Honors Senior Project

Department of Economics

Welcome to the Neighborhood: A Spatial Analysis of Crime and Housing Values

Anthony Senick

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I. Abstract

Crime is an obvious unwanted problem in any population anywhere in the world. Not only does it present problems for public safety, but it crime has negative monetary costs as well. One such way these costs can be observed is in their effect on property values. Past studies have examined this relationship between crime and housing values using the hedonic housing price model and spatial analysis, and I attempt to perform a similar analysis, but with the inclusion of new variables and spatial techniques, for the City of Akron, Ohio. With 2017 housing sale data provided by the Summit County Fiscal Office, and 2017 criminal arrest records gathered from the City of Akron's Police Department Records, I analyze the spatial impact between 10 different types of crimes and their effects on nearby housing values. Using an OLS model that incorporates a high school area controlling variable, this study quantifies the effect the presence a particular crime within a mile and half mile of a house has on that houses property value. This study finds that crimes become more damaging the closer they get to a property, and that violent crimes tend to be more damaging than property crimes.

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II. Introduction

It is well understood that high levels of crime are a negative externality for a city. This concept has led to much public debate on the best way to reduce crime, as policy makers weigh options such as police or education funding in an attempt to reduce crime as a whole. There are areas on this subject however, economists can provide unique and important insights related to the effects of crime. One such area of interest is the affect that crime can have on housing/property values. It is the goal of this study to more specifically examine how the spatial proximity of crimes to houses affects housing prices and to see if there is a significant difference between different, specific types of crimes in the city of Akron.

Knowing the impact of a certain kind of crime as well as its proximity to houses has on property values can have enormous implications for policy makers and police forces. Certainly homicide is one of the “worst” kinds of crimes, but when trying to revitalize a city and reduce the overall feeling of blight that many urban cities have suffered, should officials focus on trying to reduce the number of drug charges or vandalism first? Does the amount of assaults in a city have more of an effect on its property values than the frequency of rape, or vice versa? Knowing this kind of information would be crucial to policy makers to understand what affects residents most. It can guide policymaker in trying to improve their cities housing values, as it’s been demonstrated that reducing crime is not only important from a public safety point of view, but that it can trickle in unexpected benefits such increasing property tax revenues, which can affect city planning and the cities overall economy immensely (Hellman, & Naroff, 1979).

Akron specifically is a very interesting city to run this analysis in. As typical with other major urban areas in the rustbelt, Akron has been in decline for the last few decades as the U.S. shifts from an industrial economy to a more knowledge focused economy. While Akron city planners and politicians have made efforts to revitalize the city and attract firms and individuals back into Akron, one area that has not been focused on is Akron's level of crime. Per capita Akron is currently only safer than 5% of other U.S. cities. Akron has over double the rate of murders, rapes, robberies and assaults per 1,000 residents than the national averages. And in terms of Ohio, a person is more than twice as likely to be a victim of violent crime in Akron than anywhere else in Ohio (Neighboorhoodwatch.com). Akron has a crime problem (see Appendix A, Figure 1 for specific map demonstrating crime locations), and understanding how this problem affects the housing values in Akron could prove to be incredibly valuable as Akron tries to rejuvenate itself.

In affirmation that these statements are not simply a "hunch", it is a deeply researched concept in urban economics that the amount of crime in a given city directly impacts the housing/property values in that given area (Congdon-Hohman, 2013; Hellman & Naroff, 1979; Ihlanfeldt & Mayock, 2010; Pope, & Pope, 2012). While it is well established that the Hedonic Pricing Model is the appropriate theory to employ when attempting to demonstrate the affect crime has on housing values, there is disagreement regarding the effect of crime amongst prominent studies that have analyzed this relationship. In addition, there is little previous literature examining the effect of the spatial relationships between crimes and the houses immediately near where they occurred. Part of this problem comes from how crime is actually classified. There are studies that try to distribute crime into broader categories like violent and property (Pope, & Pope, 2012), and then some which look at impacts of more specific crimes (Ihlanfeldt, & Mayock, 2010). Each of these studies also used different scopes of analysis (the former was a national analysis; the latter analyzed a single county in Florida). In addition to these two examples, there are numerous other instances where, because of factors such as how the authors accounted for endogeneity and how specific their data was, papers examining similar problems came to different conclusions.

In addition to a need for clarity amongst studies, there also seems to be very limited research on the effect of the proximity of a crime to a house as whether different types of crime have different effects on the housing values. It is understood that if your house is in a "bad" neighborhood, it will be worth less. But what constitutes a bad neighborhood? If there is a robbery a block down the street, how much more will that impact your housing price than if it happened two streets over? There is very little literature on that kind of analysis. Additionally, it is certainly a reasonable assumption to believe that there is a distinct difference between how crimes like larceny or drug charges are viewed by the public as opposed to crimes such as assault or robbery. Such distinctions between types of crime make grouping crimes into general classifications very unspecific and can allow for some important analysis to be lost to generalization. There has been only one study that analyzes specific types of crime, but only the 8 provided by the FBI's UCI crime reports, and the study's area of analysis was an entire county in Florida divided into subsections. Given the large number of different types of crime, the results of this study should be expanded upon, which is one of the aims of this study.

