**Poverty and Crime: Does Concentrated Poverty Have Different Accelerating Effects on Violent Crime and Non-Violent Crime**

Dallas Griffiths\*

Dr. L. Boyd\*\*

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1. **Introduction**
   1. **Testable Hypothesis**

This research tests the hypothesis: higher relative poverty levels increase non-violent crime rates and have no impact on violent crime rates. Ever-changing factors motivate people to perform actions in their every-day lives. At the center of these motivations is the natural desire to survive, an ideology introduced by Hobbesian theory. By this notion, individuals who are desperate to live will do what they must to survive even if their solution is illegal. However, the research intuitively does not see acts of violent crime, such as rape, murder, or aggravated assault, to be motivated by survival, but rather caused by several mental illnesses. Additionally, this research hoped to answer the following two questions: (1) Which economic conditions increase or decrease rates of non-violent crime? (2) Which economic conditions increase or decrease rates of violent crime? Answering these questions is important to academia as well as local communities. It will provide additional support for past research and it can be used as a stepping-stone for future studies. Advancing the value of academia in this area of study is important because it enables meaningful preemptive actions to be taken by local communities.

* 1. **Purpose**

For over a century, economists have performed empirical and theoretical examinations on these complex relationships that remain controversial due to ever-changing societal conditions and humans’ nature and nurture desire to improve things. (Locke, 1887; Patterson, 1991; Hobbes, 1651) Moreover, there is reason to believe that many of the existing estimates are biased because measures of poverty contain errors which are confounded with disturbances in the estimated models. (Bailey. 1984) Nonetheless, it is still controversial as to what causes higher rates of crime. On one hand, several studies claim that poverty dense communities have higher rates of violent crime. (Loftin & Parker, 1985) Though, contradictory evidence claims this is not the case. (Bailey, 1984) On the other hand, several studies claim poverty dense communities have higher rates of non-violent crime. (Martin. 2002) Again, several studies argue that poverty levels have nothing to do with crime rates. In fact, some studies find poverty to be statistically significantly negatively correlated with crime. (Messner. 1982; Blau. 1982) The question remains: Why is this problem so important to researchers? If statistical models can predict crime rates for individual areas, then those models can help determine where to deploy police or how to provide other preemptive actions to better protect the citizens living in those communities. Further, if statistical models can determine what types of crime are relatively prevalent in communities, police forces can better strategize and train for the more prevalent crimes. Even further, if statistical models can decipher which economic conditions are exacerbating crimes in a community, local legislative actions can be taken to alleviate the influential economic conditions to prevent crimes from happening. In choosing a key independent variable, poverty just happens to be the most controversial economic measure in estimating crime.

* 1. **Problem Statement & Data Sources**

This research intends to bring empirical clarity to the debate about poverty’s impact on crime by investigating violent crime rates and non-violent crime rates for several zip-codes in Austin, Texas. This research used Ordinary Least Squares (OLS) regression models to estimate the impact several economic conditions, one being poverty, had on non-violent and violent crime rates. After adjusting for data and model issues, the research decided upon final models for each dependent variable that identifies influential economic conditions. To begin, I gathered two tables of data, both from Austin, Texas’ government website. One table was taken from the 2014 Comprehensive Housing Market Analysis (CHMA) for the City of Austin and it documents demographic and housing summary data for 35 zip-codes. The other table contains victimization data that encompasses all part 1 crimes in Austin, Texas from January 1, 2015 - December 31, 2015. This table is provided to the public for informational use from the Austin Police Department. The cleaned, reformatted, ready-to-use data set contains 42 rows where each row represents a zip-code. Unfortunately, further models can only regress using 35 of the 42 observations because the CHMA did not provide estimations for every zip-code. Continuing, the ready-to-use table contained 32 columns where 30 of them represented independent variables as economic measurements for each zip-code and the remaining two represented dependent measurements of violent crime rates and non-violent crime rates. A codebook of the variables can be referenced in Table 1.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 1: Data Code Book for All Variables | | | | |
| Variable | **Description** | **Measurement** | **Predicted Sign**  **non\_violent\_pc** | **Predicted Sign**  **violent\_pc** |
| *non\_violent\_pc* | Non-violent crime rate per capita | Continuous –  (# crime/pop) \*1000 | NA | NA |
| *violent\_pc* | Violent crime rate per capita | Continuous –  (# crime/pop) \*1000 | NA | NA |
| *trans\_cost* | Average cost of transportation for a zip-code | Continuous in dollars | - | - |
| *transitStop* | Percent of homes 14 miles from a transit stop | Discrete Numeric | + | - |
| *rent\_change* | Median rent change from 2000 – 2012 | Continuous Numeric | - | 0 |
| *rent\_poor\_cond* | Percent of homes in poor condition | Discrete Numeric | + | + |
| *pp\_ch* | Percent Chhange in percent of population in poverty from 2000 – 2012 | Continuous Numeric | + | 0 |
| *rent\_aff\_serv* | Percent of rental units affordable to service workers | Discrete Numeric | + | 0 |
| *pop\_pov* | Percent of population below poverty level | Discrete Numeric | + | 0 |
| *pop\_dense* | Population density as conventional # of people per square mile. | Continuous  (population/area) | + | + |

Table 1: Reports the description, measurement and predicted signed for each variable. The response variables have NA predicted signs because they are being predicted. The 0 represents there is no expected correlation. The character “/” represents division.

