Using GIS Analytics to Define Risk Factors in High Eviction Census Tracts to Explore County Outreach Support – A Case Study of Hennepin County, Minnesota

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Abstract

Evictions have a more detrimental effect on people than just the risk of homelessness. Being evicted can often lead to loss of employment increasing the odds of someone ending up in a homeless shelter. In Hennepin County, Minnesota, there is an observable increase of housing instability and eviction filings that are overly represented to just a few ZIP codes. For residents at risk of losing their housing and facing homelessness, finding information on available resources and services can be challenging and difficult. This project serves to examine common risk factors associated with high eviction rates using geographic information systems (GIS) and explores areas within these high-eviction census tracts for outreach opportunities. Using Ordinary Least Squares (OLS) regression analysis, a combination of community and demographic data from the American Community Survey (ACS) were used to define risk factors explaining variables within the high rates of evictions in areas of Hennepin County.

Introduction

This project explores census tracts in Hennepin County, Minnesota that have the highest rates of eviction and explores key sociodemographic information to explain why eviction rates are higher in those areas. Hennepin County includes the metropolitan area of Minneapolis and the western suburbs. Focus is on 38 census tracts that fall in or near the four ZIP codes with the highest eviction rates.

Hennepin County is the largest county by population in Minnesota with 1,279,981 residents reported in 2019 by the Minnesota State Demographic Center (2020). Despite being the most populated, Hennepin County is the least equal county for income in the state (Legg and Nguyen, 2015).

About 6,000 evictions are filed for residents in Hennepin County every year, with nearly half of those in Minneapolis alone (Holdener, Nelson, Quint, Rea, Svitavsky, Uhrich, Whelan, and Zanoni, 2018). From 2013 to 2016, approximately 45% to 48% of eviction filings were from households located in just two ZIP codes, 55411 and 55412 (Minneapolis Innovation Team, 2016).

Hennepin County offers financial assistance programs for individuals and families facing housing instability. For individuals there is Emergency General Assistance (EGA) and for families there is Emergency Assistance (EA). In a survey

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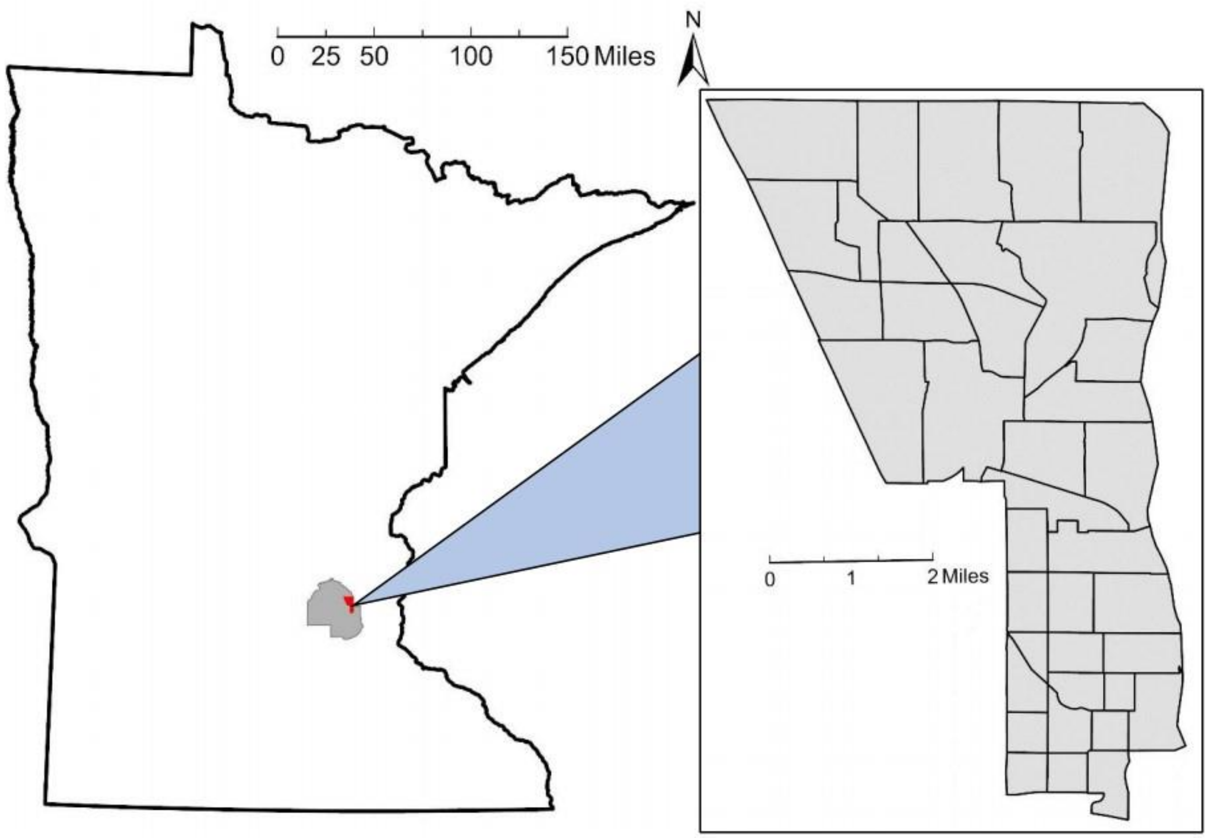

Figure 1. State of Minnesota with Hennepin County and study area of 38 census tracts that have the highest eviction rates in the county.

conducted in Hennepin County, roughly two thirds of the people facing evictions had not heard about the assistance programs (Holdener *et al.,* 2018).

A goal for Hennepin County is to have homelessness be “rare, brief, and non-recurring” by taking steps to prevent people from losing housing through eviction or foreclosure (Hennepin County, 2019). In the event a household needs to enter a shelter, the goal is to find stable housing as soon as possible and work to ensure people are not at risk of reentering an emergency shelter.