III. Survey of the Literature

In nearly all the economic literature reviewed regarding the subject of crime and property values, it is widely established that higher crime levels negatively affect housing values. To what extent, and how these conclusions are drawn wildly differ paper to paper however. Specifically, most of the literature differs on two key aspects: the specification of the Hedonic Pricing Model, and how to best deal with the endogeneity of the crime variables.

Differences in use of the Hedonic Model

Nearly all the papers reviewed use the Hedonic Pricing Model as a basis for their analysis. The only exception, (Hellman, & Naroff, 1979) uses the traditional model of assessing housing values (house demand as a function of price and income), but this is likely because the paper puts more emphasis on the effect that the lower house values have on issues like property tax and police spending, and not as much on the per house effect itself. The other papers reliance on the Hedonic Model makes sense, as crime is typically considered a qualitative determinant affecting property values, and thus lends itself to Hedonic analysis. Papers often differ in how they categorize crime, such as one reviewed by Ihlanfeldt and Mayock (2010) regarding the specific impact of different crime types, or one by Pope and Pope (2012) which groups crimes into two different categories, violent and property crimes. Despite this difference however, both use a modified version of the Hedonic Model to come up with their analysis of the impacts of crime. The Ihlanfeldt and Mayock (2010) paper found that aggravated assault and robbery were the only two crimes that negatively impacted housing values, and the Pope and Pope (2012) paper found an increase in property values of up to 19% in zip codes that had the largest reduction of overall crime rates. Other papers researched further expand upon the Hedonic Model by running their analysis with difference-in-difference method using geographical data. One such paper show that the busting of a nearby meth lab drops nearby houses sale prices by 10-19% within a year of a meth lab discovery in comparison to a house that is the furthest away from the lab while still in the same neighborhood (Congdon-Hohman, 2013).

The Problem of Endogeneity

The major struggle of doing research in this area is the inherent endogeneity. Crime can be endogenous in numerous ways. For example, more affluent areas report crime more often than other areas, and criminals might self-select to live in low income neighborhoods and do their crimes in their own neighborhood (Ihlanfeldt, & Mayock, 2010). Another example of this issue would be that sometimes problems with housing conditions can lead to crime. In a study reviewing vacancies caused by foreclosure, it can be seen that vacant homes can increase nearby violent crime rates up to 19% (Lin & Walsh, 2015). Most papers attempt to control this problem in different ways. Pope and Pope (2012) argue that since they use of the Case Shiller Index (which exempts them from needing to control for physical housing characteristics) and that since their analysis is conducted at zip codes level, they have accounted for endogeneity. Other papers that have narrower datasets have tackled the issue with a combination of using first differences estimators and instrumental variable to eliminate for correlation between the crime measures and current and past values of the idiosyncratic error in the hedonic price equation (Ihlanfeldt, & Mayock, 2010). A final, and very specific attempt to control for these problems is the use of a difference-in-difference approach. By treating crime as a quasi-random event, and having geographically specific crime data, Congdon-Hohman (2013) and Cui and Walsh (2015) were able to observe how the presence of a specific event (meth labs in Congdon-Hohman and house vacancies in Lin Cui & Randall Walsh) affect nearby houses.

It is the goal of this paper to further the research done in this previous literature, but also to improve upon it in a new niche. This study will examine crimes at an individual level, but with a focus on only one city. There are many advantages to examining a singular city, mainly that a singular city will be a much more homogeneous sample. Studies that have examined data at county or nationwide levels need to account for variation amongst different cities, but a singular city will have standardized amenities and utilities throughout (police quality, school funding, etc.). In addition to the focus on a single city, the use of specific spatial analysis with exact crime locations is something rare in the literature, and the combination of both make this paper unique.

IV. Theoretical Model

The estimation strategy adopted in this study is based upon the concept of the Hedonic Pricing Model. The basis of this theory is "that economic agents choose a place of residence by making informed tradeoffs between housing characteristics and various local amenities. Housing values (a measure of revealed preference) are then used to isolate the implicit price of a particular housing attribute or neighborhood characteristic." (Pope and Pope, 2012). This allows economists to determine how much qualitative, or non-price, determinants affect the overall housing price. The basic Hedonic Model looks as follows:

$$P_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

where P_i is typically the sale price of a property, and β is the marginal value that each explanatory variable adds to the sales price. While this model is often used to quantify how variables such as pollution affects housing prices or to understand consumer preferences in the housing market (for example, how much people willing to pay to be near a scenic view), it is also the best way to determine the effect crime has on housing values. While quantitative information regarding crime exists (crime rate, density, etc.) how people value crime, or more specifically for this paper, how much individuals would pay to not be near crime is inherently qualitative. Therefore, the use of the Hedonic Model in this area of study is understandable.