Table 1 includes the predicted signs of each independent variable. Some intuitively make sense, however, others do not. The purpose of this section is the illustrate the logic behind why estimated signs are in the direction they are for certain variables. For example, *trans\_cost* has a predicted negative sign because lower average transportation costs are in areas that have more public transportation because it is cheaper than driving one’s own vehicle. Therefore, this variable, intuitively, should follow closely behind the poverty variable. *TransitStop* has a positive predicted sign for non-violent crim and a negative sign for violent crime because, intuitively, people should be more motivated to steal in a crowded area and less likely to rape or murder in such an area because of the likelihood of being caught under these circumstances. Notably, violent crime estimators are majority predicted 0, which is not concerning because the sample size is 35 observations (as can be seen in Table 2), which is appropriate for 3 independent variables. Moreover, these variables had the highest Pearson Correlation coefficients for *violent\_pc* comparative to the all the 30 independent variables. Though, it does not make sense for the 0 estimate sign variables to be causal to violent crime, which is why I assigned their predicted sign to be 0.

Matrix 1 displays a Pearson Correlation matrix of the set of variables. All the variables exhibit relationships in the expected directions with respect to the dependent variable *non\_vio\_pc*, and all the variables are statistically significant (p >.5). Most noticeable are the correlations between *trans\_cost* and *transitStop*. The strong positive correlation between these variables (p>.7) suggests there are issues of multicollinearity, which will be addressed in later sections. Continuing*, non\_vio\_pc* is statistically significantly correlated (p>.05) with both these variables. A positive correlation between *non\_vio\_pc* and *transitStop* suggest higher proportions of houses close to transit stops increase the rate of crimes in a community. And a negative correlation between *trans\_cost* and *non\_vio\_pc* suggest communities with higher average transportation expenses have lower rates of crime. Other variables display relationships in the expected directions but will be ignored to avoid redundancy. Indicators of poverty are positively related with crime suggesting poverty may increase rates of non-violent crime, although, the correlations are relatively weaker than expected (p=.29). Notably, the correlation matrix including violent\_pc is not present in this paper. The variable *violent\_pc* had significant correlation with pop\_pov, pp\_ch, and trans\_cost (p>.5).

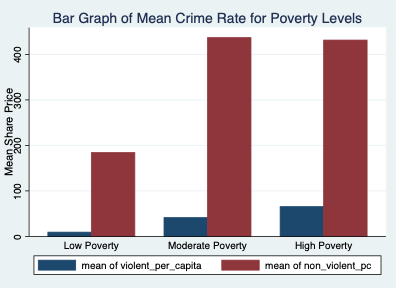
|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Matrix 1**  *Pearson Correlation Matrix* | | | | | | | | | |
| Variable Name | Non\_vio\_pc | trans\_cost | homes\_tranStop | med\_rent\_ch | rent\_poor\_cond | | pp\_ch | rent\_aff\_serv | pop\_pov |
| Non\_vio\_pc | 1.00 |  |  |  | |  |  |  |  |
| trans\_cost | -0.67\* | 1.00 |  |  |  | |  |  |  |
| homes\_tranStop | 0.55\* | -0.83\* | 1.00 |  |  | |  |  |  |
| med\_rent\_ch | 0.48 | -0.35 | 0.35 | 1.00 |  | |  |  |  |
| rent\_poor\_cond | 0.34 | -0.25 | 0.50\* | 0.25 | 1.00 | |  |  |  |
| pp\_ch | -0.31 | 0.39 | -0.50\* | 0.25 | -0.30 | | 1.00 |  |  |
| rent\_aff\_serv | 0.30 | -0.29 | 0.49 | 0.26 | 0.90\* | | -0.32 | 1.00 |  |
| pop\_pov | 0.29 | -0.40 | 0.55\* | 0.23 | 0.55\* | | -0.27 | 0.58\* | 1.00 |
| ***Pearson Correlation Coefficient: P \* > 0.5*** | | | | | | | | | |

* 1. **Data Descriptions**

**1.4.1 Response Variables**

The two response variables are named *Non\_violent\_pc* and *Violent\_pc.* Each variable represents a rate of what is commonly considered violent or non-violent crimes. Violent crime commonly accounts for rape, murder, and aggravated assault and non-violent crime commonly accounts for crimes, such as, theft, auto theft, robbery, and burglary. These standards were kept the same in this research.Each response variable is a per capita crime rate, multiplied by 1000. So, the crime rate for a given zip-code is calculated by the number of crimes divided by the total population of that zip-code, and then multiplied by 1000. The research chose to multiply the per capita value by 1000 so that the regression coefficients and standard errors were large enough to be interpretable in the OLS table results. This up-scale represents the crime rate per 1000 people in a zip-code. Though, some coefficients will remain small in the OLS results as crime rates have a wide range of values. Importantly, a scale up of 1000 is a good option for the dependent variables because scaling by 10000 would make many of the coefficients too large for the OLS results tables.

Graph 1 compares average crime rates for different levels of poverty. Notice the clear positive correlation poverty has with violent crimes, which is a trend that was not expected in this research. The research expected poverty to have no influence on violent crime, but this graph shows otherwise. Although this graph is interesting, it does not control for the issues mentioned later in the research. Again, notice the trend poverty has with non-violent crime. Notably, the trend is not linear as the research expected, but rather shows a bar graph trend that potentially shows diminishing returns. This trend is surprising because most literature claims that poverty has a linear effect on crime rates.



Graph 1: Low Poverty represents zip-codes with at most 15-percent of the population above the poverty line. Moderate Poverty represents zip-codes with between 15-percent to 30-percent of the population above the poverty line. High Poverty represents zip-codes with more than 30-percent of the population above the poverty line. The y-axis represents the non-logged average crime rate for every one-thousand people for each level of poverty.

