**Exploring the Conditional Effects of Bus Stops on Crime**


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# Exploring the Conditional Effects of Bus Stops on Crime

**Keywords:** public transportation, bus stops, crime, spatial analysis

**Abstract**

Public transportation is a major element of social life in most cities, and the most common mode of public transportation is busing. This study examines whether bus stops are a robust predictor of crime, net of other factors, and whether the effect of bus stops on crime is conditioned by socio-economic and land use factors. We use geocoded Indianapolis crime and bus stop data for 2010 to predict crime counts in 500-feet X 500-feet square grid cells, using negative binomial models. Net of other factors, bus stops are associated with variation in counts of Uniform Crime Reports (UCR) reported rape, robbery, aggravated assault, burglary, and larceny in a cell. In addition, the effect of bus stops on crime was conditioned by land use characteristics. In particular, the effect of bus stops on crime was greater in commercial and industrial areas, but dampened in areas with high density residential housing.

**Exploring the Conditional Effects of Bus Stops on Crime**

Transportation is a daily necessity of modern life, and public transportation is common in most cities. And as we move further into the 21st Century, many argue that public transportation is a key element for developing sustainable, livable cities (e.g. Loukaitou-Sideris, 2010). Given the ubiquity of public transportation and its central role in the visions of planners for livable cities, it is reasonable to examine how public transportation and crime are related. We focus here on busing because it is the most common mode of public transportation across cities.[1] Because entry and exit to buses is based on set times and locations, routine activities theory (Cohen & Felson, 1979; Felson, 2002; Kennedy & Forde, 1990), for example, would suggest that crime might be higher near bus stops, which are expected to bring relatively large numbers of potential targets and would-be offenders into close proximity, with potentially limited guardianship. On the other hand, bus stop locations are not randomly assigned, therefore higher crime near bus stops might be a function of the factors that drove the placement of a bus stop in a given location. So it is reasonable to examine whether bus stops themselves have independent effects on crime, or whether it is the characteristics of the location in which the bus stop is placed that drive crime. One might also wonder whether the effect of bus stops on crime varies across crime types, affecting robberies and assaults but not burglary, for example. Finally, as will be discussed further below, it could be that the bus stop-crime relationship is conditional.

The goal of this study is to systematically explore whether and how bus stops and crime are related and whether the relationship is direct or conditional. To do this, first we review

[1] Although we focus on bus stops in this study, there is a large body of research on other types of public transit (see Smith & Clarke, 2000 for a review). Research on public transportation and crime has often taken the form of situational crime prevention studies (see Clarke, 1996; Newton, Johnson, & Bowers, 2004; Smith & Cornish, 2006; van Andel, 1989) or case/small N studies (e.g. Liggett, Loukaitou-Sideris, & Iseki, 2004; Loukaitou-Sideris, Liggett, & Iseki, 2002; Morta and Castro, 2010; Pearlstein & Wachs, 1982). Not all studies of rapid transit have found that these areas are associated with higher crime (cf. Billings, Leland and Swindell, 2011; Liggett, Loukaitou-Sideris, and Iseki, 2003b; Poister, 1996).

existing research on bus stops and crime. Then, we discuss the data and methods used in the current study. Because the impact of a bus stop on crime is expected to be limited to a fairly small geographic area, we employ 500-feet X 500-feet square grid cells as the unit of analysis. We conduct negative binomial analyses of direct and interaction effects of bus stops on 2010 Uniform Crime Reports (UCR) crime counts in the grid cells. We conclude with a discussion of next steps and policy implications from the current findings.

**Bus Stops and Crime**

There is no shortage of theoretical reasons why bus stops and crime might be related. Yu (2009) describes three common criminological perspectives used by researchers examining the relationship between bus stops and crime: routine activities/opportunity theories, rational choice theories, and crime pattern theory. According to Cohen and Felson (1979), people's routine daily activities follow consistent patterns which differentially place potential offenders and potential targets in close proximity. From the routine activities perspective, crime is more likely when a motivated offender encounters a suitable target in the absence of a capable guardian. Similarly, rational choice theories suggest that would-be offenders choose their targets based on rational calculations that maximize the likely payoff of crime and minimize the likelihood of apprehension. From both perspectives, areas near bus stops might make good candidate locations for robberies because potential victims are forced to wait in a public place with little or no obvious protection, particularly when these areas are in remote locations or deserted. Finally, crime pattern theory would suggest that bus stops and crime are related. Brantingham and Brantingham (1984, 1993) argue that potential offenders rationally choose their crime locations but that this choice is affected by their "awareness space." Offenders are generally aware of areas near their homes, near their work (if they are employed), and near areas where they typically “hang out”. These areas are called “nodes” in crime pattern theory. The travel routes between these nodes (such as from home to work) are called “paths”. Crime is much more likely to occur near a criminal’s nodes or along the paths between these nodes because they have a greater knowledge and awareness of these spaces, which in turn increases their comfort level regarding the potential factors that would lead one to choose a crime location and victim (maximum likelihood of success with minimal likelihood of apprehension). To the extent that public transportation facilitates travel to and from various areas of a city, it is likely that bus stops could become nodes for potential criminals (who may not have access to private transportation) or that bus routes could become pathways.[2] In the next section, we discuss research on bus stops and crime.

Bus Stop—Crime Research

Most extant bus stop—crime studies have been small N/case studies. For example, Levine, Wachs, & Shirazi (1986) conducted a telephone survey in Los Angeles to identify high crime bus stops. They conducted extensive research at three locations to identify the factors that appeared to drive crime at each, which included drug trade at one, crowding at another, and proximity to a high school in the third case. Newton (2008) focused on three bus routes in England, noting that crime was higher at bus stops in high crime areas. Similarly, Loukaitou-Sideris & Liggett (2000) examined factors influencing crime at 10 bus stop crime “hot spots” in Los Angeles (see also Loukaitou-Sideris, 1999).[3] They noted that the stops associated with serious crimes such as robbery appeared to be different than those areas where public nuisance or

[2] Crime pattern theory also includes the concept of “edges” which are breaks between areas that have distinct land use or visual configurations. Lersch and Hart (2011) note that crime can be higher along edges because people from areas on either side of the edge are less likely to know each other, and the risk of crime is even greater if edges are connected by public transport systems.
[3] Newton & Bowers (2007) also studied a single crime: damage to bus shelters.

minor crimes predominated. Loukaitou-Sideris, Liggett, Iseki and Thurlow (2000) studied 60 randomly sampled bus stops in Los Angeles and determined that the environment surrounding the bus stop was an important determinant of crime. Liggett, Loukaitou-Sideris, Iseki (2003a) expanded on the prior study somewhat to include 100 Los Angeles bus stops, and focused on the presence of obvious escape routes (alleys), land use patterns, condition of the area (vacant lots and incivilities), characteristics of the stops and the street. They found that the presence of liquor stores, litter, wait time, "visibility", and whether the stop was in the "historic core" of the city were significant predictors of the natural log of the number of crimes per 100 riders.