By defining risk factors in the study area, analysis can be completed to locate areas where outreach would be most beneficial for people who are facing eviction or housing instability.

Study Area

The area of the project is focused on 33 census tracts located within four ZIP codes (55411, 55412, 55429, and 55430) that have the highest rates of eviction in Hennepin County and 5 additional census tracts in adjoining ZIP codes that have specific apartment buildings with high numbers of evictions (Figure 1).

Systemic Issues and Neighborhood Instability

There can be many contributing factors to eviction, but the uniqueness of high-eviction neighborhoods is that high eviction rates often lead to more evictions because they cause neighborhood instability (Shelton, 2018).

Residential mobility is an issue for neighborhood instability that is closely linked to evictions. People who have been evicted are often forced into subpar and unsuitable living conditions and into neighborhoods of higher poverty and violent crime (Desmond, Gershenson, and Kiviat, 2015; DeLuca, Garboden and Rosenblatt, 2013). In a study on forced relocation, it was also found that when people are evicted and move into unsuitable housing, there was a significantly higher likelihood of them moving a second time soon after being evicted, often to housing that is more suitable to the household's needs (Desmond *et al*., 2015).

Evictions are also linked to higher rates of poverty, financial hardships, and homelessness. Emotional and mental trauma and physical health problems are often linked to forced relocation. With other research showing that mental illness and/or substance abuse being connected to high rates of eviction, these causes of high eviction rates are often also a result of evictions (DeLuca *et al*., 2013; Brisson and Covert, 2015).

Significance of Research

In Minneapolis, the average amount of past due rent for people facing eviction is $2000 and the median amount is $1700. In nearly 75% of the cases the tenant is only behind two months of rent before the landlord files for eviction (Minneapolis Innovation Team, 2016).

With eviction cases, randomized studies have found that there is a higher chance of an eviction hearing going in favor of the tenant when the tenant has legal representation in court, but in Minneapolis, 98% of cases have tenants who are unrepresented (Desmond *et al*., 2015). In some cases, tenants do not even show up to the hearing. When a tenant appears for a hearing, there is a higher likelihood of the case being settled. A court order is issued in 89% of the cases when only the landlord appears in court. When the tenant is present, only 17% of the cases result in a court order (Minneapolis Innovation Team, 2016). In situations such as these, targeted outreach may help by locating tenants who are either not aware of available resources or have barriers that prevent them from accessing or using resources that could result in a favorable outcome.

In previous studies, financial hardship, household characteristics such as household size, number of children, and women in inner-city black neighborhoods, substance use, and mental or physical health conditions were found to be connected to areas with high numbers of evictions (Tsai and Huang, 2018; Brisson and Covert, 2015).

Exploring the connections of evictions to area demographic statistics, can help facilitate outreach opportunities to prevent homelessness caused by housing instability.

Methods

The methodology used to complete this project included statistical analysis of independent variables to explain high rates of eviction in selected census tracts in Hennepin County. A visual workflow supporting the methodology is presented in Figure 2.

Data Collection Process

Data were collected from multiple sources including the American Community Survey (ACS) estimates for 2019, demographic data from Census.gov, and eviction statistics obtained from Hennepin

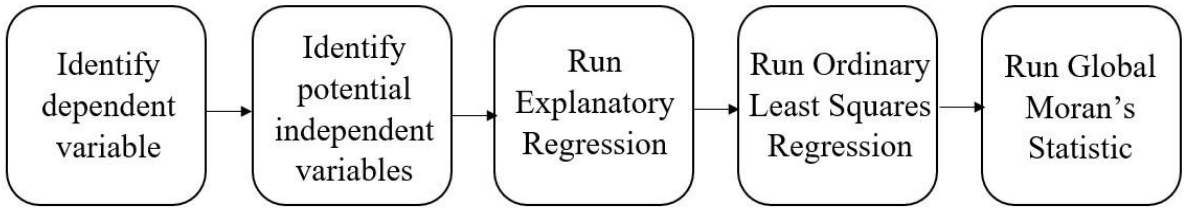

Figure 2. Project workflow used to determine statistically significant independent variables to explain high numbers of evictions and steps taken to validate the findings.

County. Additionally, shapefiles of census tracts and county boundaries were used to pare down the data to what was needed for the project.

The demographic data that was initially used included racial demographics, household and family sizes, median income, geographic mobility of the population, citizenship, native language, residents on public assistance, disability status, unemployment, and crime statistics of the area. These data sets were selected based on previous research that showed these or related data are linked to poverty and/or evictions (Desmond, An, Winkler, and Ferriss, 2013; Desmond and Gershenson, 2016; Tsai and Huang, 2018; Brisson and Covert, 2015).

When analysis showed statistically insignificant correlation to most of these data, different variables were looked at, including average cars per household, Internet subscription, and computer access. These variables were chosen based on research showing people in poverty, especially in urban neighborhoods, are frequent users of libraries for computer and Internet use and the lowest socio-economic quartile likely have more difficulty with access to transportation (Gilpin and Bekkerman, 2020; Hertel and Sprague, 2007; Koontz, Jue, and Lance, 2004).

Other variables that were chosen for analysis based on previous research included the number of bedrooms in rental units, types of rental housing (including detached and attached houses and apartment buildings with various numbers of units), and the years that residential buildings were built. These variables could imply temporary and emergency residential mobility of the neighborhood which is linked to high eviction rates (Desmond *et al*., 2015; DeLuca *et al*., 2013).

Data Manipulation Process

Data from the Census Bureau was exported into separate Excel spreadsheets based on the topic in which it was categorized on the website and listed by the 38 census tracts that were selected for this project.

The data were cleaned of any extraneous data and then extracted by the type of data that was used. In most instances the data were total counts of the variables, but in a few instances, the average or median of a variable, like income, family size, or area rent, were used as they represented the data more clearly.