**1.4.2 Key Independent Variable**

The key independent variable is named *pop\_pov* and is a discrete numeric percentage. This variable represents an estimation of the percent of the population that is below the poverty level in each zip-code. A person is living below the poverty threshold in Austin, Texas if their living situation meets one of the following guidelines: (1) One-person household under the age of 65 with a total annual income of $12,119 or less. (2) Family of 2 (one adult; one child) earning a total annual income of $16,057 or less. (3) Family of 3 (one adult; two children) earning a total annual income of $18,769 or less. (4) Family of 4 (two adults; two children) earning a total annual income of $23,624 or less. For *pop\_pov,* on average, 18-percent of a given zip-codes population is living in poverty which is approximately 7-percent higher than the national average of 11.5-percent. Therefore, it would not be wrong to hypothesize that there is a common characteristic about Austin, Texas that may be causing higher levels of poverty. Notably, this shall serve as one artifact of why only focusing on Austin, Texas crimes is a limitation in determining poverty’s effect on communities across the country.

Notably, each variable has at least one observation that is at least 2 deviations from the mean value. This suggests there are outliers in the data that may negatively affect the performance of the true interpretations of the OLS model results. Or it may mean that certain factors may be responsible for the extreme levels of poverty in communities. To note, possible poverty influencing factors will be discussed in the paragraph. However, these extreme values be beneficial in estimating crime, not model hindering.

It is important to understand why poverty varies from community to community. To begin, community disorganization creates a situation in which inhabitants of disadvantaged areas have limited opportunities, lack access to social institutions, and therefore have decreased interaction with members of mainstream society. (Hipp & Yates. 2011) These neighborhoods in turn become undesirable and are avoided by those who have the means to distance themselves from this type of environment. Therefore, Wilson argued that the steady outmigration of middle‐ and working‐class families “creates a ripple effect resulting in an *exponential increase* in related forms of social dislocation” (1987: 56–7, emphasis added). This argument implies that such neighborhoods will be qualitatively different as they suffer numerous deleterious consequences. (Hipp & Yates. 2011) Therefore, powerlessness and poverty increase the chances that needs are so little satisfied that crime is an irresistible temptation to actors alienated from the social order and that punishment is non-credible to actors who have nothing to lose. (Braithwaite. 1991) For example, if someone is starving, stealing food all the sudden does not sound like a bad idea because the worst punishment you can receive is “free” food and “free” housing.

1. **Literature Review**
   1. **Relevant Literature**

What follows is not meant to be an exhaustive review of literatures on economic conditions and crime. Instead, it focuses on the conclusions drawn from contradictory literatures as they relate to the effects of poverty on violent and non-violent crimes.

The tradition of empirically testing these ideas employing cities, states, and nations as units of analysis began in earnest in the late 1960s and early 1970s. (Pridemore. 2011) Dozens of studies of homicide have been published. Pridemore performed research that looked at poverty’s impact on violence by analyzing numerous studies on the subject. Nearly all the studies he mentioned had reported an association between inequality and homicide, leading scholars to draw strong conclusions about this relationship. Unfortunately, each of these studies failed to control for poverty, even though poverty is the most consistent predictor of area homicide rates in the US empirical literature and a main confounder of the inequality–homicide association. (Pridemore. 2011) When effects for poverty and inequality were estimated in the same model, there was a positive and significant poverty–homicide association, while the inequality–homicide association disappeared in two of three models. These findings were consistent across different samples, data years, measures of inequality, dependent variables (overall and sex-specific homicide rates) and estimation procedures. (Pridemore. 2011) The new results are consistent with what we know about poverty, inequality and homicide from the US empirical literature and suggest that the strong conclusions drawn about the inequality–homicide association may need to be reassessed, as the association may be a “spurious result of model misspecification”. (Pridemore. 2011) US studies have consistently found poverty to be associated with homicide rates, while the results of tests for an association between inequality and homicide have been inconsistent. (Pridemore. 2011) In summry, Pridemore proved that inequality as a regressor for estimating homicide, to be not statistically significantly when controlling for poverty. Because of the presence of convincing evidence for this effect, the research chose to build on Pridemore’s findings by not including an inequality measure, and to include a poverty measurement.

Another study done by Messner (1982) controlled for poverty, but the findings are quite confusing. In short, the study conducted by Messner found no support for the argument that poverty leads to homicide. Messner advocated a renewed effort to evaluate the empirical validity of the subculture-of-violence thesis (Messner, 1983) Messner initially estimated an equation, using an Ordinary Least Squares (OLS) model, which included relative and absolute deprivation measures plus five control variables: regional location (SMSA’s) proportion of the population that is black, population size, population per square mile as a measure of density, and proportion of the population 15 to 29 years-of-age. The two population measures (size and density) and the proportion 15 to 29 were included in the analysis, according to Messner (1982:107), "because of their frequent appearance in earlier studies." (Williams. 1984) The primary objective of these studies was to estimate the effect of income inequality and poverty on the homicide rate. Messner's analysis yielded no significant effect of income inequality, but a surprising negative effect of poverty on the homicide rate was found. Messner concluded that the findings call for a serious reconsideration of the linkages between poverty, inequality, and homicide. (Williams. 1984)

However, Williams argues that Messner’s findings are a consequence of specification error. To adjust Messner’s mistake, William goes on to test the hypothesis that the conventional measurement of absolute poverty is positively significant in estimating homicide. The units of analysis of William’s research are 125 SMSAs of 250,000 population or more in 1970 which is an idea borrowed from Blau (1982). William claims that appropriate units of analysis for this type of research is certainly debatable. One can argue, as did Messner, that states are arbitrary statistical aggregations, and SMSA’s approximate more meaningful social communities. (Williams. 1984) Acknowledging both sides of the debate, Williams picks the SMSA sample location measurement randomly because he was torn between them. Moreover, Williams notes that this issue should be kept in mind when reviewing his research and further studies should attempt to resolve the matter. To adjust for the specification error, Williams found that it was being caused by non-linearities within the percent black population independent variable. After squaring this term, which adjusted for the polynomial function it took on, his model found the absolute deprivation key feature to be positively statistically significant. (Williams. 1984) His findings suggest that if Messner would have more accurately specified the relationships of the features, Messner would not have reported a surprising statistically significant negative effect of poverty on homicide rate. (Williams. 1984) Despite this seeming solution Williams provides, I argue that a percent black population predictor variable is irrelevant in their research all together as recent research has detected that percent black population and poverty levels are almost indistinguishable in the United States’ society. (Hipp & Yates. 2011) Cautiously, there are numerous studies that find percent black population to be positively statistically significant with crime, indicating that crime is motivated in black communities due to cultural effects. Yet, none of those studies control for the percent of black population in poverty, which would intuitively make percent black population statistically insignificant.