To date only three large N studies (that we are aware of) have examined bus stops and crime. Weisburd, Groff, and Yang (2012) included a measure of the number of bus stops in their study of 24,023 Seattle street segments from 1989 to 2004. Included as an indicator of "opportunity", the authors found that the number of bus stops is an indicator of the street segment having a "chronic-crime trajectory" versus a crime free trajectory in multinomial logistic regression models. However, this variable was included mainly as a control variable and was not really the focus of the study. Yu (2009) examined the bus stop—crime relationship in Newark New Jersey as the focus of her dissertation. Using 2,602 Thiessen polynomials as the unit of analysis and controlling for land use characteristics, Yu (2009) found that bus stops were associated with higher crimes for robbery, aggravated assault, burglary, motor vehicle theft, and thefts from vehicles using a variety of multivariate statistical models. Finally, Kooi (2007) studied 114 "block group neighborhoods" that contained 638 bus-stop locations in Lansing Michigan. In it, he compared crime in block groups in 97 block groups with bus stops to 17 with no bus stops. In logistic regression analyses, net of population, disadvantage, immigrant concentration, and residential stability measures, block groups with bus stops had statistically significantly higher rates of armed and unarmed robbery, assault, disorderly conduct, domestic abuse, truancy, and weapons violations.

With few exceptions (cf. Loukaitou-Sideris 1999), extant studies have found that bus stops and crime are related. Yet, studies that focus specifically on bus stops tend to be case/small N studies. To date, only three larger N studies (Kooi, 2007; Weisburd et al., 2012; Yu, 2009) have been undertaken and all of these find that bus stops are associated with higher crime. Prior large N studies have generally examined only direct bus stop—crime relationships, yet, many of the small N studies suggest that crime is higher at some bus stops than others, often based on characteristics of the areas surrounding bus stops (Levine et al., 1986; Loukaitou-Sideris, 1999; Newton, 2008). Other studies have found that rapid transit and crime are associated only under certain conditions. For example, Block and Davis (1996) found that robberies were higher near Chicago El stations in low crime neighborhoods but not in high crime neighborhoods (see also Block, 2012). And Ceccato, Uittenbogaard, and Bamzar (2013) found that the ecological characteristics of the areas surrounding underground rapid transit stations contributed substantially to the explanation of variation in crime across stations in Stockholm, Sweden. And several recent studies of land use and crime suggest conditional relationships (e.g. Smith et al., 2000; Authors, 2009; Wilcox, Quisenberry, Cabrera, & Jones, 2004; Wilcox, Quisenberry, & Jones, 2003). For example, Authors (2009) found that the effect of socio-economic disadvantage on crime was conditioned by land use factors such as commercial and industrial activity.

We focus on four conditional relationships in this study. We hypothesize that the bus stop—crime relationship will be conditional on: commercial activity, industrial activity, socio-economic disadvantage, and the density of residential housing. Commercial activities in an area around bus stops might raise the likelihood of crime by placing concentrations of motivated offenders and suitable targets in proximity. Research has also focused on the presence of industrial land uses. For example, Authors (2009) found that the presence of industrial land uses dampened the effect of disadvantage on crime. Social disorganization/collective efficacy perspectives suggest that neighborhood characteristics may enhance or impede the ability to maintain informal social control by affecting the number of strangers in an area and reducing the ability of residents to distinguish locals from outsiders or increasing disorder (see Kurtz, Koons, & Taylor, 1998; McCord, Ratcliffe, Garcia, & Taylor, 2007; Taylor, Koons, Kurtz, Greene, & Perkins, 1995; Wilcox et al., 2004; Wilcox, et al., 2003). Thus, one might hypothesize that bus stops in disadvantaged areas could be more likely to be sites of crime because there are more strangers in proximity or fewer people willing / able to maintain informal social control. Thus, the effect of bus stops on crime would be conditional on the socio-economic disadvantage of the area. Finally, the density of residential housing has been shown to affect crime (McNulty and Holloway, 2000). Therefore the presence of absence of high density housing near bus stops may affect the likelihood of crime by increasing the potential for motivated offenders and suitable targets to be in close proximity. Although by no means an exhaustive examination of the relationships that could be explored, prior research suggests reasons to believe that these factors may condition the bus stop—crime relationship.

In sum, the goal of the current study is to examine whether bus stops and crime are related using a large N strategy and to determine whether the effects of bus stops on crime are direct or conditional on characteristics of the areas surrounding the bus stops such as land use. We will also examine whether the effect depends on the type of crime because it is possible that bus stops would be more likely to be associated with personal crimes such as robbery and assault than some others such as burglary (it is hard to imagine a burglar hauling much loot onto a bus). In the next section, we discuss the data and methods used in the current study.

## DATA AND METHODS

The primary data for this study include the number of crimes reported by the Indianapolis Metropolitan Police Department (IMPD) in 2010, bus stop locations (as of 2010) from the City of Indianapolis, Division of Planning, and socio-economic characteristics from the census bureau. Socioeconomic data for the cells came from 2010 census tract data because census tract was the smallest unit for which current socio-economic information was available. In 1970, the city of Indianapolis consolidated with Marion County. To make the study more comparable with other cities, the study area is limited to approximately the Indianapolis city boundaries before city-county consolidation.

### Unit of Analysis

The units of analysis for this study are 500-feet X 500-feet square grid cells overlaid on the IMPD service area within the city of Indianapolis (see Map 1). We chose uniformly sized square grid cells for the analysis rather than census tracts or block groups because both vary substantially in size. [4] For example, Indianapolis census tracts (if square) would vary from approximately 2,350 to 10,300 feet on a side with an average of 4,800 feet. Thus, they would be five to twenty times larger than the current cells that are 500 feet on a side. If the relationship between bus stops and crime depends on distance then aggregation to census tracts of varying size could introduce bias.[5] Therefore, we chose a unit that we believed was small enough to capture localized crime effects in the immediate area around the bus stops as opposed to the

[4] For additional examples of this approach see Authors 2009, 2012.
[5] The modifiable areal unit problem (MAUP) occurs when point level data are aggregated to arbitrarily, geographically zonal, modifiable boundaries (see Heywood, Cornelius, & Carver, 1998). The bias may occur as non-uniform boundaries are modified. For this reason, this study employs uniform grid boundaries over the study area.

much larger area that would be encompassed in a census tract. The counts for number of crimes and bus stops were calculated for each cell within the former Indianapolis Police Department service area. The final dataset consisted of the 7,494 cells which fell entirely within the defined study boundaries and which had a cell population greater than zero (because socio-economic characteristics could not be included if there was no resident population in an area).

Map 1 about here

Dependent Variables

The 2010 IMPD crime data include the Uniform Crime Reports (UCR) crimes. IMPD personnel created a geocoded dataset that is publicly available.[6] We explore the bus stop—crime relationship for individual UCR crime counts for homicide, rape, robbery, aggravated assault, burglary, and larceny. For each outcome variable, the number of incidents per cell was calculated using ArcGIS. Because the dependent variables in this study are counts of particular UCR crimes, and crime varies across the city, there are many cells with no crimes. Therefore, we estimate negative binomial models to account for this issue. For additional details on the modeling strategy see Appendix A.