After extraction, the data was loaded into a new spreadsheet and sorted by the census tract. If data were missing from some census tracts, they were not chosen for evaluation with the Exploratory Regression tool. If the variables were likely to have significance to the project, more complete data was sought, so of the variables used in this study, all of the census tracts had reportable data.

Ordinary Least Squares Regression Analysis

Ordinary Least Squares (OLS) regression was used to determine the best set of independent variables to explain the dependent variable (Figure 3).

In order to determine the validity of the OLS model, six statistical checks must be performed to verify that the model is properly specified and trustworthy (Esri, 2021). These checks include the following list of steps:

1. Are the explanatory variables helping the model?
    - An asterisk next to the probability of the coefficients denotes a statistically significant relationship.
2. Are the relationships as expected?
    - Each coefficient is assigned a positive or negative sign to indicate the type of relationship between the dependent and independent variables.
3. Are any of the explanatory variables redundant?
    - If a variable is higher than 7.5 on the Variable Inflation Factor (VIF), it may be redundant.
4. Is the model biased?
    - If the p-value for the Jarque-Bera statistic is denoted with an asterisk, it indicates the model is biased and cannot be deemed trustworthy.
5. Are all key explanatory variables used?
    - Statistically significant spatial autocorrelation or clustering residuals implies missing variables.
6. How well is the dependent variable explained?
    - The Adjusted R-Squared value shows how much the explanatory variables explain the dependent variable. Aikake's Information Criterion (AIC) can also be used and the lower the value indicates a better model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n + \epsilon$$

Figure 3. Ordinary Least Squares equation where Y equals the dependent variable, X equals the independent variables, β are the coefficients that explain the strength and relationship between the variables, and ϵ is the random error term.

Dependent Variable

Eviction data was obtained from Hennepin County's Office of Housing Stability for the years of 2018 and 2019. More recent data was available, but following the COVID-19 pandemic, there was an eviction moratorium in place that prevented landlords from filing evictions against tenants for non-payment and non-payment evictions make up 93% of the cases in Minneapolis (Minneapolis Innovation Team, 2016).

The data was pared down to the census tract level to show the total number of evictions that occurred during 2018 and 2019 for each of the 38 census tracts used in this project.

The median number of evictions for the study area was 27 with the lowest number being 3 and the highest being 185. In the case of the 185 evictions for one census tract, 99% of those evictions were

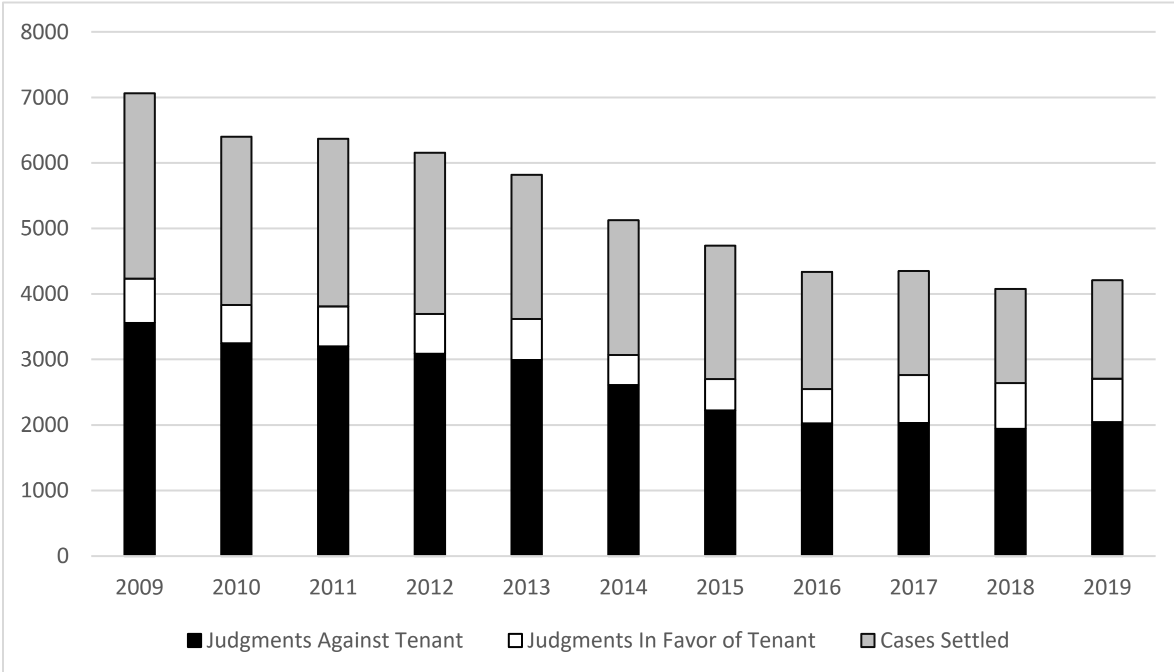

Figure 4. Most eviction judgements are in favor of the landlord. On average, roughly 12% of the eviction filings in Hennepin County between 2009 and 2019 were in favor of the tenant.

from one apartment complex in Brooklyn Park (Hennepin County, 2021).

Thinking that the selected project years led to the apartment complex being an outlier, further exploration found that between 2009 and 2019 that same Brooklyn Park apartment complex consistently had one of the highest number of evictions in all of Hennepin County. For comparison, the Brooklyn Park apartment complex averaged 66 evictions per year, being the top non-public-housing rental company for evictions and filings, while the next highest averaged 37 evictions per year for the same time period (Hennepin County, 2021).

The fact that no other non-public-housing apartment complex or rental management company had nearly as many evictions or eviction filings as the Brooklyn Park complex could mean the apartment complex itself is the outlier with possible explanations of poor management or other issues that are not directly related to the people being evicted. The census tract in which the Brooklyn Park complex is located was kept in the final project data because the historical data showed it consistently had high numbers of evictions (Hennepin County, 2021).

