and 2014, there is a high positive coefficient for the %_Turnout variable in an area on the west side of Chicago. For both years, this area on the west side also has a higher local $R^2$ value compared to the rest of Chicago. A band of community-areas with negative coefficients for %_Turnout can be observed along the north side and south side of Chicago – a pattern that is particularly pronounced in 2014. Examining the %_Turnout coefficients and local $R^2$ indicates that the association between voter turnout and homicide rate varies from negative or positive depending on spatial location. Finally, the residuals of the homicide model are randomly distributed, indicating a reasonably well-specified model.

Map 13: Local Coefficients, Log Homicide vs. %_Turnout, 2010

Map 14: Local Coefficients, Log Homicide vs. %_Turnout, 2014
Map 15: Local $R^2$, Log Homicide vs. %_Turnout, 2010

Map 16: Local $R^2$, Log Homicide vs. %_Turnout, 2014

Map 17: Residuals, Log Homicide vs. %_Turnout, 2010

Map 18: Residuals, Log Homicide vs. %_Turnout, 2014
3.3.2 Rape

As with homicide, rape also exhibits a unique spatial pattern, with high coefficients for \%_Turnout clustering broadly in central Chicago and low coefficients for \%_Turnout clustering along the city’s north side and south side. However, compared to the homicide model, rape and \%_Turnout did not have as strong of a negative association on Chicago’s south side. The local $R^2$ value, as with the homicide model, is consistently highest in an area on the northwest side of Chicago and lowest on the southwest side, indicating spatial variation in the explanatory power of the rape model. As with homicide, these patterns remain consistent for years 2010 and 2014. The residuals are randomly distributed.
3.3.3 Assault

Generally speaking, in terms of the %_Turnout coefficient, assault follows the same trend seen in the homicide and rape models. The %_Turnout coefficient is high in central Chicago and low along the north and southwest portions of the city. For both 2010 and 2014, the highest $R^2$ (80% or greater) is observed in a cluster of community areas on the northwest side. Interestingly, from 2010 to 2014, much of the southwest side sees a significant rise in local $R^2$ values. Again, the residuals are randomly distributed.
Map 27: Local $R^2$, Log Assault vs. %_Turnout, 2010

Map 28: Local $R^2$, Log Assault vs. %_Turnout, 2014

Map 29: Residuals, Log Assault vs. %_Turnout, 2010

Map 30: Residuals, Log Assault vs. %_Turnout, 2014
### 3.3.4 Robbery

With respect to robbery, the general pattern holds. Again, the %_Turnout coefficient is highest in a broad area of central and west Chicago. From 2010 to 2014, the %_Turnout coefficient increases in a few select community-areas on Chicago’s west side. As with homicide, rape, and assault, the %_Turnout coefficient is lowest along the north and southwest sides of the city. The residuals are randomly distributed.
Map 33: Local $R^2$, Log Robbery vs. \% Turnout, 2010

Map 34: Local $R^2$, Log Robbery vs. \% Turnout, 2014

Map 35: Residuals, Log Robbery vs. \% Turnout, 2010

Map 36: Residuals, Log Robbery vs. \% Turnout, 2014
3.3.5 Burglary

With respect to burglary, the pattern is somewhat unique. While coefficients for \%_Turnout are still generally highest on the west side of Chicago, in 2010 there is a distinct “L” shape of community-areas with \%_Turnout coefficient values between 1.0 and 3.0. It is not clear why this is. In addition, the \%_Turnout negative coefficient values on the north side of Chicago decrease from 2010 to 2014, indicating that the negative association between turnout and burglary here becomes even stronger over this time period. As in prior models, the residuals are randomly distributed spatially.
Map 39: Local $R^2$, Log Burglary vs. \%_Turnout, 2010

Map 40: Local $R^2$, Log Burglary vs. \%_Turnout, 2014

Map 41: Residuals, Log Burglary vs. \%_Turnout, 2010

Map 42: Residuals, Log Burglary vs. \%_Turnout, 2014
3.4 Summary of GWR Patterns

The GWR model does fairly well in explaining the relationship between different crime types and voter turnout. Moran’s I was used to measure the degree of spatial autocorrelation present in the residuals. Across all crime types and years, the residuals were randomly distributed, indicating that the residuals are independent of one another and the errors are distributed randomly. The distribution of local $R^2$ values over different Chicago community areas reveals an interesting pattern: $R^2$ is highly variable over space, with some communities having an $R^2$ of over .80, and others with an $R^2$ of less than .20. The coefficients for the %_Turnout variable are also highly variable, with a negative sign in some community areas and a positive sign in others.