There are problems with the Hedonic Model however, as there is an inherent risk of omitted variable bias. There are often times numerous unobservable factors that can correlate with variables in the model, and if they are omitted from the regression, they could influence the variables in the regression, thus distorting and biasing the results. There are numerous examples of how this problem could be prevalent in research on crime (it is not a stretch to see how factors such as school quality, police expenditure, or neighborhood average income could affect the amount of crime in a given area), which is why endogeneity and unobserved heterogeneity are such major problems when studying this subject.

Using a modified version of the Hedonic Price Model that uses both a traditional hedonic OLS while including high school area dummy variables to account for neighborhood effects, this study plans to expand upon the work of previous economists in this field by examining how specific types of crime each individually affect housing values. It is the hypothesis of this paper that there are significant differences between the effects that each type of crime has on housing values. This is important to understand because it will give policy makers information on what kind of crime most hurts the city of Akron. It was previously established in the literature that crime negatively impacts housing values. But that claim is relatively vague to policy makers trying to increase their cities housing values. For example, knowing that an increase in crime leads to a 10% decrease in housing values does not help a policy maker resolve the issue other than to try to reduce all crime. If it were known, however, that arson caused 30% of that variation in the data, burglaries 20%, drug charges 10%, and all other crimes the remaining 40%, that would give policy makers a clearer view of the problems facing their city, and how to more efficiently solve them. This study will also be unique in analyzing the spatial relationship between crime and housing values, something that has been seen sparsely in the literature using a real city as a base for analysis

The specific OLS Model this study will use is as follows:

$$lnP_i = \beta_0 + \beta_1 Crime_i + \beta_k X_i + \varepsilon_i$$

where lnP_i is the log of the sale price of house *i,* and the explanatory variables will be the various crimes (*Crime*) as well as the gathered dwelling specific variables and high school area dummy variables (*X*). This model takes into account spatial analysis created from the ArcGIS software. This model will be run twice, with two different GIS modifiers affecting the data. The first model will include all crimes that happen within a mile of a given house. The second model will limit that data to crimes that occur within just .5 miles of a house. These models will be run to see if the effect of a crime increases as it occurs closer to a property, the core focus of this study. The models will also be re-run with the violent and property crimes aggregated into just two categories, as much of the previous literature warns of types of crime are often correlated with one another, and this can serve as a safeguard.

While this study recognizes a year fixed effect model is more robust and accurate than a simple OLS, this was simply not possible for this study. The availability of the data as well as the intense amount of time it takes to properly prepare this data limited this study to only the year of 2017, preventing a fixed effect model. To counteract this limitation, the inclusion of the high school area dummy variables will capture much of the different neighborhood effects that influence house prices, and hopefully will lead the model to being more accurate.

V. Data

The variables that this study intends to use to test its hypotheses are found in Table 1 in Appendix A below. As can be observed, among this variable list is numerous different types of crime. While some of these types of crimes have been tested in other studies (Ihlanfeldt, & Mayock, 2010), the crimes of arson, drug/narcotics violations, and rape have never been tested for in previous economic literature found in this studies scope. The other crimes on the list have been tested before but will still be included in this studies model to account for omitted variable bias and to account for different types of crime correlating to one another. All crime data is specific to the City of Akron and from the year 2017, and the data was collected and maintained by The City of Akron Police Department. While not a perfect representation of crime in Akron (the data is only of the crime arrests that occurred, leaving room for omitted, unreported crimes, as well as issues regarding arrest interpretations to be discussed later) this database is an accurate and detailed data source for most crime that occurs in the city.

The housing information gathered in the table was collected from The Summit County Fiscal Office. The log of the sales price of most single-family homes in Akron sold during 2017 is the dependent variable of the model. The data on housing was limited to single family homes as is the typical tradition when doing research in this area. The other dwelling characteristics (number of bedrooms, sfla. and the age of the house) are all included as is required by the hedonic price model. In addition to these traditional housing characteristics, dummy variables for the style of a house are also included to try and capture more variation between the houses themselves. Colonial style houses were the reference group excluded from the model. Then, in an attempt to also capture neighborhood effects that would influence the house price, dummy variables for the high school area the house is located in are also included (map of high school areas can be found in Figure 2 in Appendix A). The Firestone High School area was the reference group excluded from the model. While not as accurate as running a fixed effect model would be, these addition variables create a more robust model, and attempt to resolve some of the issues with endogeneity and omitted variable bias.