Bus Stops

Geocoded bus stop locations as of 2010 were provided by the Indianapolis Planning Department. We created variables representing the number of bus stops in a cell and a categorical variable for whether a cell contained a bus stop.

[6] A small number of crimes (N=154) were excluded from the analysis because they did not include point location information or enough specific address or location information that would allow for geocoding. Given that there were over 70,000 records, this is unlikely to affect the results reported below.

Land Use Variables

We argued above that the bus stop—crime relationship could be conditional on land use characteristics in an area. Therefore, we generated land use information for the cells in the study from 2002 parcel data from the Indianapolis Department of Metropolitan Development. To generate a relatively exhaustive look at land uses, we include a categorical variable to indicate the presence of the following land uses: schools, cemeteries, and hospitals, as well as the percentage of cell land that was devoted to parks, water, or was vacant (for additional discussion of the research on land use and crime see Authors, 2009). Prior research has also focused on the impact of commercial businesses (e.g. Smith, Frazee, & Davison, 2000). Therefore, we include the percentage of the cell land that is commercial. Others have suggested that industrial land uses might be associated with crime (see Authors, 2009; Felson, 1987; Lockwood, 2007). Therefore, we include the percentage of the cell land associated with industry.[7] Finally, McNulty and Holloway (2000) found that crime was associated with high density housing in their study of Atlanta. We, therefore, include a categorical variable indicating the presence of housing with eight or more units per acre within the cell to capture high density housing. Finally, because crime might be more likely on roads with additional traffic (see Greenberg, Rohe, Williams, 1982), we include a categorical variable for whether the cell contains primary or secondary highways (as opposed to local streets).

Socioeconomic Variables

To determine whether bus stops affect crime (and whether the effect varies across socioeconomic contexts), it is necessary to control for relevant socioeconomic predictors of crime. Therefore, consistent with numerous prior studies (e.g. Land, McCall, & Cohen, 1990;

[7] The parcel data used in the current study allowed us to examine several specific land uses but precluded us from drilling down into the data to distinguish between bars and liquor stores and other types of commercial establishments. We hope to examine this issue with different data in the future.

Parker & McCall, 1999) we include socio-economic characteristics for the cells from the 2010 census. We include the percent Black, and percent Hispanic, as well as an index of disadvantage comprised of percent female headed-households, percent unemployed, and percent poor. Principal components analysis generated a single factor with loadings ranging from 0.77 to 0.91.

## RESULTS

Descriptive Statistics

Table 1 shows basic descriptive statistics for the variables used in the analyses broken down by the number of bus stops in the cell. Nearly six thousand cells did not contain a bus stop (N=5,912), 810 contained one bus stop, 675 cells contained two bus stops, and 97 cells contained 3 or more bus stops. Perhaps not surprisingly, the average number of reported UCR violent and property crimes was lowest when there were no bus stops in the cell and increased as the number of bus stops in the cell increased.

This pattern also held across all individual crimes examined in this study. The disadvantage index, however, did not appear to show a clear pattern by the number of bus stops. Recall this index has an overall mean of zero and standard deviation of 1. Mean values of the disadvantage index were positive for cells with zero and three or more bus stops, which means that socio-economic disadvantage in these cells was slightly higher than the overall average. For cells with one or two bus stops, the mean value was negative, suggesting that disadvantage was slightly below average. Similarly, the mean percent of Black and Hispanic residents of census tracts in which the cell centroid was located did not vary much by the number of bus stops in the cell. In terms of land uses, percent commercial was higher in cells with bus stops and increased with the number of bus stops. Percent industrial was actually lower where the number of bus stops was higher. And the percentage of cells with high density housing (8 or more units per acre) was higher in cells with bus stops (See Appendix B for the correlation matrix for variables in the study).

Table 1 about here

Because we are interested in whether the effect of bus stops on crime is direct or conditioned by other factors, we explored this question using bivariate analyses. Figure 1 shows mean UCR crime counts by the number of bus stops in a cell and at varying levels of commercial activity in the cell. The easiest way to interpret this figure is to look at the slopes of the lines. The line with the least slope (flattest) depicts mean crime counts associated with more bus stops in a cell and less than 10 percent commercial land use in the cell. The line with the steepest slope is when the commercial activity is fifty percent or more of the cell. Thus, figure 1 suggests that even with simple plots of the data that crime varies both by the number of bus stops and the percent of the land use that is devoted to commercial activity. Of course, one must be cautious about interpreting bivariate data but certainly this figure suggests that the bus stop—crime relationship could be conditional.

Figure 1 about here

Negative Binomial Models

Turning to multivariate models, Table 2 shows the results of negative binomial regression analyses of the effects of various socio-economic characteristics, land uses, and bus stops on individual UCR crimes. Recall that these models include a spatial lag variable, which is the average of the crime counts for each crime type in the eight cells surrounding the instant cell in a 3x3 neighborhood. This helps to control for spatial auto-correlation and creates a fairly conservative modeling strategy. Note also that we include a population offset (not shown in the tables) to account for the fact that cells in areas with larger populations could be expected to have higher crime counts. As shown in table 2, the spatial lag variable is positive and statistically significant ($p < 0.05$) for all crimes except homicide. Thus, crime counts are higher when counts are higher in nearby areas, as might be expected. The percentage of tract residents that were Black or Hispanic did not exhibit consistent relationships with crime in the models in Table 2. The disadvantage index was statistically significantly positively related to all UCR crimes ($p < .10$ for homicide). High density housing did not exhibit a consistent relationship with crime in the cells, however, the percentage of a cell devoted to commercial activities was consistently positively associated with UCR crime counts. The percentage of the cell that was industrial was also a significant predictor of crime counts for aggravated assault, rape, theft, and burglary. Water and cemeteries in the cell did not consistently predict crimes. Schools, hospitals, and the percentage of the cell that was vacant land were only associated with higher reported thefts (and fewer burglaries for schools). Higher traffic roads were also associated with higher crime counts for all crimes except homicide.

Turning to the main variable of interest in the study, the number of bus stops in the cell was significantly positively associated with all UCR crimes except homicide. And bus stops were associated with higher levels of both property and violent crimes. Thus, there is strong evidence that the presence of a bus stop in the cell is associated with higher crime counts, even net of a host of other factors thought to be related to crime.