A study looking at Social Disorganization theory tested the impact certain community contexts had on the amount of burglary a community had. Martin found poverty to be positively statistically significant in estimating burglary, which is categorized as a non-violent crime. (Martin. 2002) He draws heavily from several recent studies who have advanced the social disorganization theory of crime. This perspective views the presence of “community” as a key factor that helps maintain order in neighborhoods, even in the presence of structural criminogenic conditions such as concentrated poverty. (Martin. 2002)

* 1. **Contribution**

There has been limited research done accounting for the previously mentioned issues in this area of study. Many studies have forgotten to control for important factors in estimating crime and as a result many studies have came to incorrect conclusions about which factors effect crime. This research has gone a step further by following convincing literature and excluding predictor variables that have proven to be irrelevant in estimating crime. By combining the inclusion of features based on intuitive reasoning, past literature and correlation coefficients, this research made an advancement in the knowledge of this field. Past literature has introduced the causality of variables such as poverty and transit stop prevalence. It is not straight forward, however, that the proportion of homes available to service workers or the proportion of homes in poor condition may be influential to estimating crime.

1. **Model Results & Discussion**
   1. **Empirical Model Results & Discussion**

The purpose of this section is to report the OLS regression results for both dependent variables, violent\_pc and non\_violent\_pc. The results for the response variable violent\_pc are reported in Table 3. In Table 3, column Model A1 represents OLS regression results for the base OLS model that estimates violent\_pc. The last column, Model A5, is the final OLS model. The results for the response variable non\_violent\_pc are reported in Table 4 of which follows the same format as Table 3. This section will describe each model progression and the econometric reasoning behind them. For both Table 3 and Table 4, the chronological model progressions work from left to right. I will then interpret each final models’ results and then I will discuss the implications and limitations of those results.

In the base model of Table 3, trans\_cost, transitStop, rent\_change, and rent\_poor\_cond were all statistically significant at the 5-percennt level. Notably, the key independent variable, pop\_pov, is statistically insignificant. However, this model has several issues that needed to be adjusted for.

According to the Variation Inflation Factor (VIF), there is an issue of multicollinearity with variables rent\_poor\_cond, rent\_aff\_serv, and transitStop as all three of their VIF values were above 5. (VIF = 6.11, 6.07, 5.54) Moreover, the Pearson Correlation coefficient for these two variables is greater than .70 (PCC= .94, .83, .91) indicating that multicollinearity is an issue between these three independent variables. However, the predicted signs for these variables were as expected so the research chose to make further adjustments and then reconsider model progressions due to multicollinearity.

Many statistical analyses assume normality amongst data distribution. As mentioned by Ross (2020), violent crime rates are right skewed in distribution. As a result, if this skew is present for violent\_pc, then the asymmetrical distribution may cause bias in the model. Therefore, I wanted to see if it would be beneficial to log violent\_pc as it may be non-normally distributed. To do this, I ran a Box-Cox test. After running the test, the resulting theta value of .03 indicated that I should log violent\_pc according to the .05 theta value threshold. The logged violent\_pc variable can be seen in Model A2-ModelA5. After logging violent\_pc, the only statistically significant variable remaining were rent\_poor\_cond, which is statistically significant at the 10-percent level.

I tested for heteroskedasticity using the Breusch-Pagan Test and the White Test. According to both tests, there are no issues heteroskedasticity at the 10-percent level. (BPT = .55; WT =.42)

Next, this research checked for issues of outliers. This step was motivated by the summary statistics provided in Table 2. The dependent variable violent\_pc had a maximum crime rate value six deviations from the average violent crime rate. This suggested there was a major outlier in the data. Importantly, those results were looking at the non-logged version of violent\_pc. Considering I logged the response variable, log transformation can often increase – not reduce – variability of data whether or not there are outliers. Therefore, the research was further encouraged to check if there were model influencing outliers. To do this, I created a leverage plot. The leverage plot exposed three seeming outliers. (zip-codes: 78732, 78705, and 78701) To see which outliers had a substantial negative impact on the model, the research compared the adjusted R-squared value for models with and without each outlier. The zip-code 78705 was the only observation that substantially decreased the adjusted R-squared. This progression can be seen in Model A3. Notably, the adjusted R-squared increased from .507 to .628, which is a substantial increase. However, the research did not want to immediately exclude this observation because the available sample size is already limited at 35 observations. Instead, the research tried to control for this outlier using a population density variable that measured the number of people per square mile. The reasoning behind the selection of this variable is because this zip-code differed from all others in that it is an urbanized area. Research has shown several factors within urban neighborhoods cause higher rates of crime, one being population density. Therefore, the research decided to include this variable to control for the urbanized zip-code. Unfortunately, adding this variable did not improve the model after all adjustments, so I decided to exclude it from both Table 3 and Table 4. For further studies, I would incorporate the other two factors mentioned by Ladbrook (1988) to control for outliers caused by urbanized areas; (2) the greater rates of migration and population growth in urban populations, and (3) the differences in demographic structures between urban and rural areas, urban areas having greater proportions of young people. Unfortunately, due to time constraints, this research could not control for those factors in either model.