It should be noted that between 2009 and 2019 the percentage of eviction filings that resulted in an eviction judgment was roughly between 47% and 51%. For the years of 2018 and 2019, 47.67% and 48.52% of eviction filings, respectively, resulted in the tenant being evicted (Figure 4). The percentage of cases that ruled in favor of the tenant for 2018 and 2019 were 17.05% and 15.8%, respectively, which is consistent with previous studies done in Hennepin County (Hennepin County, 2021; Minneapolis Innovation Team, 2016).

Independent Variable Considerations

Using the data from the Census Bureau and the ACS's 2019 estimates, specific data sets were used based on previous research including households with children, female heads of household, income, public assistance, percentage of income spent on rent, and number of households living in poverty (Desmond *et al*., 2013; Desmond and Gershenson, 2016; Tsai and Huang, 2018).

Exploration of the data showed potential connections with previously unexamined independent variables like the average cars per household, households without Internet, and the number of rental units in apartment buildings.

Results

Using the Exploratory Regression tool in ArcGIS, 40 independent variables were analyzed to find a statistical model that could explain the number of evictions in the 38 census tracts.

The Exploratory Regression tool was run with 760,098 trials and a model of five independent variables were identified to best explain the high number of evictions. The five variables found were population of white people, median rent, one-unit attached rental properties, buildings built before 1939, and rental units with one bedroom. These five variables were then run through OLS regression which showed that all five variables were statistically significant with p-values under 0.05, which means there is a 95% confidence level that these variables are statistically significant which meets the first statistical check in determining the validity of the OLS model (Table 1).

The coefficients for the variables were positive for one-unit attached rental properties, buildings built before 1939, and rental units with one bedroom, meaning the variables were positively correlated with the dependent variable. As evictions are higher so are the variables with positive coefficients. The coefficient was negative for the population of white people meaning the variable was negatively correlated with the dependent variable. As evictions are higher, the variable with a negative coefficient is lower. Since these coefficients make sense for the variables, this fulfills the second statistical check.

In the case of the variable of median rent, the coefficient was listed as positive in the OLS model, but when the regression was plotted in a scatterplot (Figure 10), it showed the relationship as negative. When only the median rent variable was run in OLS, it resulted in a negative coefficient to match the graph. The likely cause for this discrepancy is that some or all of the four other variables used in the model suppressed the result of the median rent variable meaning the other variables used in the model impacted the significance of the median rent variable and its relationship to the dependent variable (Falk and Miller, 1992).

Table 1. Variables with their coefficients and p-values. Negative coefficients indicate the independent variable has a negative correlation with the dependent variable. A smaller p-value means the independent variable is more statistically significant.

Variable	Coefficient	p-value
Median rent	0.031322	0.012535*
Population of white people	-0.007534	0.024569*
1-unit attached rental property	0.134795	0.016890*
Buildings built before 1939	0.103585	0.000428*
1-bedroom rental units	0.164785	0.000000*

The variables all had a VIF below 7.5 which indicates that the selected variables are not redundant which would make the model invalid (Table 2). The Jarque-Bera statistic for this OLS model was 3.308909 and was not denoted as statistically significant meaning the model is not biased. These data fulfill the third and fourth statistical checks for a valid model.

Table 2. The variables run through OLS with the variable inflation factor that indicates if a model is redundant. If a VIF is higher than 7.5 it indicates redundancy.

Variable	VIF
Median rent	1.492022
Population of white people	1.511269
1-unit attached rental property	1.145078
Buildings built before 1939	1.313925
1-bedroom rental units	1.392534

Using the Global Moran's I statistic to determine spatial autocorrelation on the OLS residuals resulted in a z-score of -0.552154 which has a p-value of 0.580843. These data determined the OLS residuals were random and not clustered (Figure 5). This implies that it is less likely for a variable to be missing in the model. This fulfills the fifth statistical check.

Lastly for the statistical checks of model validity is the Adjusted R-Squared value and the Akaike's Information Criterion (AICc) to determine how well the model explains the dependent variable. The Adjusted R-Squared value was 0.846140 which means that the model can explain almost 85% of the high numbers of evictions. The AICc was 315.338591 which was the lowest reported statistic of all the models tested by the Explanatory Regression tool.

The results of this project showed that the five dependent variables of population of white people, median rent, one-unit attached rental properties, buildings built before 1939, and rental units with one bedroom passed the six statistical checks of model validity and could explain nearly 85% of the evictions in the study area.

Discussion

Project Variables and Previous Research

The variables that were determined to be statistically significant may have connections to previous research about residential mobility (Desmond, Gershenson, and Kiviat, 2015; DeLuca, Garboden, and Rosenblatt, 2013). Because people who are evicted are often forced to move into housing conditions that do not fit their needs, families may have to move into 1-bedroom rental units when more bedrooms are needed.

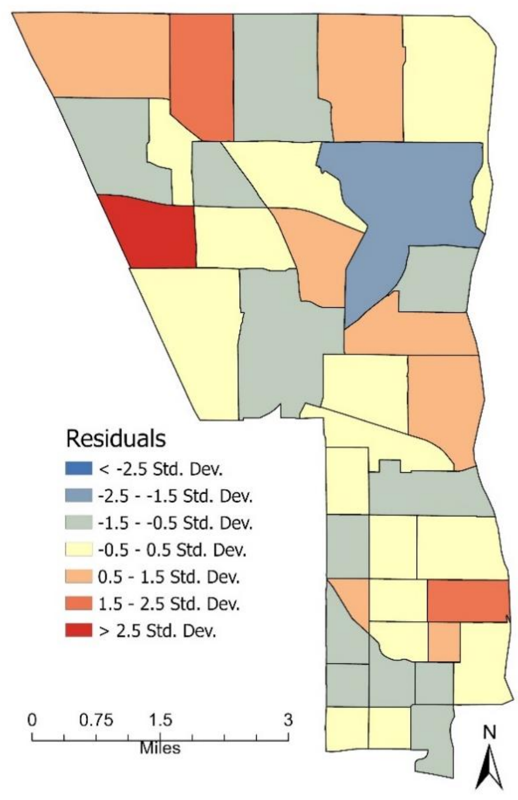

Figure 5. OLS residuals from Global Moran's I statistic showing residuals are random and not clustered making the OLS model valid and unlikely that there are any missing variables.