In comparing the $R^2$ values for the bivariate analysis of log crime vs. voter turnout, the model produces a reasonably high $R^2$ for all crime types, with rape having the lowest $R^2$ for both 2010 and 2014 (Table 3). This may be due to the fact that certain crime types such as homicide and rape, as Glaeser, Sacerdote, and Scheinkman (1996) point out, are less influenced by social conformity than other types of crime. Therefore, voter turnout, as a measure of social conformity, may explain less of the variation in rape compared to other types of crime.
Upon examination of the GWR maps depicting the relationship between voter turnout and crime, a distinct pattern can be observed that is consistent across multiple crime types and over time (years 2010 and 2014). Broadly speaking, there are four regions that consistently exhibit relatively high or low %_Turnout coefficients (Map 43). Region #1, extending across Chicago’s north side, and Region #3, on Chicago’s southwest side, consistently have a negative coefficient for %_Turnout, meaning that in these areas, voter turnout is negatively associated with crime rate. Region #2, mostly centered around Chicago’s west side, and Region #4, on Chicago’s southeast side, consistently have a high positive coefficient for %_Turnout compared to other areas of the city, meaning that the voter turnout and crime rates are positively associated in these areas.

<table>
<thead>
<tr>
<th></th>
<th>Log Homicide vs. %_Turnout</th>
<th>Log Rape vs. %_Turnout</th>
<th>Log Assault vs. %_Turnout</th>
<th>Log Robbery vs. %_Turnout</th>
<th>Log Burglary vs. %_Turnout</th>
</tr>
</thead>
<tbody>
<tr>
<td>R² 2010</td>
<td>.638</td>
<td>.473</td>
<td>.728</td>
<td>.782</td>
<td>.759</td>
</tr>
<tr>
<td>R² 2014</td>
<td>.492</td>
<td>.491</td>
<td>.815</td>
<td>.799</td>
<td>.694</td>
</tr>
</tbody>
</table>

Table 3: R² for Log Crime Types vs. %_Turnout using GWR, years 2010 and 2014
Map 43: Patterns of %_Turnout coefficient across multiple crime types and years
Given that the spatial pattern of the relationship between voter turnout and crime rate does not appear to be random, a descriptive approach can be taken in order to understand the spatial pattern. How can socioeconomic spatial patterns be used to explain the spatial patterns observed in the GWR analysis? The next section (3.5) addresses this question.

3.5 Spatial Distribution of Other Explanatory Variables

In order to explain the pattern observed for the relationship between voter turnout and crime rate, it is helpful to know whether the coefficient surface produced by GWR (detailed in section 3.3) resembles the distribution of crime’s explanatory variables, including race/ethnicity, income, poverty, and voter turnout. To compare the spatial pattern of the relationship between voting and crime with the spatial pattern of other explanatory variables, the spatial distribution of individual explanatory variables must be mapped (Maps 44 – 46). The primary question is whether any of them exhibit the same spatial pattern as the voter turnout coefficient produced in GWR.

Of the six variables examined (%_Black, %_Latino, %_Minority, %_HHPoverty, Income, and %_Turnout), the spatial pattern of %_Black, %_HHPoverty, and Income appear to mostly closely resemble the GWR voter turnout coefficient spatial pattern. The regions labeled on the %_Black, %_HHPoverty, and Income maps (Map 44, Map 45, and Map 46, respectively) correspond to the high and low %_Turnout coefficient regions depicted earlier in Map 43. Generally speaking, most high-coefficient community-areas in terms of %_Turnout are predominantly lower income and higher minority (high concentration of black, Latino, and/or Asian residents) while most low-coefficient community-areas in terms of %_Turnout are predominantly higher income and lower minority. An examination of the socio-economic and
racial composition of the community-areas with the lowest and highest %_Turnout coefficients may help to explain the variation in the %_Turnout coefficient.

Map 44: %_Black

Map 45: %_HHPoverty

Map 46: Income
3.6 Community-Area Characteristics

Using the example of log assault vs. %_Turnout for 2010 (Map 47), what are the characteristics of community-areas with a %_Turnout coefficient greater than 3.0? These communities are Brighton Park, East Garfield Park, Gage Park, Humboldt Park, Kenwood, McKinley Park, New City, North Lawndale, South Lawndale, and West Garfield Park. Generally speaking, these are all low-income, high minority, and low voter-turnout community-areas.