After removing outliers, the research further progressed the model by logging the predictor variables that increased the adjusted R-squared value. First, this research chose to log predictor variables to improve model fit. After logging trans\_cost, transitStop, and rent\_change, the adjusted R-squared increased from .628 to .643 as can be seen from Model A3 to Model A4. Second, logging these three predictor variables only made their impact on violent\_pc easier to interpret.

From Model A4, the research decided to reconsider issues of multicollinearity by referring to the new VIF values from the remaining original predictor variables and the new logged predictor variables. The research found predictor variables rent\_poor\_cond and rent\_aff\_serv still have VIF values above 5 which suggests there is still multicollinearity. Notably, after logging transitStop, the VIF value dropped to 3.88 which suggests this variable does not experience multicollinearity.

Last, in aim of simplicity and precision, the research chose to drop statistically insignificant regressor variables (p-value >.30). If a predictor variable obtained a p-value threshold above .30, it was completely excluded from the model. This progression can be seen from Model A4 to Model A5 where the only regressor removed was ln\_transitStop. To note, this progression seems contradictory to the final VIF values previously mentioned, however, the VIF values for rent\_poor\_cond and rent\_aff\_serv are not substantially greater than 5. (VIF = 6.68, 6.65) Additionally, the predicted signs of these variables are as expected as well as statistically significant to the .30 conventional p-value threshold. Moreover, ln\_transitStop had its predicted sign, but did not meet the 0.30 conventional p-value level of statistical significance. Therefore, I decided to drop ln\_transitStop and keep rent\_poor\_cond and rent\_aff\_serv in the final model. The final model progression, Model A5, which progressed by excluding ln\_transitStop, slightly improved the adjusted R-squared value from .643 to .646 from Model A4 to Model A5.

In Model A5, the final adjusted R-squared value is .646. The final statistically significant variables are pop\_pov\_change, pop\_pov, and ln\_trans\_cost according to the 10-percent p-value threshold. As a result of this model, we can reject part of the testable hypothesis that states poverty does not influence violent crime rates. Moreover, the economic conditions that influence violent crime rate are rent\_poor\_cond, pop\_pov\_change, rent\_aff\_serv, pop\_pov, ln\_trans\_cost, and ln\_rent\_change.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 3: OLS Regression Results for Violent Crime** | | | | | |
|  | **Model A1** | **Model A2** | **Model A3** | **Model A4** | **ModelA5** |
| ***Constant*** | **332.819** | **3.345** | **4.369** | **21.626** | **16.378** |
|  | **(120.8)\*\*** | **(2.920)** | **(2.599)** | **(10.66)\*** | **(8.750)\*** |
| ***trans\_cost*** | **-0.427** | **-0.002** | **-0.004** |  |  |
|  | **(0.152)\*\*\*** | **(0.0036)** | **(0.0033)** |  |  |
| ***transitStop*** | **-1.032** | **0.003** | **-0.003** |  |  |
|  | **(0.473)\*\*** | **(0.0114)** | **(0.0103)** |  |  |
| ***rent\_change*** | **0.736** | **0.002** | **0.008** |  |  |
|  | **(0.350)\*\*** | **(0.0084)** | **(0.0077)** |  |  |
| ***rent\_poor\_cond*** | **68.458** | **1.476** | **0.916** | **0.984** | **0.835** |
|  | **(32.64)\*\*** | **(0.789)\*** | **(0.721)** | **(0.715)** | **(0.691)** |
| ***pop\_pov\_change*** | **-0.061** | **-0.001** | **-0.002** | **-0.002** | **-0.002** |
|  | **(0.0457)** | **(0.0011)** | **(0.0009)\*** | **(0.0011)\*** | **(0.0008)\*** |
| ***rent\_aff\_serv*** | **-2.360** | **-0.033** | **-0.059** | **-0.062** | **-0.051** |
|  | **(2.080)** | **(0.0503)** | **(0.0452)** | **(0.0455)** | **(0.0432)** |
| ***pop\_pov*** | **0.476** | **0.025** | **0.078** | **0.075** | **0.071** |
|  | **(0.680)** | **(0.0164)** | **(0.0231)\*\*\*** | **(0.0218)\*\*\*** | **(0.0212)\*\*\*** |
| ***ln\_trans\_cost*** |  |  |  | **-3.055** | **-2.332** |
|  |  |  |  | **(1.553)\*** | **(1.306)\*** |
| ***ln\_transitStop*** |  |  |  | **-0.202** |  |
|  |  |  |  | **(0.232)** |  |
| ***ln\_rent\_change*** |  |  |  | **0.254** | **0.201** |
|  |  |  |  | **(0.216)** | **(0.206)** |
| ***N*** | **35** | **35** | **34** | **34** | **34** |
| ***Adj. R-Squared*** | **0.399** | **0.507** | **0.628** | **0.643** | **0.646** |
| ***SEE*** | **41.134** | **0.994** | **0.877** | **0.858** | **0.855** |
| ***F-ratio*** | **4.220** | **5.998** | **8.955** | **9.500** | **11.057** |
| ***SSR*** | **45683.955** | **26.679** | **19.984** | **19.159** | **19.717** |
| ***Source: Austin Government Website; \* p<0.1, \*\* p<.05, \*\*\* p<.01*** | | | | | |

In the base model of Table 4, trans\_cost, transitStop, rent\_change, and pp\_ch were all statistically significant at at least the 10-percennt level. Notably, like the base model in Table 3, the key independent variable, pop\_pov, is not statistically important in explaining non-violent crime rates.