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Table 2 about here

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Interaction Effects

We now turn to the question of whether the bus stop—crime relationship is direct or conditional. Table 3 includes interaction effects to test the four interactions we hypothesized that might condition the bus stop—crime relationship. To reduce the number of models to a manageable level, the equations in Table 3 model UCR violent crime count totals in a cell. Equation 1 contains only main effects but is included for comparison. Equation 2 includes an interaction between the percent of a cell devoted to commercial activity and the number of bus stops. One way to determine significance of interaction effects in non-linear models is a likelihood ratio chi square (LRCS) test.[8] We do this by comparing the log likelihoods of equations 1 and 2. In this case, the LRCS value = 14.77 which is highly significant ($p < .001$), suggesting that equation 2 fits the model significantly better than equation 1 and that the inclusion of the interaction effect produces a better model fit. Thus, the effect of bus stops on violent crime is actually greater in areas with commercial activity. Because the interpretation of interaction effect coefficients is not particularly intuitive, we graph these predicted effects. Figure 2 shows a depiction of the predicted violent crime counts (sum of cell homicide, aggravated assault, rape, and robbery counts) for cells with 0, 1, 2, and 3 bus stops when commercial activity is low (10 percent of land use), moderate (50% of land use) and high (100 percent of land use).[9] When commercial land use is low or moderate (10 and 50 percent), the increase in violent crime counts associated with additional bus stops in a cell is moderate. However, when the cell consists entirely of commercial land use and there are 3 bus stops, violent crime counts can be expected to be approximately five times higher than when only 50 percent of the cell is commercial.

[8] Recently, several authors have noted that the interpretation of interaction effects in nonlinear models is more complex than those of linear models (see Greene 2010; Hilbe 2011; Karaca-Mandic et al. 2012). Karaca-Mandic et al. note that one approach to considering the significance of interaction effects is to examine whether their addition produces a better fitting model. To assess whether the interaction effects examined here produced a significantly better fitting model, we employed likelihood ratio tests. The likelihood ratio value is twice the difference between the log- likelihoods of the models being compared, which is then compared to the $\chi^2$ distribution, with 1 degree of freedom because there is only one parameter difference between the two models (Osgood and Chambers, 2000).

[9] The predicted values were generated using coefficients from a model with all UCR violent crimes and include all variables in the model. For simplicity, all other numerical variables are set at their means and binary variables are zero (meaning the absence of that feature).

Table 3 about here

Equation 3 of Table 3 includes the interaction effect for disadvantage level in the cell and the number of bus stops. Although there were statistically significant direct effects of both bus stops and disadvantage, the likelihood ratio test comparing equation 3 to equation 1 produced a LRCS value of 2.90, which is not statistically significant. This means that the inclusion of this interaction effect did not produce a significantly better fitting model. Thus, contrary to what one might expect, net of other factors the effect of bus stops on crime does not appear to be conditioned by the socio-economic characteristics of the area.

Figure 2 about here

Equation 4 explores whether housing density conditions the relationship between bus stops and crime. The LRCS value of 46.92 ($p < 0.001$) suggests that this interaction effect does produce a significantly better fitting model than equation 1. Although the main effect of bus stops remains significant in the interaction model, the main effect for high density housing drops to non-significance. Interestingly, unlike the percentage of land use that is commercial, the interaction effect (bus stops*high density housing) was statistically significant but *negative*.

To illustrate the nature of the conditional relationship between high density housing and the presence of bus stops on violent crime, Figure 3 shows a depiction of the predicted violent crime counts by the number of bus stops where there is no high density land use in the cell, and when the cell contains high density residential housing. The left-hand columns in each pair represent the main effect of bus stops on crime in the cell because the interaction effect drops out of the prediction equation since the high density housing variable is zero. Expected violent crime counts are much higher as the number of bus stops increases from 0 to 3. The right-hand columns reflect predicted UCR violent crime counts when there is high density residential housing (8 or more units per acre) in the cell. Because the interaction term is negative, the presence of high density residential housing dampens the increases in expected UCR violent crime counts with additional bus stops in the cell. In fact, with three bus stops in a cell, violent crimes counts are predicted to be four times higher when high density housing is absent than when it is present. This finding is somewhat surprising, given that one might expect the presence of high density housing to *increase* the effect of bus stops on crime by providing additional opportunities for motivated offenders to interact with suitable targets. However, high density housing (recall that these models control for disadvantage and other socio-economic factors) may be associated with enough foot traffic that would be criminals do not feel that they could successfully complete their crimes without detection.

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Figure 3 about here

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Equation 5 explores whether industrial activity in a cell conditions the relationship between bus stops and crime. The LRCS value of 20.72 ($p < 0.001$) suggests that this interaction effect does produce a significantly better fitting model than equation 1. Figure 4 shows a depiction of the predicted violent crime counts for cells by the number of bus stops where the industrial land use in the cell is low (10 percent of land use), moderate (50% of land use) and high (100 percent of land use). When industrial land use is low or moderate (10 and 50 percent), the increase in predicted violent crime counts associated with additional bus stops in a cell is moderate. However, when the cell consists entirely of industrial land use and there are 3 bus stops, violent crime counts can be expected to be approximately five times higher than when only 50 percent of the cell is industrial.

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Figure 4 about here

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Taken together, these results show that there is a clear relationship between bus stops and crime but that this relationship is not uniform across land use contexts. Commercial and industrial land uses increase the strength of the relationship between bus stops and crime, whereas high density residential housing dampens the effect of bus stops on crime. Prior large N studies of bus stops and crime have not examined interaction effects but the results presented here suggest that future studies should.

To examine the robustness of these findings, we ran models that included a binary variable for the presence or absence of a bus stop in the cell. Results were substantively similar. We also checked for several additional interaction effects but did not find any that were robust. Finally, a model using 1,000 feet cells and 2006 UCR crime data produced comparable results so the size of the cell does not appear to influence the results. We also ran models that did not include the spatial lag variable to explore whether this variable (which as one might expect is correlated with the dependent variable) affected results. We found that a few of the variables dropped to non-significance (the main effects for high density residential housing and percent industrial) but model fit was substantially worse, suggesting the necessity of including the lag variable.

## DISCUSSION AND CONCLUSIONS

The current study adds to a growing number of studies that consider the relationship between public transit and crime. We focused here on bus stops because many cities have some form of public busing but fewer have light rail. Most prior bus stop—crime studies have been small N or case studies. The three large N studies that we could find all showed that bus stops were associated with higher crime but only examined direct effects. One goal of the study was to consider whether bus stops affected only some crimes and not others. The current study found that bus stops were associated with consistently higher UCR violent and property crime counts in grid cells in Indianapolis using 2010 data (except for homicide). We also hypothesized, and the results showed, that the relationship between bus stops and crime was conditioned by land use configurations. In particular, we found that commercial and industrial land uses enhanced the bus stop—crime relationship but the presence of high density housing dampened it. Somewhat surprisingly, however, the socio-economic disadvantage in an area did not condition the bus stop—crime relationship.