VI. Results

Results-Individual Crime OLS		
Variable Dependent variable: Lnhousep	**1 Mile Model** **Coefficient(t-stat)**	**.5 Mile Model** **Coefficient(t-stat)**
Housesfla	0.00054546(18.39)**	0.00053812(18.22)**
Houseage	-0.00987(16.45)**	-0.00953(15.68)**
Housebed	.00876(.44)	0.01920(0.98)
Naggasm	-0.00987(8.85)**	-
Narsonm	-0.01867(3.14)**	-
Nbem	0.00078229(.81)	-
Nbutheftm	0.00298(2.27)**	-
Ndopm	-0.00059193(1.22)	-
Ndrugm	-0.00270(1.80)*	-
Nlarcm	0.00217(2.59)**	-
Nmvtheftn	0.00657(2.89)**	-
Nrapem	0.00611(1.18)	-
Nrobm	-0.01394(3.75)**	-
DCBD	2.01303(1.53)	3.74878(3.46)**
Harson	-	-0.05963(7.53)**
Haggas	-	-0.02876(10.88)**
Hbe	-	0.00077430(0.62)
Hbu	-	0.01341(5.98)**
Hdop	-	-0.00148(1.66)*
Hdrug	-	-0.00225(0.95)
Hlarc	-	0.00517(3.56)**
Hmvt	-	0.00264(0.85)
Hrape	-	-0.01426(1.87)*
Hrob	-	-0.01513(2.78)**
DRANCH	-0.01922(0.56)	-0.00260(0.08)
DCAPECOD	0.10982(3.02)**	0.10944(3.05)**
DSPLITLEVEL	-0.21550(2.62)**	-0.19976(2.45)**
DSINGLE	0.03718(0.38)	0.07396(0.76)
DBUNGALOW	-0.08995(1.72)*	-0.06072(1.17)
DTUDOR	0.38769(3.06)**	0.35174(2.80)**
DCTEMPORY	-0.14019(0.68)	-0.11892(0.58)
DBILEVEL	-0.04593(0.40)	0.00245(0.02)
DBuchtel	-0.15826(2.54)**	-0.25188(4.78)**
DKenmore	-0.33886(4.64)**	-0.48736(8.64)**
DCentral	-0.45693(5.22)**	-0.64255(8.62)**
DEast	-0.37596(6.50)**	-0.39909(7.40)**
DEllet	-0.25969(4.27)**	-0.34230(6.36)**
DGarf	-0.29119(4.69)**	-0.36359(6.82)**
DNorth	-0.31450(5.05)**	-0.42972(8.24)**
DBlank	-0.09664(0.32)	-0.15819(0.53)
R-Squared	.5040	.5098
Adj. R-Squared	.5006	.5064
F-Value	144.75	148.16
Number of Observations	4304	4304
Note: All T-Values given in absolute value. ** and *, respectively, denote statistical significance at the 5%(or better) and 10% levels		

Results-Aggregated Crime OLS		
Variable Dependent Variable: Lnhousep	**1 Mile Model** **Coefficient(t-stat)**	**.5 Mile Model** **Coefficient(t-stat)**
Vcrimem	-0.016699(12.57)**	-
PCrimem	0.00097932(6.80)**	-
Ndrugm	-0.00144(1.01)	-
Hvcrime	-	-0.03087(12.22)**
Hpcrime	-	0.00115(4.30)**
Hdrug	-	-0.00147(0.64)
DCBD	1.04052(0.85)	3.84101(3.51)**
DRANCH	-0.02500(0.72)	-0.01745(0.51)
DCAPECOD	0.10438(2.88)**	0.10198(2.81)**
DSINGLE	.02609(0.27)	0.01660(0.17)
DSPLITLEVEL	-0.20234(2.45)**	-0.18514(2.24)**
DBUNGALOW	-0.09262(1.77)*	-0.07334(1.40)
DTUDOR	.39894(3.13)**	0.39401(3.09)**
DCTEMPORY	-0.14410(0.69)	-0.13282(0.64)
DBILEVEL	-0.04482(0.39)	0.02413(0.21)
Housesfla	0.00054961(18.50)**	0.00053365(17.94)**
Houseage	-0.00977(16.26)**	-0.00950(15.69)**
Housebed	0.00974(0.49)	0.01946(0.98)
DBlank	-0.13698(0.45)	-0.22503(0.74)
DBuchtel	-0.18111(3.33)**	-0.34208(6.67)**
DKenmore	-0.30296(4.57)**	-0.48662(9.16)**
DCentral	-0.33427(4.74)**	-0.48472(7.14)**
DEast	-.042788(8.00)**	-0.50449(9.56)**
DEllet	-0.23615(4.23)**	-0.32295(6.06)**
DGarf	-0.22456(4.15)**	-0.34640(6.91)**
DNorth	-0.36652(6.33)**	-0.42051(8.12)**
R-Squared	.4958	.4951
Adj. R-Squared	.4931	.4924
F-Value	183.02	182.50
Number of Observations	4304	4304
Note: All T-Values given in absolute value. ** and *, respectively, denote statistical significance at the 5%(or better) and 10% levels		

The results of the SAS analysis have provided interesting data for analysis. First, it can be seen that the control variables used in the models follow with traditional results for Hedonic Price evaluation. In the one mile individual model, an increase in one SFLA results in a .054% increase in a houses property value (as the model uses the natural log of the housing price in order to maintain a normal distribution of the data, the parameter estimates are interpreted as percent changes house housing prices). Using the mean house price of $74,780.85 that can be calculated as an additional $40.38 dollars of value per SFLA added. This is in line with other studies using the hedonic pricing model, and the other control variables follow tradition as well, as an additional year of age has a slight negative percent change across all models, and bedrooms was insignificant as it likely correlates with SFLA. It can be seen the styles of house also seem to follow traditional hedonic properties, as nicer house styles have a positive percent change of housing prices and worse, less desirable styles result in a negative percent change.