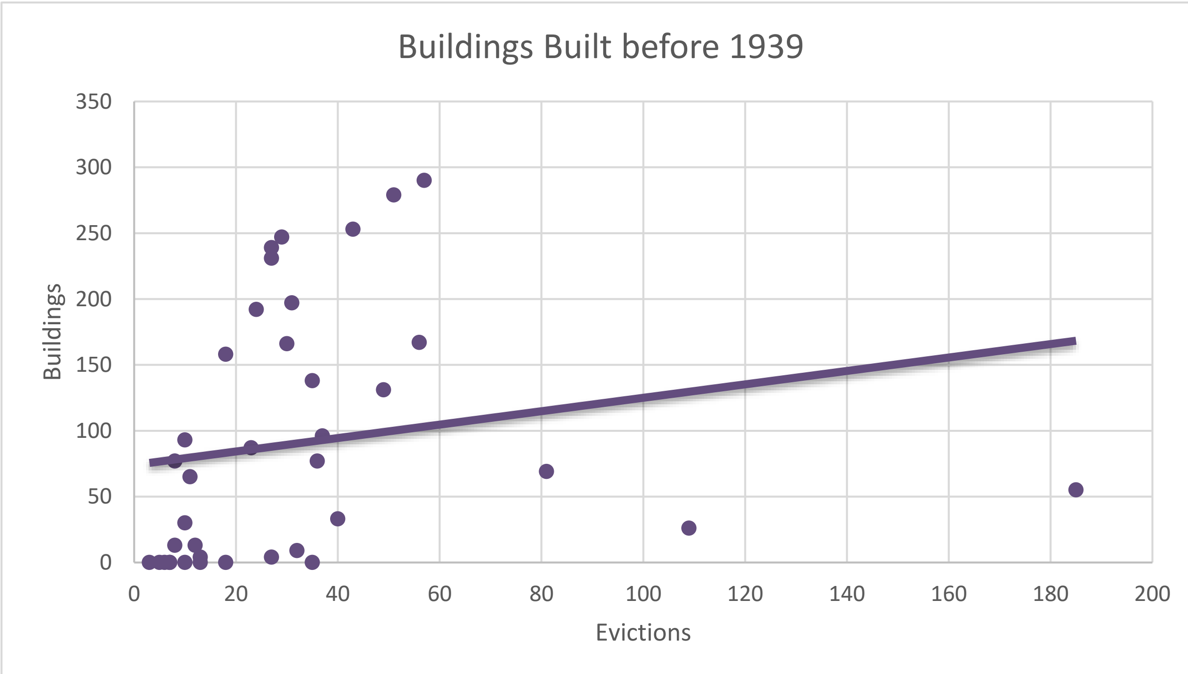

Figure 6. Scatterplot of the independent variable for buildings built before 1939. The trend line shows the significance of the independent variable, buildings built before 1939, as being slightly impactful on the dependent variable (number of evictions).

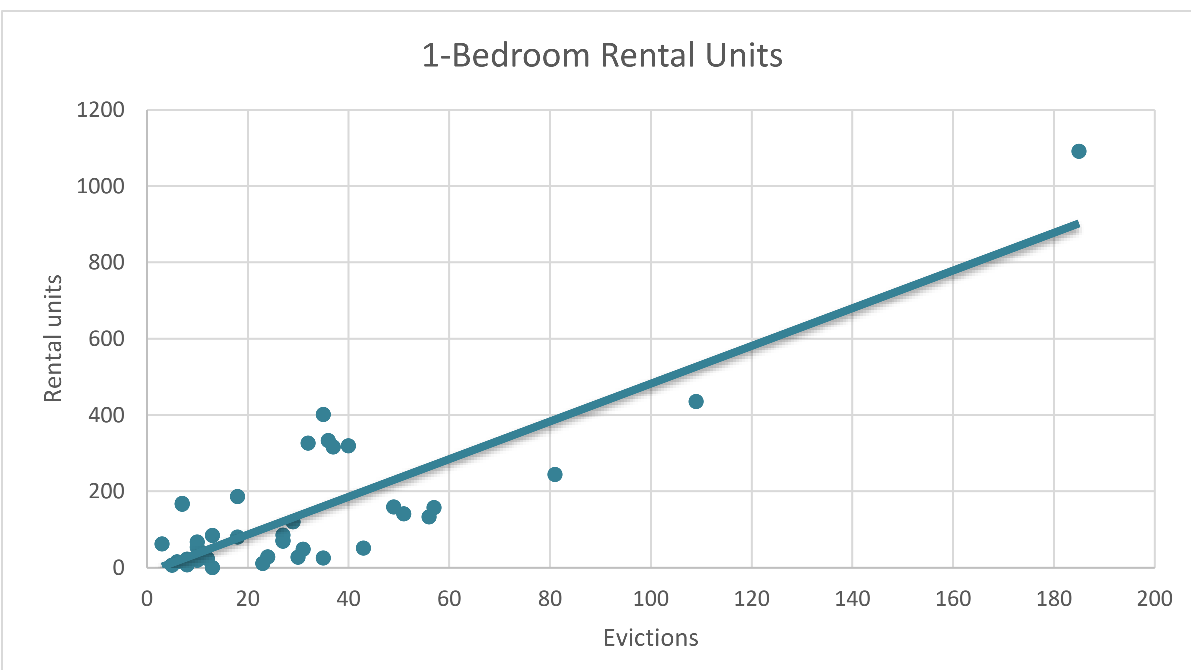

Figure 7. Scatterplot of the independent variable of rental units with one bedroom. The trend line shows the significance of the variable, rental units with one bedroom, has a strong impact on the dependent variable (number of evictions).