This study is not without its limitations. First, it should be noted that the current study relies on reported crime (which has widely-recognized limitations), and focuses on a single city. It could be that bus stops in Indianapolis are uniquely located and therefore have a different relationship to crime than in other cities. Although possible, this seems unlikely and this is an empirical question that can only be answered by additional studies in other cities. This study also does not delineate between crimes that occur on the bus versus near the bus stop. It is possible that some crimes that occurred on a bus are listed as having occurred at the bus stop (see Newton 2004). The nature of the available data precluded examination of this question. We were also not able to examine specific characteristics of each bus stop itself such as dilapidation, graffiti, number of entry/exit points and other characteristics that have been explored in some small N studies. We acknowledge that some aspects of the bus stop location that could not be measured may be worth considering but such a study was beyond the scope of resources available as it would have required direct examination of over 2,000 bus stop locations. We believe that controlling for crime in the surrounding cells should mitigate some of the effects of these types of variables, though perhaps not all. Future work certainly could explore this issue further. We were also unable to zero in on certain types of land uses that prior research suggests are associated with crime such as taverns due to the nature of the available land use data. The next phase of the research is to examine the effects of alcohol outlets on crime and once the locations of alcohol outlets are plotted, we will examine whether their presence influences crime near bus stops.

From a policy standpoint, the current study suggests the value of thinking in more nuanced ways about bus stops. Certainly the results show that bus stops have independent effects on crime but also showed that this effect is conditioned by other aspects of the area, specifically land uses. With the rapidly growing availability of information and expertise at the local level on GIS, police managers, for example, could use the ideas presented here to think about how to approach transit crime in a relatively more efficient way. Compared to approaches that require direct examination of the physical area surrounding a transit station or bus stop, the approach here may allow policy makers to allocate police resources based on knowledge of the larger characteristics of the area such as the degree of commercial activity or other land use characteristics. This is not to downplay the value of direct examination of highly problematic stops and what might be done at those locations but suggests a more economical approach to identifying areas to target more broadly for additional police patrols or other preventative or remedial measures to reduce crime. These results also may be of use to those planning for locations of bus stops, such that bus stops in certain areas could be the focus of special attention to reduce their likelihood of becoming concentration points for crime. For example, special attention might be focused on bus stops in and around commercial areas to minimize the crime associated with them.

In sum, this study was consistent with some prior large N studies showing that bus stops and crime are related. Yet, the interaction effects found here suggest that more nuanced thinking about the land use contexts within which bus stops are located is necessary to fully understand the "land use—transit crime nexus" and how to combat this problem.[10] Given the centrality of public transportation in the planning for sustainable cities in the 21st Century, this additional focus seems warranted. The current study begins to take steps in that direction.

**Map 1. Indianapolis Study area, Bus Stops, and 500 feet Grid Cells**

[10] I am grateful to an anonymous reviewer for both the term and suggesting that I frame my thinking in these terms.