What is more interesting and important to examine is how crime effects the dependent variable. What can be observed in the one-mile analysis model is that the crimes of agg. assault, arson, drug violations and robbery are all significant and have a negative parameter estimate. The occurrence of one of these crimes within a mile of a house can be interpreted as decreasing that house's values by .987%, 1.86%, .27% and 1.39% respectively. While small percentages, when considering the average house price from above, it can be calculated that one agg. assault occurring within a mile of a house would result in a lost value of $738.08 simply because the assault occurred. What is even more interesting is that all of these crimes(other than drug charges which becomes insignificant) more than double their parameter estimates when the .5 mile model is run. So now in the closer model, the presence of that assault would result in a property value decrease of $2,150 dollars. The crimes of destruction of property and rape also become significant at this closer measure (a chart of all the significant crimes at .5 miles and the monetary loss they cause can be found in Figure 3 in Appendix A) . These results demonstrate that as a crime gets closer to a house spatially, its impact on the houses value becomes greater.

Not everything is entirely clean from the model results however. Curiously, many of the significant property crimes (specifically building theft, motor vehicle theft, and larceny in the one mile model, and building theft and larceny in the .5 model) have positive parameter estimates. In more plain language, what this shows is that the occurrence of these crimes near houses actually improves the value of the house. There are two possible explanations for this phenomenon. The first is the way the data is recorded. Each data spot entered as a crime is really an arrest record made by the City of Akron police department documenting where an arrest occurred. This would not lead to any interpretation issues for crimes like arson, where the house would already be burnt down once the arrest happens. But for simpler property crimes like larceny, if an arrest occurs, that typically means a crime was stopped from occurring. Therefore, these arrests might actually indicate an effective police force which is good at catching criminals in the act, which would increase housing values as people positively value efficient police forces. Alternatively, these positive parameter estimates could be signaling that criminals are targeting nicer houses with more things inside them in hopes of a greater payoff than trying to steal from poorer properties. Thus, a nicer house would have more attempted thefts, and could lead to these parameter estimates signaling nicer houses. This theory is also supported in previous literature.

Finally, it can be seen that all of the relationships described for the individual OLS analysis hold for the aggregated OLS analysis. While less specific, this model does not need to be concerned about similar types of crime correlating with each other. While OLS cannot reliably eliminate the issue of specific types of crime correlating with one another, at least the two different models demonstrate a similar relationship.

One oddity that should be noticed is the incredible high parameter estimate associated with the DCBD variable. This study has found that taking distance outputs straight from GIS without any kind of adaptation (creating buffer analysis for example) results it incredibly high parameter estimates for even small variations (in this circumstance, it is distance from the CBD in terms of miles). The value was still reported for model integrity, but its value should be doubted. A study with a more advanced understanding of GIS might be able to analyze this relationship better.

VII. Conclusion

Even with some of its flaws, the data presented in this paper shows that this information has real value to policy makers and politicians for the city of Akron. The crimes that occur near houses, specifically the violent crimes, cause real and negative loss to the property values of those houses. Looking at just the aggravated assaults that occurred in Akron alone, Akron's housing market lost $1,481,125.81 in value on its houses sold during 2017 in the .5 mile model. And with each house having on average ~12.5 agg. assaults in the .5 mile model, the amount of lost value per each individual house would be $26,875. With a price tag that steep, especially when taking into account all the types of crimes that occur within Akron, this loss is something that cannot be ignored if Akron wants to try and attract individuals and firms to its city, as nobody would want nearly 36% of their houses value lost to just one type of crime

It is the recommendation of this paper that Akron begin to target the specific crime that causes the most damage to housing values in Akron, which this study has identified to be aggravated assault. While not for the purpose of housing values, this kind of targeted policing has happened before. The City of St. Louis had a very legitimate drug problem. When traditional policing techniques continued to fail, the city switched its approach to a "problem-oriented policing" strategy. This kind of strategy involves identifying one specific crime (for St. Louis this was their drug problem) and treating it separately than the rest of the crimes in the city. This involved creating specific task forces, drug crime specific training, and coordination amongst multiple different forces in order to create a city unified attack on drugs. The results of this method was a marketable reduction in the amount of drug use and drug crimes in the city of St. Louis (Hope, 1994). It is the recommendation of this paper that the City of Akron employ similar tactics to address aggravated assault and the deep impact it has on the city's housing values and help reduce the housing blight that is present within the city.

Despite its best efforts, this study recognizes there are still limitations that this analysis cannot account for. The data for this paper is limited to just one year of analysis (2017) due to availability and the intense amount of time it takes to prepare this data. Also, while this paper does have variables that account for differences in dwelling qualities as well as location, research in this field is prone to omitted variable bias. While this study does have the benefit of all the data being within the same city (many amenities such as police expenditures and utility costs will be uniform for all the houses across the city), future studies may want to include more variables such as a house's proximity to other desirable amenities to try to create a more robust picture of what affects housing prices, and thereby a more robust model. Future studies would also benefit from an additional year of data, from which a true fixed effect model could be run. Additionally, this study did not compare any differences from when a crime occurred and a house was sold. The amount of time between the two events likely has an impact on how the crime would affect housing values, so this is something that future studies should investigate.