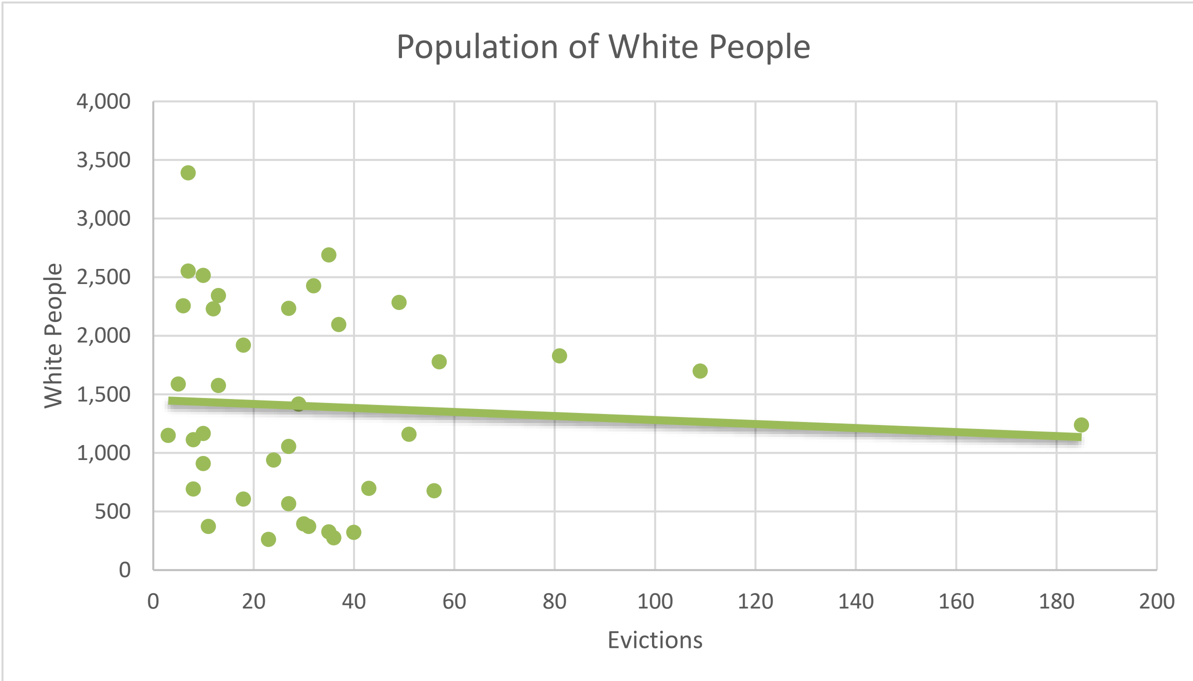

Figure 8. Scatterplot of the independent variable of the population of white people. The trend line shows the significance of the variable, population of white people, has a small impact on the dependent variable (numbers of evictions).

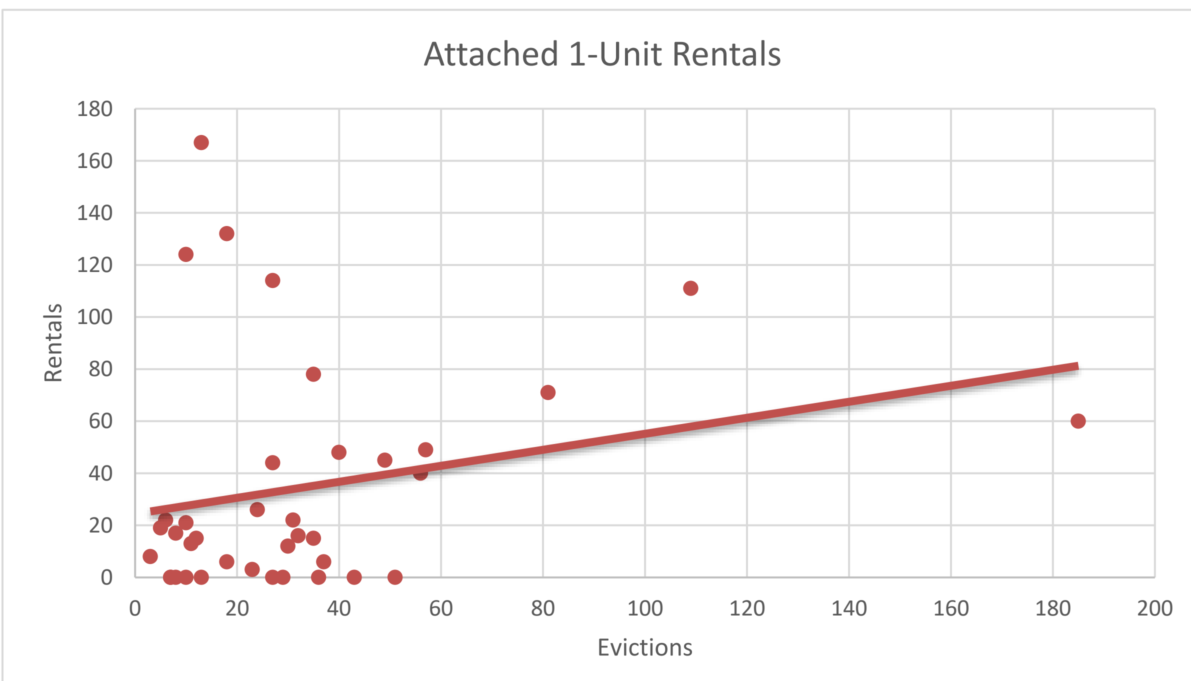

Figure 9. Scatterplot of the independent variable for attached 1-unit rentals. The trend line shows a relatively significant impact of the independent variable, attached 1-unit rentals, on the dependent variable (numbers of evictions).