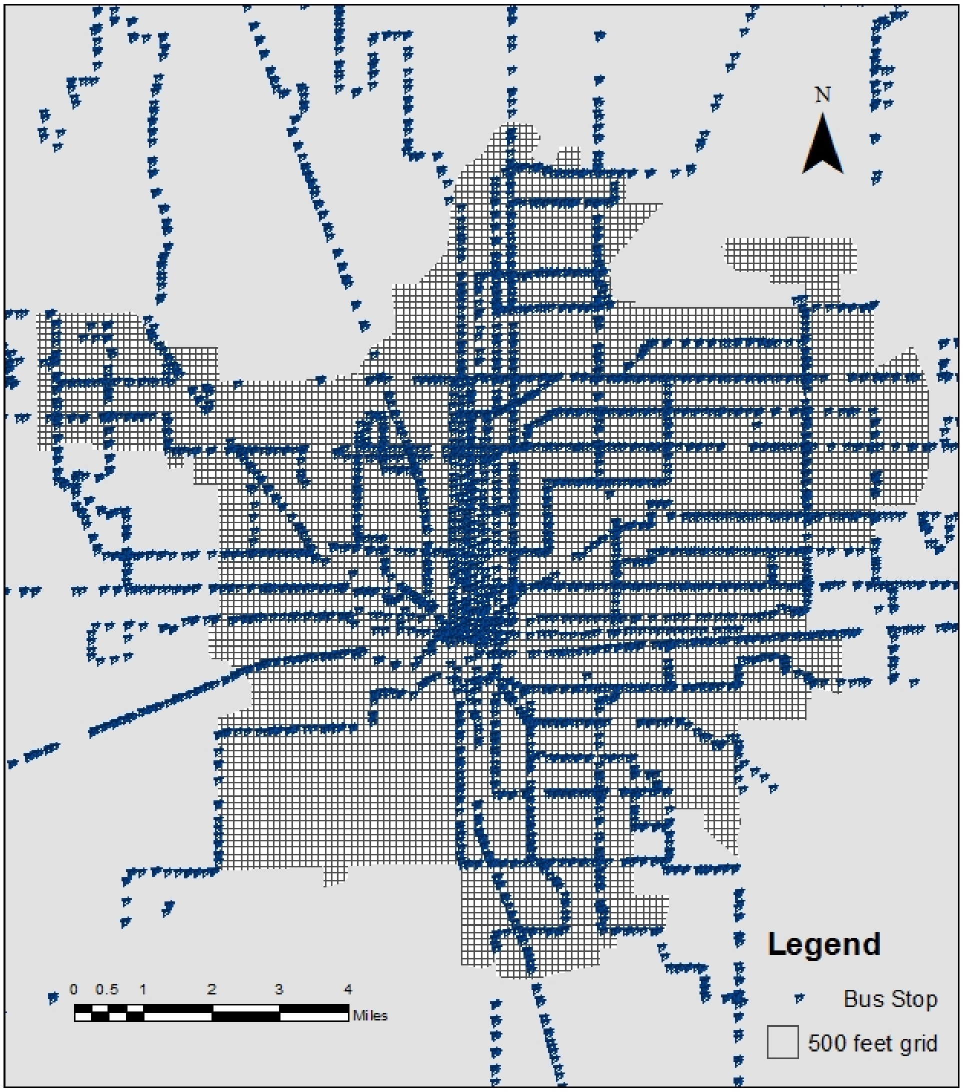



**Table 1. Univariate Statistics for Variables Used in Multivariate Analysis (N=7,494).**

| | Bus stops in cell | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Zero | | One | | Two | | 3 or more | |
| **N** | **5,912** | | **810** | | **675** | | **97** | |
| **Variable** | **Mean** | **std dev** | **Mean** | **std dev** | **Mean** | **std dev** | **Mean** | **std dev** |
| **UCR violent** | 0.58 | 1.37 | 1.21 | 1.19 | 1.62 | 2.57 | 2.51 | 3.00 |
| **UCR property** | 2.27 | 3.91 | 4.42 | 6.77 | 4.95 | 7.39 | 8.12 | 7.62 |
| **Homicide** | 0.01 | 0.09 | 0.02 | 0.12 | 0.01 | 0.13 | 0.03 | 0.23 |
| **Rape** | 0.03 | 0.17 | 0.04 | 0.21 | 0.06 | 0.27 | 0.12 | 0.33 |
| **Robbery** | 0.18 | 0.57 | 0.47 | 1.01 | 0.67 | 1.3 | 1.24 | 2.08 |
| **Aggravated Assault** | 0.37 | 1.01 | 0.68 | 1.30 | 0.88 | 1.61 | 1.11 | 1.46 |
| **Burglary** | 0.86 | 1.49 | 1.15 | 1.77 | 1.29 | 1.62 | 1.57 | 1.79 |
| **Theft** | 1.13 | 3.03 | 2.84 | 5.98 | 3.06 | 6.65 | 5.46 | 6.63 |
| **Percent Black** | 41.2 | 31.6 | 43.0 | 30.5 | 43.0 | 31.3 | 42.2 | 32.2 |
| **Percent Hispanic** | 9.8 | 9.1 | 8.7 | 8.7 | 9.1 | 9.1 | 7.4 | 6.6 |
| **Disadvantage Index** | 0.01 | 0.99 | -0.01 | 1.00 | -0.03 | 1.04 | 0.02 | 1.08 |
| **Commercial Percent** | 6.11 | 16.42 | 13.04 | 19.77 | 15.02 | 19.99 | 20.48 | 22.04 |
| **Industrial Percent** | 7.65 | 20.45 | 4.2 | 13.32 | 4.27 | 12.75 | 2.39 | 9.06 |
| **Water percent** | 0.89 | 6.93 | 0.54 | 4.74 | 0.3 | 2.570 | 0.25 | 1.7 |
| **Park percent** | 2.44 | 12.02 | 1.87 | 9.29 | 2.74 | 11.61 | 1.05 | 4.16 |
| **Vacant percent** | 3.90 | 10.1 | 4.42 | 9.78 | 3.67 | 7.39 | 4.06 | 10.02 |
| **Cemetery in cell** | 1.5% | | 1.7% | | 1.2% | | 1.0% | |
| **Hi Density Residential** | 65.9% | | 74.9% | | 78.2% | | 78.4% | |
| **Busy road** | 26.5% | | 76.2% | | 87.4% | | 84.5% | |
| **School in cell** | 6.3% | | 7.8% | | 10.1% | | 7.2% | |
| **Hospital in cell** | 1.3% | | 2.8% | | 2.5% | | 4.1% | |

**Note: For binary variables (high density housing, busy roads, cemetery, school, and hospital) the value refers to the percentage of cells with that feature present.**

**Table 2. Negative Binomial Regressions of Land Uses and Socioeconomic Variables on UCR Violent Crimes in 500 X 500 Feet Grid Cells in Indianapolis (N=7,494).**

| | **Homicide** | **Aggravated Assault** | **Rape** | **Robbery** | **Theft** | **Burglary** |
|---|---|---|---|---|---|---|
| **Intercept** | -9.4100*** | -5.2597*** | -7.3415*** | -5.9357*** | -3.3963*** | -4.5766*** |
| | (0.6114) | (0.1142) | (0.2875) | (0.1300) | (0.0821) | (0.0779) |
| **Spatial Lag** | 0.1557 | 0.0779*** | 0.1689$^{+}$ | 0.0645*** | 0.0206*** | 0.0218*** |
| | (0.3440) | (0.0058) | (0.0979) | (0.0087) | (0.0014) | (0.0027) |
| **Percent Black** | 0.2269 | 0.0825 | -0.6868* | 0.0172 | -0.6495*** | 0.3331*** |
| | (0.6231) | (0.1231) | (0.3213) | (0.1419) | (0.0909) | (0.0826) |
| **Percent** | 0.5190 | 0.6777* | -0.1201 | 0.2056 | -1.0979*** | 0.6016** |
| **Hispanic** | (1.5419) | (0.3273) | (0.7806) | (0.3596) | (0.2415) | (0.2149) |
| **Disadvantage** | 0.2323 | 0.1493*** | 0.2664** | 0.2553*** | 0.1432*** | 0.1120*** |
| **Index** | (0.1807) | (0.0370) | (0.0929) | (0.0423) | (0.0265) | (0.0246) |
| **Hi Density** | 0.6002 | -0.1961** | -0.1021 | -0.1084 | -0.5352*** | 0.2252*** |
| **Residential y/n** | (0.4316) | (0.0712) | (0.1892) | (0.0838) | (0.0489) | (0.0515) |
| **Commercial** | 0.0146$^{+}$ | 0.0174*** | 0.0212*** | 0.0298*** | 0.0295*** | 0.0099*** |
| **Percent** | (0.0086) | (0.0017) | (0.0037) | (0.0017) | (0.0012) | (0.0013) |
| **Industrial** | 0.0098 | 0.0055* | 0.0125* | 0.0027 | 0.0125*** | 0.0064*** |
| **Percent** | (0.0123) | (0.0023) | (0.0054) | (0.0030) | (0.0014) | (0.0016) |
| **Water percent** | 0.0135 | -0.0115 | -0.0420 | 0.0044 | 0.0080$^{+}$ | -0.0117$^{+}$ |
| | (0.0378) | (0.0103) | (0.0463) | (0.0095) | (0.0047) | (0.0069) |
| **Park percent** | -0.0076 | 0.0079* | 0.0071 | 0.0085* | 0.0129*** | 0.0025 |
| | (0.0240) | (0.0032) | (0.0091) | (0.0036) | (0.0020) | (0.0023) |
| **Busy road (y/n)** | -0.0892 | 0.5086*** | 0.3738* | 0.5674*** | 0.5691*** | 0.2238*** |
| | (0.3335) | (0.0651) | (0.1620) | (0.0727) | (0.0464) | (0.0429) |
| **Cemetery in cell** | -21.1149 | -0.1313 | -0.04864 | -0.0663 | 0.1370 | -0.0086 |
| **(y/n)** | (54240.12) | (0.2998) | (1.0209) | (0.3522) | (0.1947) | (0.1953) |
| **School in cell** | 0.3313 | 0.0604 | -0.0095 | -0.2194$^{+}$ | 0.4506*** | -0.1620* |
| **(y/n)** | (0.4786) | (0.1088) | (0.2720) | (0.1329) | (0.0775) | (0.0732) |
| **Hospital in cell** | 0.7572 | 0.0915 | -0.0303 | 0.1198 | 0.5128*** | -0.0822 |
| **(y/n)** | (0.8207) | (0.2192) | (0.5363) | (0.2358) | (0.1430) | (0.1405) |
| **Vacant percent** | 0.0111 | -0.0018 | 0.0107 | -0.0060 | 0.0064** | 0.0004 |
| | (0.0157) | (0.0035) | (0.0081) | (0.0043) | (0.0022) | (0.0022) |
| **Bus stops in cell** | **0.2380** | **0.2080*****| **0.1837*** | **0.3595***** | **0.2435***** | **0.1097***** |
| | **(0.1847)** | **(0.0393)** | **(0.0885)** | **(0.0399)** | **(0.0286)** | **(0.0267)** |
| **Dispersion** | 9.4266 | 1.8968 | 1.6576 | 1.4554 | 1.5007 | 0.7808 |
| | (5.2653) | (0.0971) | (0.6978) | (0.1115) | (0.0439) | (0.0367) |
| **Log Likelihood** | -362.0 | -4371.6 | -1023.8 | -3473.9 | 309.7 | -5046.7 |

Note: Standard errors in parentheses, $^{+}$ p < .10, * p < .05, ** p < .01, *** p < .001 (2-tailed tests).