It must be reported that is very likely that the results of this study are over-valuing the impact crime has on housing values, and that should a stronger model like the fixed effect or 2SLS be used, there is a chance the individual crimes would no longer be significant. With that being said, the results of this study are still useful in serving a guide, or at least a recognition that crimes do have a significant impact on housing values, and the proximity of crimes to houses changes that impact. This is a problem that the City of Akron could see considerable improvement upon housing values should it be addressed.

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X. Appendix A

Variables Used		
Variable	**Description**	**Source**
Lnhousep **(dependent variable)**	Logged price of a single family house	Summit County Fiscal Office
Housesfla	Sqft. of livable area in a house	Summit County Fiscal Office
Houseage	Age of the house	Summit County Fiscal Office
Housebed	Number of bedrooms in a house	Summit County Fiscal Office
Naggasm	Number of agg. assault arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Narsonm	Number of arson arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nbem	Number of breaking and entering/burglary arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nbutheftm	Number of building theft arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Ndopm	Number of destruction of property arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Ndrugm	Number of drug violation arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nlarcm	Number of property crime arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nmvtheftn	Number of motor vehicle theft arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nrapem	Number of rape arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Nrobm	Number of robbery arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
DCBD	Distance from a house to the central business district in miles	ArcGIS

Vcrimem	Number of aggregated violent crime arrests within a mile of a house.	City of Akron Police Department and ArcGIS Analysis
Pcrimem	Number of aggregated property crime arrests within a mile of a house	City of Akron Police Department and ArcGIS Analysis
Harson	Number of agg. assault arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Haggas	Number of arson arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hbe	Number of breaking and entering/burglary arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hbu	Number of building theft arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hdop	Number of destruction of property arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hdrug	Number of drug violation arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hmvt	Number of property crime arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hlarc	Number of motor vehicle theft arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hrape	Number of rape arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hrob	Number of robbery arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hvcrime	Number of aggregated violent crime arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
Hpcrime	Number of aggregated property crime arrests within a half mile of a house	City of Akron Police Department and ArcGIS Analysis
DCOLONIAL	Dummy Variable for Colonial Style Houses	Summit County Fiscal Office
DRANCH	Dummy variable for ranch style houses	Summit County Fiscal Office
DCAPECOD	Dummy variable for Cape Cod style houses	Summit County Fiscal Office

DSPLITLEVEL	Dummy variable for split level style houses	Summit County Fiscal Office
DSINGLE	Dummy Variable for non-specific single family house	Summit County Fiscal Office
DBUNGALOW	Dummy variable for Bungalow style houses	Summit County Fiscal Office
DTUDOR	Dummy variable for Tudor style houses	Summit County Fiscal Office
DCTEMPORY	Dummy variable for contemporary style houses	Summit County Fiscal Office
DBILEVEL	Dummy variable for Bi-level style houses	Summit County Fiscal Office
DBuchtel	Dummy variable for house being in the Buchtel High School area	Akron Office of Information Technology
DKenmore	Dummy variable for house being in the Kenmore High School Area	Akron Office of Information Technology
DCentral	Dummy variable for house being in the Central Hower High School area	Akron Office of Information Technology
DEast	Dummy variable for house being in the East High School area	Akron Office of Information Technology
DEllet	Dummy variable for house being in the Ellet High School area	Akron Office of Information Technology
DFirestone	Dummy variable for house being in the Firestone High School area	Akron Office of Information Technology
DGarf	Dummy variable for house being in the Garfield High School area	Akron Office of Information Technology
DNorth	Dummy variable for house being in the North High School area	Akron Office of Information Technology
DBlank	Dummy variable for house being not in a high school area	Akron Office of Information Technology