According to the Variation Inflation Factor (VIF), there are no issues of multicollinearity between predictor variables. As mentioned before, the Pearson Correlation coefficients for the variables rent\_poor\_cond and rent\_aff\_serv and the variables trans\_cost and transitStop are greater than .70 (PCC=.90, -.83) indicating that multicollinearity is an issue between these variables. However, like before, the predicted signs for these variables were as expected so the research chose to make further adjustments and then reconsider model progressions due to multicollinearity.

Like in Table 3, I ran a Box-Cox Test to test if non\_violent\_pc has a non-normal distribution. After running the test, the resulting theta value of .011 indicated that I should log non\_violent\_pc according to the .05 theta value threshold. The logged non\_violent\_pc variable can be seen in Model B2-Model B5. In Model B2, the only statistically significant variable remaining was pp\_change, which is statistically significant at the 1-percent level.

To test for heteroskedasticity the research used the Breusch-Pagan Test and the White Test like before. According to both tests, there are no issues of heteroskedasticity at the 10-percent level. (BPT = .7286; WT =.419)

Again, this research checked for issues caused by outliers. This step was motivated by the summary statistics provided in Table 2. The dependent variable non\_violent\_pc had a maximum crime rate value of .23 which is 7 deviations from the average non-violent crime rate and a minimum crime rate of .0005 which is more than 10 deviations from the mean non-violent crime rate. This suggested there were at least two major outliers in the data. Again, those results were looking at the non-logged version of non\_violent\_pc. To check if the outliers had influence on the model, I used another leverage plot. The leverage plot exposed three extreme values. (zip-codes: 78732, 78705, and 78701) To see which outliers had a substantial negative influence on the models ability to explain the variation in non\_violent\_pc, the research compared the adjusted R-squared value for models with and without each outlier. The zip-code 78701 was the only observation that substantially decreased the adjusted R-squared value. This progression can be seen in Model B3. Notably, the adjusted R-squared increased from .507 to .628, which is a substantial increase. The research set a threshold of what is considered a substantial increase in the adjusted R-squared value (increase in adj R-sqrd > .03) Again, the research did not want to immediately exclude this observation because the available sample size is already limited at 35 observations. Again, the research tried to control for this outlier using a conventional population density variable that measured the number of people per square mile. This is because the zip-code 78701 is a metropolis area like 78705. Interestingly, these two zip-codes are neighboring each other. This further suggests that metropolis have different impacts on crime rates. However, it does not help determine which factors have influence on crime. As mentioned before, the research controlled for population density, though it found to have no effect on non-violent crime rates. Again, this variable has been excluded from all models in this research for concerns of space and time. Further studies should strongly consider controlling for the following factors in urbanized areas: (2) the greater rates of migration and population growth in urban populations, and (3) the differences in demographic structures between urban and rural areas, urban areas having greater proportions of young people. (Ladbrook, 2020)

After removing the outlier 78701, the research further progressed the model by logging the predictor variables that increased the adjusted R-squared value. After logging ln\_pp\_change and ln\_rent\_poor\_cond, the adjusted R-squared increased from .73 to .75 as can be seen from Model B3 to Model B4. Logging these two predictor variables made their impact on non\_violent\_pc easier to interpret and made the model fit better than in Model B3. Lastly, after logging the variables ln\_pp\_change and ln\_rent\_poor\_cond, Model B4 found variables transitStop, pp\_change, and rent\_serv to be statistically significant at at least the 10-percent level.

After reconsidering issues of multicollinearity by referring to the new VIF values from the remaining original predictor variables and the new logged predictor variables. There were no VIF values above 5 after logging the variables, which indicates there are no issues of multicollinearity.

By following the same parameters as before, the research chose to exclude certain predictor variables base on their p-values. This progression can be seen from Model B4 to Model B5 where the only regressor removed was trans\_cost. The final model progression, Model A5, slightly improved the adjusted R-squared value from .75 to .754 from Model B4 to Model B5.

In Model A5, the final adjusted R-squared value is .754. The final statistically significant variables are transitStop, pp\_ch, and rent\_aff\_serv according to the 10-percent p-value threshold. Notably, pop\_pov was not even statistically significant at the 10-percent p-value threshold. As a result of this model, we can reject the other half of the testable hypothesis that states poverty increases the rate of non-violent crimes. Moreover, the economic conditions that influence non-violent crime rate are transitStop, pp\_change, and rent\_serv.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 4: OLS Regression Results for Non-Violent Crime** | | | | | |
|  | **Model B1** | **Model B2** | **Model B3** | **Model B4** | **Model B5** |
| ***\_cons*** | **2708.569** | **7.929** | **4.940** | **2.125** | **3.938** |
|  | **(764.3)\*\*\*** | **(2.220)\*\*\*** | **(2.636)\*** | **(2.743)** | **(0.982)\*\*\*** |
| ***trans\_cost*** | **-3.344** | **-0.003** | **0.001** | **0.002** |  |
|  | **(0.961)\*\*\*** | **(0.00279)** | **(0.00335)** | **(0.00329)** |  |
| ***transitStop*** | **-5.139** | **-0.001** | **0.009** | **0.020** | **0.014** |
|  | **(2.993)\*** | **(0.00869)** | **(0.0098)** | **(0.0098)\*** | **(0.0055)\*\*** |
| ***rent\_change*** | **6.411** | **-0.000** | **-0.010** | **-0.011** | **-0.009** |
|  | **(2.212)\*\*\*** | **(0.00643)** | **(0.00807)** | **(0.00892)** | **(0.00820)** |
| ***rent\_poor\_cond*** | **350.697** | **0.983** | **0.441** |  |  |
|  | **(206.4)** | **(0.600)** | **(0.639)** |  |  |
| ***pp\_ch*** | **-0.592** | **-0.005** | **-0.004** | **-0.004** | **-0.004** |
|  | **(0.289)\*** | **(0.0008)\*\*\*** | **(0.0008)\*\*\*** | **(0.0013)\*\*\*** | **(0.0011)\*\*\*** |
| ***rent\_aff\_serv*** | **-16.048** | **-0.038** | **-0.002** | **0.055** | **0.053** |
|  | **(13.16)** | **(0.0382)** | **(0.0411)** | **(0.0236)\*\*** | **(0.0232)\*\*** |
| ***pop\_pov*** | **-1.284** | **0.007** | **0.009** |  |  |
|  | **(4.299)** | **(0.0125)** | **(0.0120)** |  |  |
| ***ln\_rent\_poor cond*** |  |  |  | **-0.346** | **-0.285** |
|  |  |  |  | **(0.237)** | **(0.219)** |
| ***ln\_pp\_change*** |  |  |  | **0.217** | **0.242** |
|  |  |  |  | **(0.184)** | **(0.179)** |
| ***N*** | **35** | **35** | **34** | **34** | **34** |
| ***Adj R-Squared*** | **0.559** | **0.719** | **0.729** | **0.750** | **0.754** |
| ***SEE*** | **260.158** | **0.756** | **0.721** | **0.702** | **0.695** |
| ***F-ratio*** | **7.149** | **13.453** | **13.696** | **14.693** | **17.391** |
| ***SSR*** | **1827425.185** | **15.419** | **13.528** | **12.308** | **12.555** |
| **Source: Austin Government Website; \* p<0.1, \*\* p<.05, \*\*\* p<.01** | | | | | |