**Table 3. Negative Binomial Regressions of Land Use and Socioeconomic Variable Interactions with Bus Stops on UCR Violent Crime Index in 500 X 500 Feet Grid Cells in Indianapolis (N=7,494).**

| | Eq. 1 | Eq. 2 | Eq. 3 | Eq. 4 | Eq. 5 |
|---|---|---|---|---|---|
| **Intercept** | -4.810*** | -4.807*** | -4.815*** | -4.990*** | -4.798*** |
| | (0.094) | (0.094) | (0.094) | (0.098) | (0.094) |
| **Spatial Lag** | 0.046*** | 0.046*** | 0.046*** | 0.046*** | 0.046*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| **Percent Black** | 0.064 | 0.073 | 0.068 | 0.105 | 0.052 |
| | (0.103) | (0.103) | (0.103) | (0.104) | (0.274) |
| **Percent Hispanic** | 0.547* | 0.551* | 0.563* | 0.582* | 0.547* |
| | (0.275) | (0.274) | (0.275) | (0.275) | (0.275) |
| **Disadvantage index** | 0.171*** | 0.171*** | 0.192*** | 0.164*** | 0.175*** |
| | (0.031) | (0.031) | (0.033) | (0.031) | (0.031) |
| **High density residential (yes / no)** | -0.208*** | -0.197*** | -0.209*** | -0.003 | -0.198*** |
| | (0.059) | (0.059) | (0.059) | (0.067) | (0.059) |
| **Commercial percent** | 0.023*** | 0.020*** | 0.023*** | 0.022*** | 0.023*** |
| | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) |
| **Industrial percent** | 0.006** | 0.006** | 0.006** | 0.006** | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| **Park percent** | 0.009** | 0.009** | 0.008** | 0.009** | 0.009** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| **Busy road (y/n)** | 0.515*** | 0.541*** | 0.515*** | 0.547*** | 0.520*** |
| | (0.054) | (0.054) | (0.054) | (0.054) | (0.054) |
| **Bus stops in cell** | 0.268*** | 0.178*** | 0.271*** | 0.630*** | 0.229*** |
| | (0.032) | (0.040) | (0.032) | (0.064) | (0.033) |
| **Commercial percent* bus stops in cell** | | 0.006*** | | | |
| | | (0.001) | | | |
| **Disadvantage * bus stops in cell** | | | $-0.049^{+}$ | | |
| | | | (0.029) | | |
| **High density residential (y/n) * bus stops in cell** | | | | -0.468*** | |
| | | | | (0.070) | |
| **Industrial percent * bus stops in cell** | | | | | 0.011*** |
| | | | | | (0.003) |
| **Dispersion** | 1.496 | 1.481 | 1.494 | 1.481 | 1.489 |
| | (0.064) | (0.063) | (0.064) | (0.063) | (0.063) |
| **Log Likelihood** | -4165.36 | -4157.98 | -4163.91 | -4141.90 | -4155.00 |
| **Likelihood ratio chi-square** | | 14.77*** | 2.90 | 46.92*** | 20.72*** |

Note: Standard errors in parentheses, $^{+}$ p < .10, * p < .05, ** p < .01, *** p < .001 (2-tailed tests). Likelihood ratio chi square value equal two times the difference between the log likelihood of equation with interaction compared to the equation without the interaction term (equation 1). This is distributed as a chi-square with 1 degree of freedom.

Figure 1. Mean violent crime counts by bus stops and percent commercial in cell

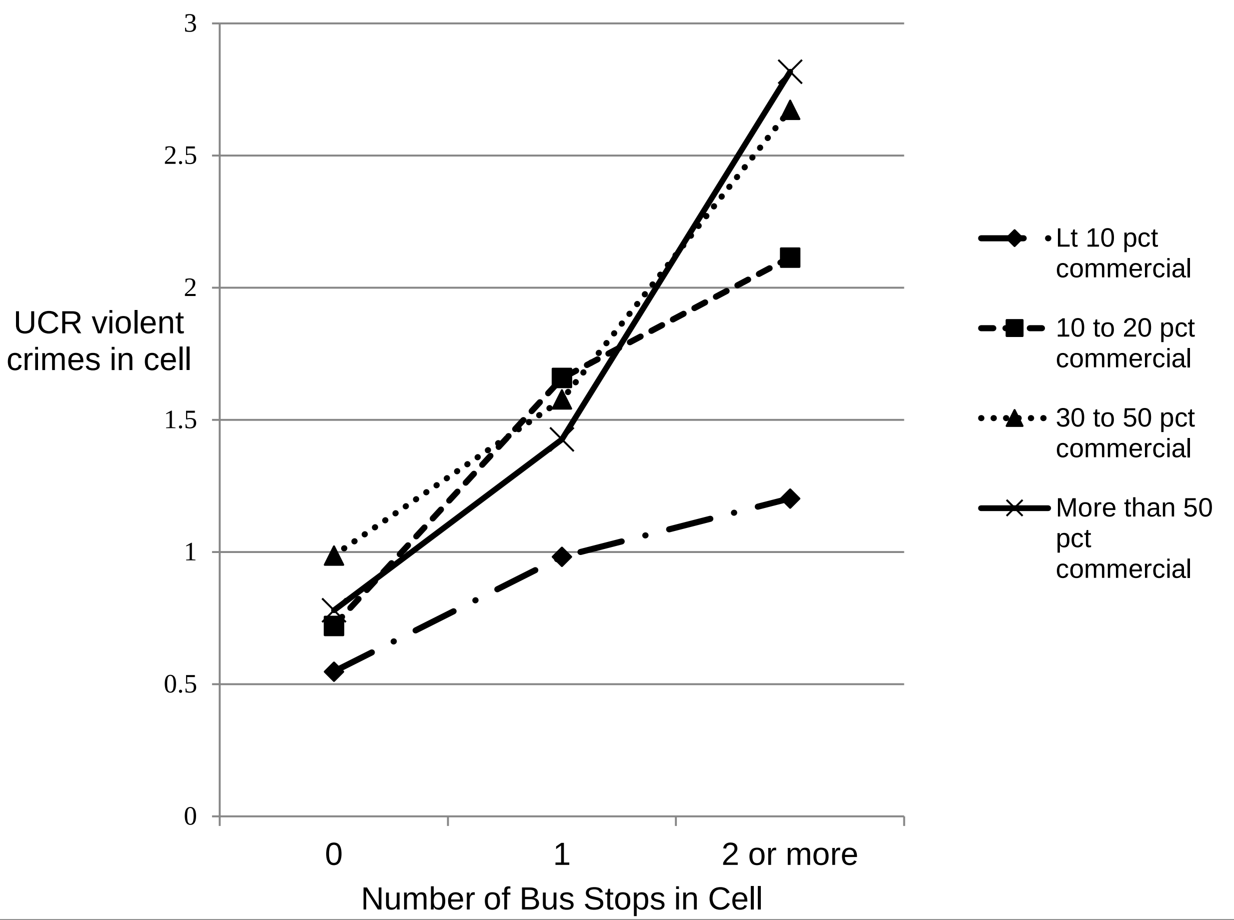


Figure 2. Predicted UCR Violent Crime Counts in Cells by Commercial Land Use and Number of Bus Stops