Table 1: Variable Definitions

Descriptive Statistics					
Variable	**N**	**Mean**	**Std Dev**	**Min**	**Max**
HouseP	4304	74780.85	94776.39	1000.00	2695000.00
Lnhousep	4304	10.7526137	1.0286178	6.9077553	14.8069088
Housesfla	4304	1364.82	568.9519413	440.0000000	9541.00
Houseage	4304	77.0480948	23.8322194	1.0000000	174.0000000
Housebed	4304	2.9814126	0.7247994	1.0000000	9.0000000
Naggasm	4304	43.6549721	32.2307097	0	117.0000000
Narsonm	4304	5.9958178	4.5832584	0	20.0000000
Nbem	4304	146.7953067	95.0934380	0	399.0000000
Nbutheftm	4304	52.5964219	33.5138585	0	231.0000000
Ndopm	4304	223.5220725	147.9327028	0	571.0000000
Ndrugm	4304	53.4709572	33.0795574	0	130.0000000
Nlarcm	4304	144.7430297	82.8593636	0	382.0000000
Nmvtheftn	4304	48.2727695	29.6370161	0	123.0000000
Nrapem	4304	10.2490706	7.8054278	0	41.0000000
Nrobm	4304	16.9014870	11.5900443	0	58.0000000
DCBD	4304	0.0500439	0.0198556	0.0047106	0.1103758
Vcrimem	4304	53.9040428	39.1327415	0	140.00
Pcrimem	4304	638.8269052	393.4376900	1	1659.00
Harson	4304	1.6905204	1.8860012	0	10.0000000
Haggas	4304	12.4502788	10.8836980	0	41.0000000
Hbe	4304	42.7760223	32.1345507	0	137.0000000
Hbu	4304	14.2042286	10.6663802	0	76.0000000
Hdop	4304	63.8194703	47.2679348	0	216.0000000
Hdrug	4304	15.2177045	11.6992982	0	53.0000000
Hmvt	4304	13.8849907	9.8739449	0	45.0000000
Hlarc	4304	41.5041822	24.8930126	0	117.0000000
Hrape	4304	2.9189126	2.7697572	0	15.0000000
Hrob	4304	4.8108736	4.2594252	0	26.0000000
Hvcrime	4304	15.3691914	12.9524987	0	48.0000000
Hpcrime	4304	182.6902881	123.3170530	0	497.0000000
Note: All the N's are 4304 because every variable is relative to the number of houses (4304) in the study. So, while their may not have been 4,304 arsons, for example, there was 4304 buffers created to observe arsons, and that is what this N is reflecting.					

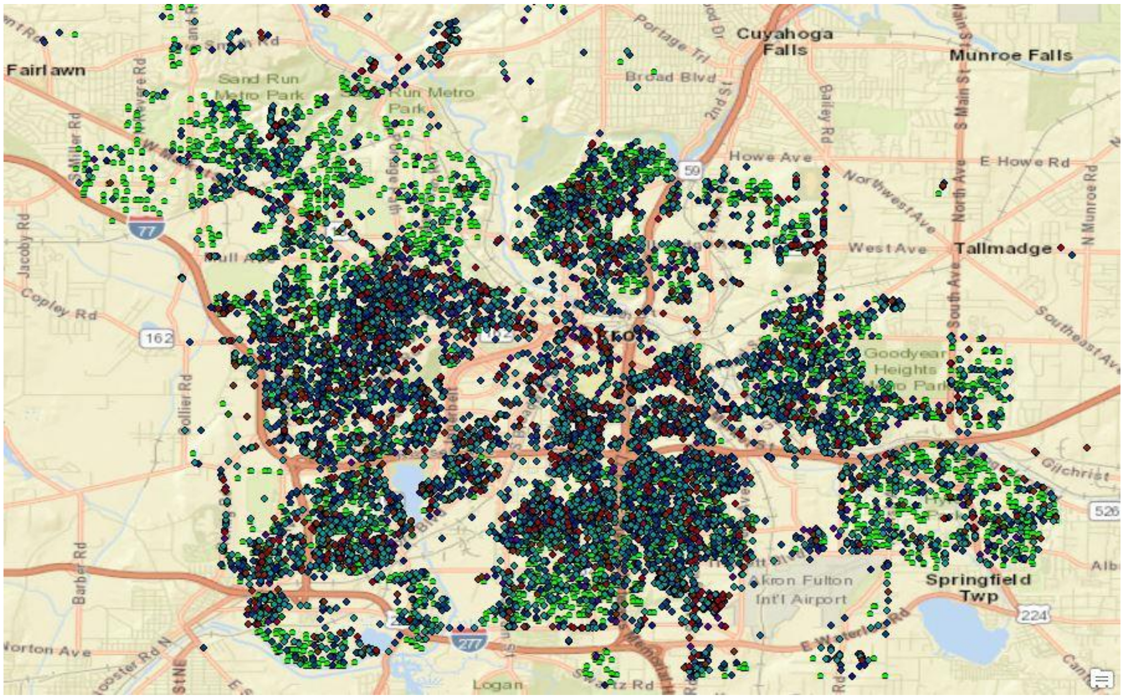


Figure 1: Map of Crime and Housing Data. Unfortunately do to a licensing issue, the copy of ArcGIS this study had access too could not create density maps, but this map shows every crime in Akron as a dot, color coded for different crimes. The bright lime green dots represent houses. Also do to the same density licensing problem, a map showing variations in house prices was not possible.