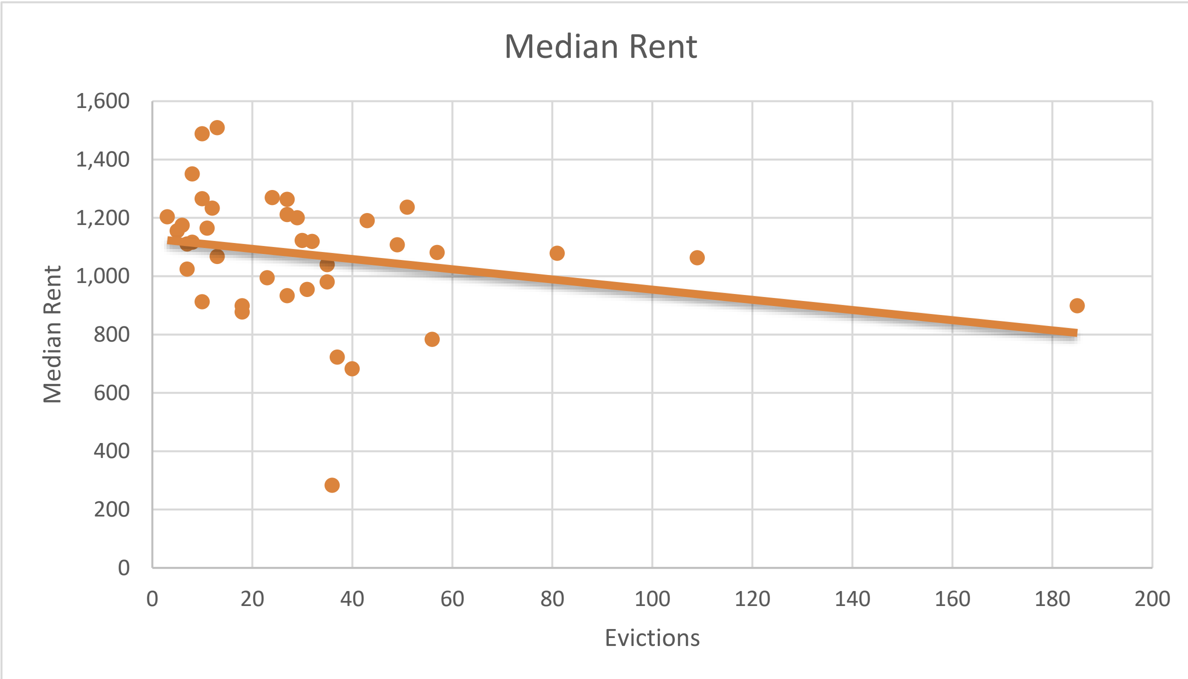

Figure 10. Scatterplot of the independent variable median rent. The trend line shows the significance of the independent variable, median rent, has a smaller impact on the dependent variable (number of evictions). The coefficient of the median rent variable was defined by OLS as positive but the scatterplot shows a negative relationship. This is likely a result of variable suppression caused by the other model variables impacting the significance of the median rent variable.

Older buildings are another possible connection to residential mobility because these buildings are often more likely to be in poorer condition and less desirable for housing unless it is an emergency situation such as being evicted.

The population of white people in this model was negatively correlated to the number of evictions meaning evictions are more likely linked to people who are of other races. As stated, women of color in historically black neighborhoods are significantly more likely to be evicted, which follows the results of this project (Tsai and Huang, 2018; Brisson and Covert, 2015). In the study by Tsai and Huang (2018), financial hardship was linked to evictions. Since the median rent was positively correlated to higher eviction rates it can be assumed that the financial of burden of high rental costs also aligns with previous research on evictions.

Other Variables and Targeted Outreach

While the five independent variables found in this project can explain 85% of the evictions in the study area, other variables used in the Explanatory Tool may be beneficial for targeted outreach.

The top variables by percentage of significance that were not part of the OLS model included households without an Internet subscription, households with only one car available, population of black people, average number of cars per household, apartment buildings with ten or more units, households without a computer, and households on public assistance (Table 3).

Research studies have shown that people experiencing financial hardships

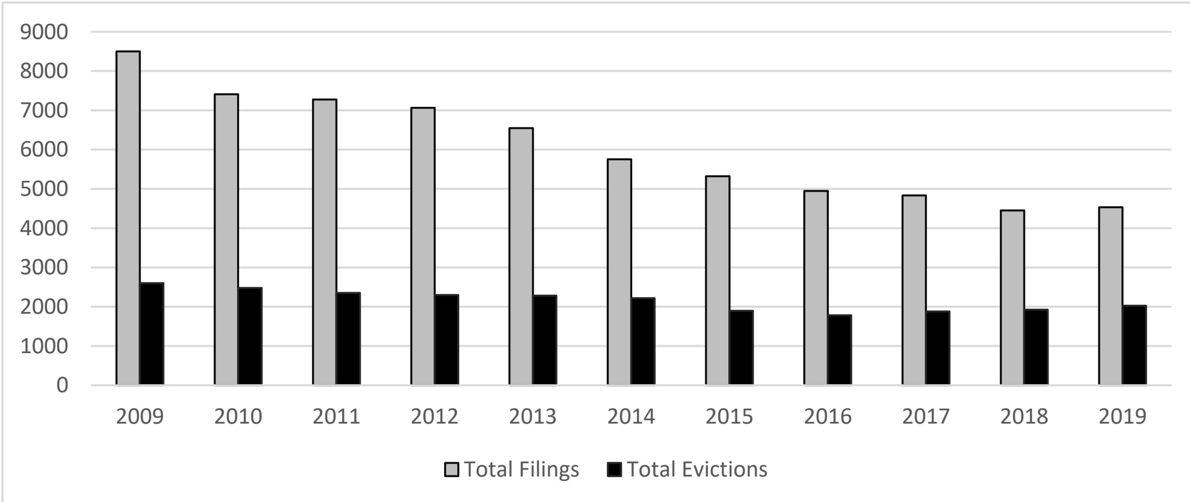

Figure 11. Hennepin County eviction filings and total evictions for the years 2009 through 2019. Less than half of eviction filings result in an actual eviction of the tenant.

are frequent users of libraries for computer and Internet use and these same people are more likely to have limited access to transportation (Gilpin and Bekkerman, 2020; Hertel and Sprague, 2007; Koontz *et al*., 2004). Since four additional variables have significant relationships to high eviction rates that are related to technology or transportation access, it would make sense to look at possible outreach opportunities in libraries located in or near the study area.