Map 47: Log Assault vs. %_Turnout, 2010
High %_Turnout coefficient community-areas
Similarly, using the example of log assault vs. \%_Turnout for 2010 (Map 48), what are the characteristics of community-areas with a \%_Turnout coefficient less than 3.0? These communities are Beverly, Dunning, Edgewater, Edison Park, Forest Glen, Jefferson Park, Lakeview, Lincoln Park, Lincoln Square, Montclare, Morgan Park, North Center, Norwood Park, O’Hare, Portage Park, Rogers Park, Uptown, and Washington Heights. Compared to the community-areas with high coefficients associated with \%_Turnout, these community-areas are relatively higher income, less minority, and exhibit higher voter turnout.
Overall, there is a clear difference between community-areas with high coefficients associated with %_Turnout and low coefficients associated with %_Turnout. A side-by-side comparison of %_Turnout, Income, %_HHPoverty, and %_Minority best illustrates this (Table 4).

<table>
<thead>
<tr>
<th></th>
<th>High %_Turnout Coefficient Community Areas (&gt; .30)</th>
<th>Low %_Turnout Coefficient Community Areas (&lt; -.30)</th>
</tr>
</thead>
<tbody>
<tr>
<td>%_Turnout</td>
<td>.27</td>
<td>0.39</td>
</tr>
<tr>
<td>Income</td>
<td>$34,600</td>
<td>$64,450</td>
</tr>
<tr>
<td>% Households in Poverty</td>
<td>0.29</td>
<td>0.11</td>
</tr>
<tr>
<td>% Minority</td>
<td>0.93</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Table 4: Comparing community-areas with high and low coefficients for %_Turnout

While it is clear that most community-areas with high coefficients for %_Turnout (regions #2 and #4) are lower income and higher minority, and most community-areas with low coefficients for %_Turnout (regions #1 and #3) are higher income and lower minority, not all lower income/higher minority community-areas fall into regions # 2 and #4, and not all higher income/lower minority community-areas fall into regions #1 and #4. For example, Greater Grand Crossing and Chatham on the south side of Chicago are nearly 100% black and low income, yet these community-areas don’t fall into region #2 or #4 as would be expected. Rather, Greater Grand Crossing and Chatham both have low or even negative values for the %_Turnout coefficient in the homicide model (Map 49).
A possible conclusion is that percentage minority and socioeconomic status, as examined above, can only tell part of the story in terms of why some community-areas exhibit a positive relationship between voting and crime. As Coleman (2002) observed in a state and county-wide analysis, crime rate peaks where voter turnout is around 50% – the point at which there is non-conformity to the voting norm. A similar phenomenon may be occurring across Chicago community-areas. In certain community-areas undergoing transition, voter turnout might be approaching the 50% “entropic” mark. If residents of a particular community-area traditionally choose not to vote rather than vote, an increase in voting may nudge the community-
area closer to the 50% turnout level, indicating a broad lack of consensus regarding the voting norm. A way to test this hypothesis would be to see whether there is a relationship between the voter turnout coefficients and deviations from 50% turnout. Theoretically, in community-areas with voter turnout hovering around 50%, an increase in voter turnout might push that community towards voting entropy (as described above) could subsequently lead to higher rates of crime. This could potentially explain how certain community-areas have positive associations between voting and crime.

Maps 50 – 51 show the spatial distribution of community-areas’ deviation from 50% voter turnout. Interestingly, for 2010, three of the four community-areas with the highest coefficients associated with %_Turnout in the assault model (depicted in figure 72) deviated 20 percentage points or less from 50% turnout. Still, a large number of community-areas with high %_Turnout coefficients have deviations between 30% and 40%, meaning that they are further away from the 50% turnout “entropy” mark but still have a positive association between voting and crime. Furthermore, the patch of community-areas on the southwest side of Chicago with voter turnout right around 50% (figure 73) has negative voter turnout coefficients, indicating a negative relationship between voting and crime. Clearly, a community-area’s proximity to 50% turnout cannot entirely explain the variation in the %_Turnout coefficients.
Chapter 4. Conclusions

This research sheds light on the relationship between voter turnout and crime at the neighborhood-level. One of the primary goals of this work was to see whether or not the results from Coleman’s (2002) study could be reproduced at a different scale of analysis – in this case – the neighborhood scale. In repeating Coleman’s study at the Chicago community-area level, a few key insights are gained. First, at the community-area scale, there does not appear to be a strong association between voter turnout and crime rate. This is evidenced by the bivariate scatterplots of % Turnout vs. various crime types, which show a weak association between the
two variables. Furthermore, %_Turnout was a statistically significant predictor for only two of the five crime types used for this analysis. With the exception of assault and robbery in year 2010, %_Turnout was statistically insignificant as a predictor variable. Finally, this study compared crime models with and without the %_Turnout variable in order to assess how the addition of %_Turnout would impact R². For each crime type, when %_Turnout is added to Coleman’s (2002) independent variables, the change in R² is minimal. It is clear that the addition of %_Turnout adds virtually no explanatory power to the model – a trend that is true across all five crime types.