**3.2 Implications**

The purpose of this section is to interpret the results of the final models, Model A5 and Model B5. Additionally, this section will compare the findings to other literature by supporting or disproving their claims. Then, this section will provide intuitive reasoning as to why the results make sense.

For final model, Model A5, the predictor variables that are statistically significant are *pp\_ch, pop\_pov,* and *ln\_trans\_cost*. For final model, Model B5, the predictor variables that are statistically significant are *transitStop, pp\_ch*, and *rent\_aff\_serv*. Notably, pop\_pov is not statistically significant, even at the .3 p-value level of significance.

To begin, every additional percent of homes 14 miles from a transit stop, the number of non-violent crimes for every 1000 people increases by 1.4-percent. Intuitively, the variable *transitStop* seems like it could not influence the number of non-violent crimes. What does a bus stop have to with crime? Transit Stops produce cesspools of theft for several reasons. First, Levine and et. al. (1986) found one of the three stops they studied to be crowded. This encouraged pickpocketing and purse snatching. Another unique bust stop served as a drug trafficking corner, which intuitively produces crime. It is possible to isolate factors contributing to crime at a location and to take preventative action. Solutions, however, must be tailored to the qualities of the location. This task is manageable because criminal incidents appear to be concentrated in a limited number of places. (Levine. & et. al. 1986)

There is a 5 percent increase in the number of non-violent crimes for every 1000 people when there is an additional percentage of households affordable to service workers. As there are more households affordable to service workers the dramatic increase in non-violent crime intuitively makes sense. To understand why this makes sense, one would have to understand the average service worker. A service worker, also known as a pink-collar worker, is a person in the service industry whose labor is related to customer interaction (waiter, cashier, etc.), entertainment, sales, or other service-oriented work. Importantly, a service worker is a person who does not necessarily make a desirable wage because of little education or experience but has the motivation to do the work. The wages service workers are paid often leave them struggling to pay for necessities. And referring to ideologies of Social Darwinism, people will do what they must to survive, like stealing food, money, or transportation. Therefore, the number of service workers present in a community is a great indicator of non-violent crimes. Furthermore, poverty is not a good indicator of non-violent crimes, however, because people living in poverty have access to more resources to government funds, such as food stamps. Government funding for necessities mitigate acts caused by phenomenon mentioned by social Darwinism theory. In turn, people in poverty will be less inclined to steal if they have the resources they need comparative to service workers who do not get funding and make hardly enough to survive. In transitioning, although this factor is a good indicator of non-violent crime, it is not a good indicator of violent crime because it would not make sense for a service worker to act out a severe crime, such as murder or rape, as it would not be to their benefit. Arguably, at first thought it may seem to make sense if this variable is substituted by a low-income variable, however, that does include anyone in poverty, which is not the population that is committing non-violent crime. A more accurate estimation of the effect of *rent\_aff\_serv* would be to include a predictor variable that represents the number of service workers in a community.

Therefore, further studies should include a variable like *rent\_aff\_serv* when estimating non-violent crimes but should not include it if estimating violent crimes. Additionally, rather than mitigating crime in poverty dense communities, local governments, leaders, and police forces should focus their plans to mitigate non-violent crime in communities with higher proportions of households affordable to service workers.

There is a .4-percent decrease in the number of non-violent crimes for every 1000 people every time there is an additional percentage point in the percent change of population below poverty from 2000 to 2012. Theoretically, this means that if the percentage of the population below poverty increased from 2000 to 2012, there would be more crimes. From what research shows about poverty’s effect on crime and this research’s testable hypothesis, it intuitively does not make sense for non-violent crimes to decrease while the amount of poverty is growing. However, this affect may be due to chance caused by a limited sample size. Limitations caused by a small sample size will be further mentioned in the conclusion.