It is already known that in Hennepin County there are apartment buildings and management companies that have significantly higher rates of eviction compared to others (Hennepin County, 2021). Using this information can prove useful in targeted outreach by focusing advertising of available resources to residents of these properties through nearby businesses or community buildings or in the buildings themselves.

Limitations of Study

Data used for this study were eviction filings from 2018 to 2019. In 2020 during the COVID-19 pandemic, a nationwide eviction moratorium was established. The State of Minnesota had a more defined and stricter moratorium in place that prevented landlords from filing non-payment evictions against their tenants. The Minnesota moratorium only allowed landlords to file evictions or terminate leases in the cases of illegal activity, damage to property, endangerment of others, or if the landlord needed to move a family member into the rental unit (Home Line Minnesota, 2021). Because of the

Table 3. Variables with the highest significance that were explored in the Explanatory Regression Tool. A (+) or (-) indicates whether the variable has a more positive or negative relationship to the dependent variable.

Variable	% Significant
1 Bedroom	99.96 (+)
Without Internet Subscription	81.44 (+)
1 Vehicle available	79.76 (+)
Black	78.42 (+)
Average number of cars	76.93 (-)
Buildings with 10+ apartments	72.35 (+)
No computer	64.92 (+)
Public assistance	55.1 (+)
White	36.23 (-)
Building built before 1939	32.14 (+)

eviction moratorium and federal funding for rental assistance, the data on evictions might be significantly different after the moratorium compared to before.

This project explored evictions only and how the independent variables could explain the high numbers of evictions. There is another side that was not explored and that was to include all eviction filings. In 2018 and 2019, there were 4,450 and 4,531 evictions filings, respectively, in Hennepin County. The number of actual evictions though were 1,923 in 2018 and 2,027 in 2019. More than half of eviction filings do not result in an actual eviction (Figure 11).

Also explored was the number of evictions in a census tracts based on another variable like the number of renter-occupied units or the population to find an eviction rate, but the variables that were found in the best-fit model were similar to the variables found for just the eviction counts.

It was previously mentioned, but the outliers of the study were looked at more closely and two specific instances were found that could skew the results of this study. The first instance was regarding a Brooklyn Park apartment complex that filed over 99% of the evictions for that census tract. Further exploration found that the apartment complex consistently filed the most evictions in all of Hennepin County for ten of the eleven years that were explored.

Because no other non-public-housing apartment complex or rental management company had nearly as many as evictions or eviction filings as the Brooklyn Park complex, the outlier could be the apartment complex and the rental management company and not some other reason related to the residents.

The second instance of an outlier was the median rent stated for one census tract. The median for the median rent variable was $1,108. The census tract with the outlier had a median rent reported as $283. The amount could be a reporting error from the Census Bureau, or it could truly be the median rent for the census tract and the census tract might have a higher number of subsidized housing properties that could account for a significantly low median rent.

Opportunities for Future Research

This project only looked at the number of evictions. Because the number of eviction filings is more than double the number of evictions, it could be worthwhile to explore how evictions and eviction filings are different in Hennepin County and potential outreach opportunities in those areas.

Using the eviction rates as opposed the number of evictions per census tracts would be beneficial for future research. The types of eviction rates that would provide the best representative information would be the number evictions per either the number of renter-occupied units or the population of the census tract.

Given there was an eviction moratorium in 2020 and 2021 which dramatically decreased the number of evictions in Hennepin County, the opportunity to look at the psychological, financial, and community benefits of fewer evictions would likely provide valuable information for the future of eviction and homelessness prevention. The information gained could help with creating policies to protect people who are facing eviction, have experienced eviction, or are living in poverty.

Because there was a significant relationship of people in the study area having limited access to transportation and such a high percentage of tenants facing eviction not attending the eviction hearing, looking at eviction prevention with lack of transportation in mind, could find crucial information that would benefit people in these situations.

Additionally, this project focused on 38 census tracts that historically had the highest number of evictions in Hennepin County. Future research could explore all census tracts in Hennepin County to better understand the disparity between areas with many evictions and few evictions. Looking at these similarities and differences could further progress how policies are currently established and whether certain cities in Hennepin County would benefit from following similar housing program models and find innovative ways for change.

Further exploration of the median rent variable and its relationship to evictions is necessary given the discrepancy in the coefficient and the scatterplot of the variable. Using additional or updated data might help to better explain how the significance of the median rent variable was suppressed by the impact of the other variables used in the model and find ways in preventing a similar result in future research.

Summary

The independent variables that were found to explain the high numbers of evictions in the 38 census tracts assessed in this project were a lower population of white people, higher median rent, more one-unit attached rental properties, more buildings built before 1939, and more rental units with one bedroom. These variables make sense when examined through the lens of neighborhood instability and residential mobility.

People who have been evicted are often forced into living conditions unsuitable for their needs. That could include rental units in old buildings or renting a 1-bedroom apartment instead of a rental unit with more bedrooms.

Conclusions

Using the Exploratory Regression Tool and Ordinary Least Squares Regression in this project produced five independent variables that can explain 85% of the high numbers of evictions in 38 census tracts of Hennepin County. These variables of a lower population of white people, higher median rent, more one-unit attached rental properties, more buildings built before 1939, and more rental units with one bedroom were supported by previous research in neighborhood instability and residential mobility.

Additionally, other variables showed high significance in relation to the dependent variable and could be used for the purpose of targeted outreach so people facing evictions can access resources that Hennepin County and other community non-profits provide.

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