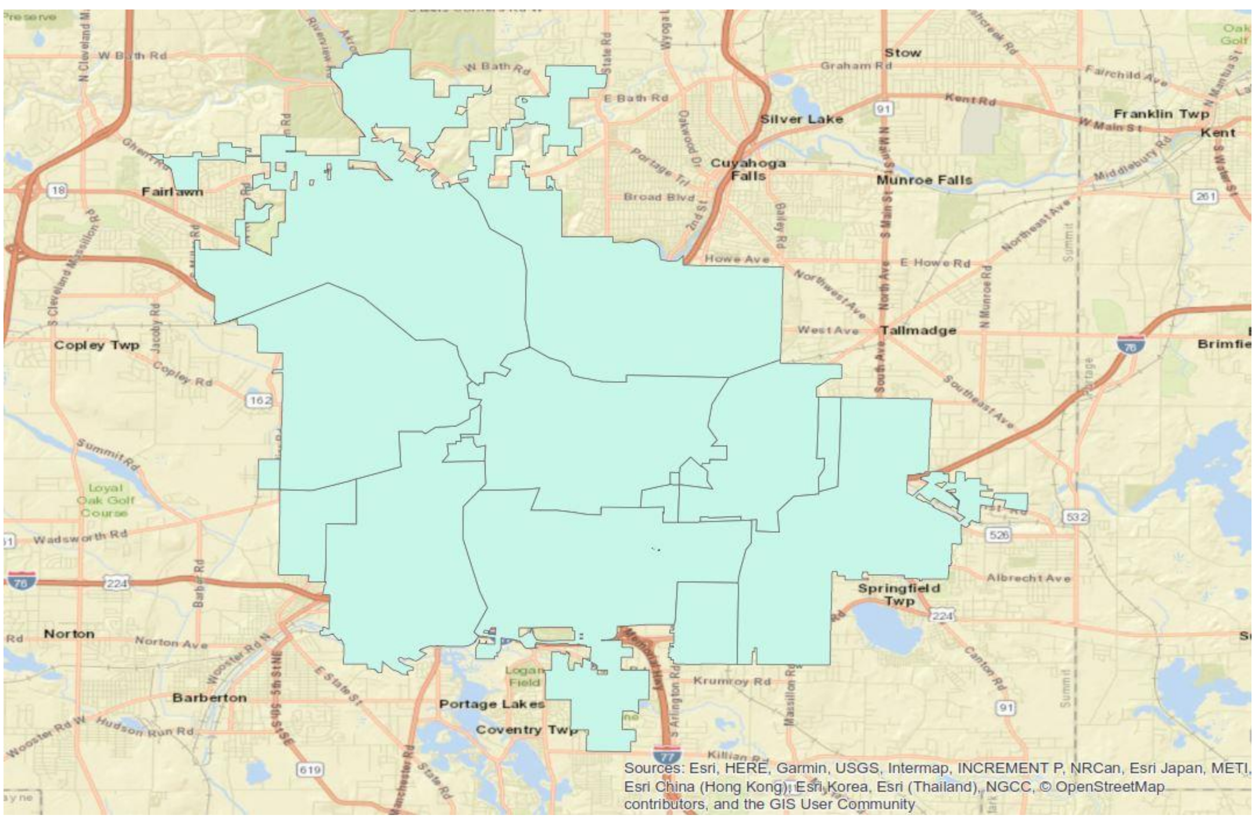
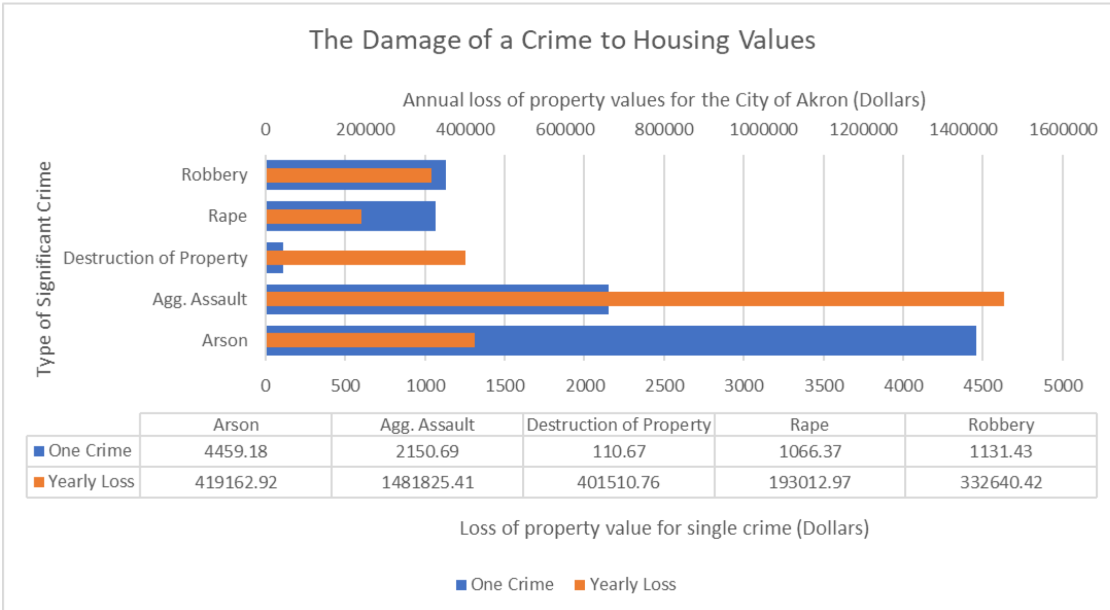


Figure 2: Map of high school areas



	Arson	Agg. Assault	Destruction of Property	Rape	Robbery
One Crime	4459.18	2150.69	110.67	1066.37	1131.43
Yearly Loss	419162.92	1481825.41	401510.76	193012.97	332640.42

Figure 3: Chart detailing the impacts of significant crimes on housing values. Results from the .5 mile individual OLS model