This research also used stepwise regression to select optimal regression models for each crime type. For each crime type, Geographically Weighted Regression (GWR) was used to assess the spatial pattern of the relationship between %_Turnout and crime rate. For each crime type, local coefficients for %_Turnout, local R², and residuals were mapped in order to assess the spatial structure of the relationship between %_Turnout and crime rate. While there were minor variations amongst spatial patterns for voter turnout vs. various crime types, the GWR maps for all crime types depicted the same general spatial pattern and demonstrated that the relationship between voter turnout and crime rate is highly localized. The maps illustrate that there are clusters of Chicago community-areas that consistently exhibit a negative association between voter turnout and crime rate, and other community-areas where the association is consistently positive. Similarly, the local variation of R² seen in the GWR maps shows that voter turnout’s ability to explain the variation in crime rate is highly variable over space.

Finally, this research attempts to explain what might underlie the observed patterns between voter turnout and crime rate. The spatial pattern of %_HHPoverty, %_Black, and Income bear close resemblance to the spatial pattern of voter turnout vs. crime rate, suggesting that the relationship between voting and crime may be partially mediated by socioeconomic and
racial factors. Furthermore, examining the socioeconomic and racial composition of community-
areas that have either strong negative or strong positive associations between voter turnout and
crime confirms this. Community-areas with strong positive associations between voter turnout
and crime rate are often low-income and high-minority, while community-areas with strong
negative associations between voter turnout and crime are primarily high-income and low-
minority.

When interpreting the GWR spatial patterns, an important caveat should be kept in
mind. Knowing from the initial bivariate scatterplots illustrated in section 3.1 that %_Turnout
and crime rate show a weak overall relationship, caution should be used when making
assumptions about community-areas with high coefficients associated with %_Turnout and
community-areas with negative coefficients associated with %_Turnout. It would be easy to say
that in community-areas with high coefficients for %_Turnout, more voting means more crime,
and in community-areas with negative coefficients for %_Turnout, less voting means more
crime. However, voter turnout may encompass other factors and may be reflective of underlying
characteristics in a particular neighborhood – an issue which this research only begins to address
– and thus it is important not to make broad generalizations from the resultant GWR patterns.

Furthermore, GWR by nature focuses on local relationships. As such, GWR models runs
the risk of being overly specified and too sensitive to local variation, and on the other hand,
overly generalized and apt to miss important details. The bandwidth selection procedures
outlined in section 2.4.5 attempt to strike a proper balance between both extremes, but the risk of
over-generalization and over-sensitivity with any GWR model nevertheless deserves mention
here. Furthermore, this research does not attempt to explain how local factors present in various
community-areas might influence the relationship between voting and crime, or how the analysis
might be overly sensitive to local “noise”, which further underscores the need to take a measured approach when interpreting the GRW spatial patterns.

Another important consideration is that any data aggregated to arbitrary spatial units is subject to the modifiable area unit problem (MAUP) – the idea that different units of analysis may produce different statistical results. The data in this study was aggregated up to the community-area, and it is possible that different results could be obtained if different spatial units of analysis were used. Furthermore, statistical results can vary depending on the overall scale at which the analysis is performed. Since this analysis was done only at the community-area scale, it is possible that alternative scales of analysis could produce more insights as to whether the observed relationships would hold with changes of scale.

Finally, the replicability of this research should be addressed – namely, whether or not the relationship between voting and crime observed in this research could be observed for cities other than Chicago. Though this research points to socioeconomic characteristics of community-areas and their level of voter turnout as two possible explanations of the observed relationship between voting and crime, no definitive explanation is given. Therefore, it is unclear whether socioeconomic factors, voter turnout, or both are responsible for the observed relationship. In a city with different socioeconomic characteristics and different levels of voter turnout, it is difficult to say whether the relationships in this study could be reproduced. Thus, future studies on these aspects would provide more insight on these relationships.

This original focus of this research was to better understand the relationship between voting and crime and the spatial structure of this relationship. In the process, new questions were brought to light – namely, what accounts for the unique spatial pattern of voter turnout and crime rate’s relationship across Chicago community-areas? While this research begins to answer that question, the explanations offered are largely speculative. While this research addresses the
overall relationship between voting and crime at the neighborhood level, and the spatial pattern of this relationship, understanding the underlying causes that impact how voter behavior and crime interact over space is deserving of further research.
References