There is a 2-percent increase in the rate of violent crimes where there is an additional percentage of the population below poverty. Initially, the research did not expect poverty to influence violent crime. However, this theoretically makes sense. Dong (2020) discusses how poverty drives city immigration and emigration which creates segregation of communities. Intuitively, there are many factors that maintain and produce poverty dense communities: if the home is affordable for someone who is in poverty, if the land lord is willing to rent to someone who is in poverty, pre-existing problems due to red-lining, a sense of belonging, generational poverty, etc. One example is that people who have committed violent crimes in the past are more likely to commit a violent crime in the future than if someone had a clean record. To the point, if an individual has violent crime on their record, they are less likely to have a job or a well-paying one at that. Therefore, these individuals will migrate to poverty dense communities to seek an affordable home, or a home that someone will rent to them. Therefore, I suggest research factor in variables like present number of citizens who have committed a violent crime. Recall an argument made by Pridemore that states once individuals are in a hopeless state where they believe “life” cannot get much worse for them, they are more likely to commit violent crimes. This is because individuals feel like they have nothing to lose, so if they did commit a terrible crime, the worst that could happen to them is they get free rent, free food, and simply experience any other situation than they are in at that moment. The cost of committing rape or murder simply does not seem better than the life they are living currently.

There is a 1-percent decrease in the number of violent crimes per 1000 people where there is an additional percentage point in the percent change of population below poverty from 2000 to 2012. This result intuitively does not make sense as *pop\_pov* is positively statistically significant. Therefore, in the most extreme case, *pp\_ch* would not be statistically significant. This suggests there are issues caused by multicollinearity or limited sample sizes. Because of this, I will not further interpret this result so there are no misleading statements.

Moving on, for each 10-percent increase in average transportation cost the number of violent crimes per 1000 people decreases by 20-percent. Initially, the research hypothesized that *ln\_trans\_*cost would be negatively collinear with poverty, thus causing issues of multicollinearity. Intuitively, this would make sense for several reasons. First, a person in poverty may not even have a vehicle to travel. Second, a person who is in poverty likely does not have pay for transportation costs to and from their job because it is likely they do not have one. Third, people in poverty tend to prefer public transportation over their own means of transportation because it is more affordable. These examples support why higher average transportation costs might be a direct effect of higher poverty. Therefore, it would make sense this is statistically significant with violent crime due to reasons like poverty’s effect on violent crime. Notably, issues of multicollinearity between these variables were not an issue as mentioned in an earlier section.

1. **Conclusion**
   1. **Findings Summary**

The research tested the hypothesis that higher levels of poverty increases the rate of non-violent crime but does not increase the rate of violent crime. In the end, the research rejected this hypothesis. In fact, the research found the case to be the opposite. The research found higher levels of poverty to cause higher rates of violent crime but has no impact on the rate of non-violent crimes. Higher levels of poverty increase violent crime rates for several reasons. One reason is that poverty drives city immigration and emigration which creates segregation of communities. An example of this effect is that it may create a community cesspool of individuals who are more prone to commit violent crimes. Another reason this effect intuitively makes sense is because individuals who are in poverty are more likely to feel hopeless. Which, in turn, increases the chances of a person committing a violent crime because they have nothing to lose. Conversely, higher levels of poverty do not increase the rate of non-violent crimes, higher proportions of homes within 14 miles of a transit stop does. The research reasoned that bus stops are cesspools for non-violent crimes for several reasons. Solutions should be tailored to the qualities of the location. For example, if crowded areas drive purse snatching, then an officer should be on stand-by or there should be warning signs. But if drug trafficking is the issue, which is not mentioned in this research, then cameras may be installed, and a sign could provide a number to report suspicious activity. Higher proportions of homes affordable to service workers is a great estimator of what causes higher non-violent crime rates. This is due to low wages service workers earn and the lack of government funding. Because many service workers tend to have a challenging time paying for necessities, they are inclined the steal, an ideology supported by Social Darwinism theory.

* 1. **Limitations & Forward-Looking Statements**

This research observed a limited sample size of around half the zip-codes within Austin, Texas. There are two likely issues caused by the characteristics of this data. First, the data looks at only one city, a state’s capital to be exact, thus, limiting the application of this research to the city of Austin. Further studies should analyze the impact of these variables for cities with different characteristics. Second, the results in this research are likely not valid because of the limited number of observations, or zip-codes. To make valid conclusions about regression results for this type of research, hundreds of observations are recommended rather than tens of observations. Models simply cannot capture all the important inferences with just 34 observations. However, the results in this research may not be completely invalid as the results intuitively make sense. Therefore, a reassessment of the effect of poverty on violent crime and non-violent crime should be done in the future, specifically building on this research.

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**Appendices**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table 2: Summary Statistics of Regression Variables** | | | | | |
| **Variable Name** | **Obs.** | **Mean** | **Std. Dev.** | **Min** | **Max** |
| **non\_violent\_pc** | **42** | **.0313** | **.0376** | **.0005** | **.23** |
| **violent\_pc** | **42** | **.0022** | **.0031** | **0** | **.018** |
| **trans\_cost** | **35** | **684.24** | **90.01** | **433** | **865** |
| **transitStop** | **35** | **47.72** | **35.09** | **0** | **100** |
| **rent\_change** | **35** | **34.56** | **26.26** | **0** | **115** |
| **rent\_poor\_cond** | **35** | **.5729** | **.5252** | **0** | **2.2** |
| **pp\_change** | **35** | **149** | **226.01** | **-20** | **1242** |
| **rent\_aff\_serv** | **35** | **7.67** | **8.19** | **0** | **39** |
| **pop\_pov** | **35** | **18.10** | **13.71** | **1** | **66** |
| **pop\_dense** | **35** | **3815** | **2629** | **90.06** | **15034** |

Table 2: reports summary statistics for each variable used in the research. Column “Obs.” represents the number of observations for a variable. Column “Std. Dev.” represents the standard deviation for a variable. The crime rate variables have 42 observations, and the independent variables have 35. This differentiation is due to the lack of estimations from the CHMA.