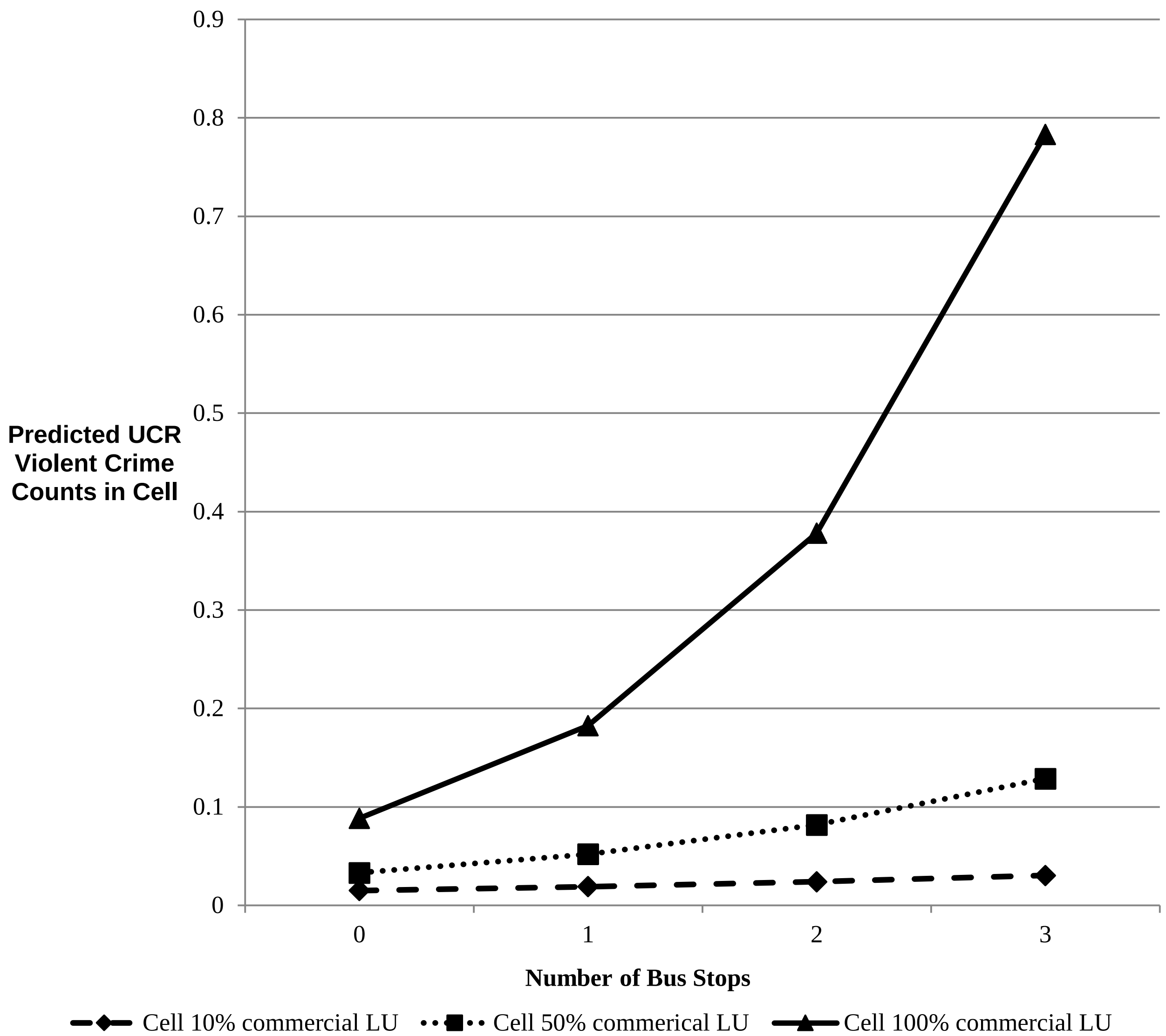


Figure 3. Predicted UCR Violent Crime Counts by Number of Bus Stops and Presence of High Density Residential Housing

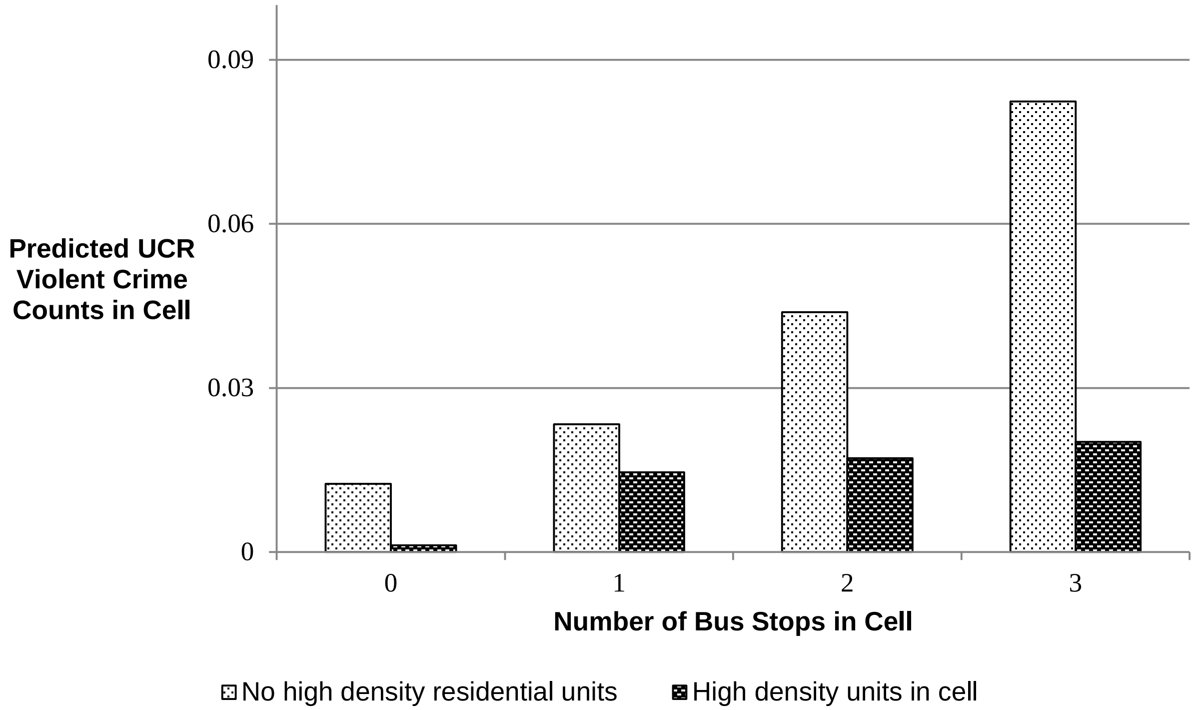
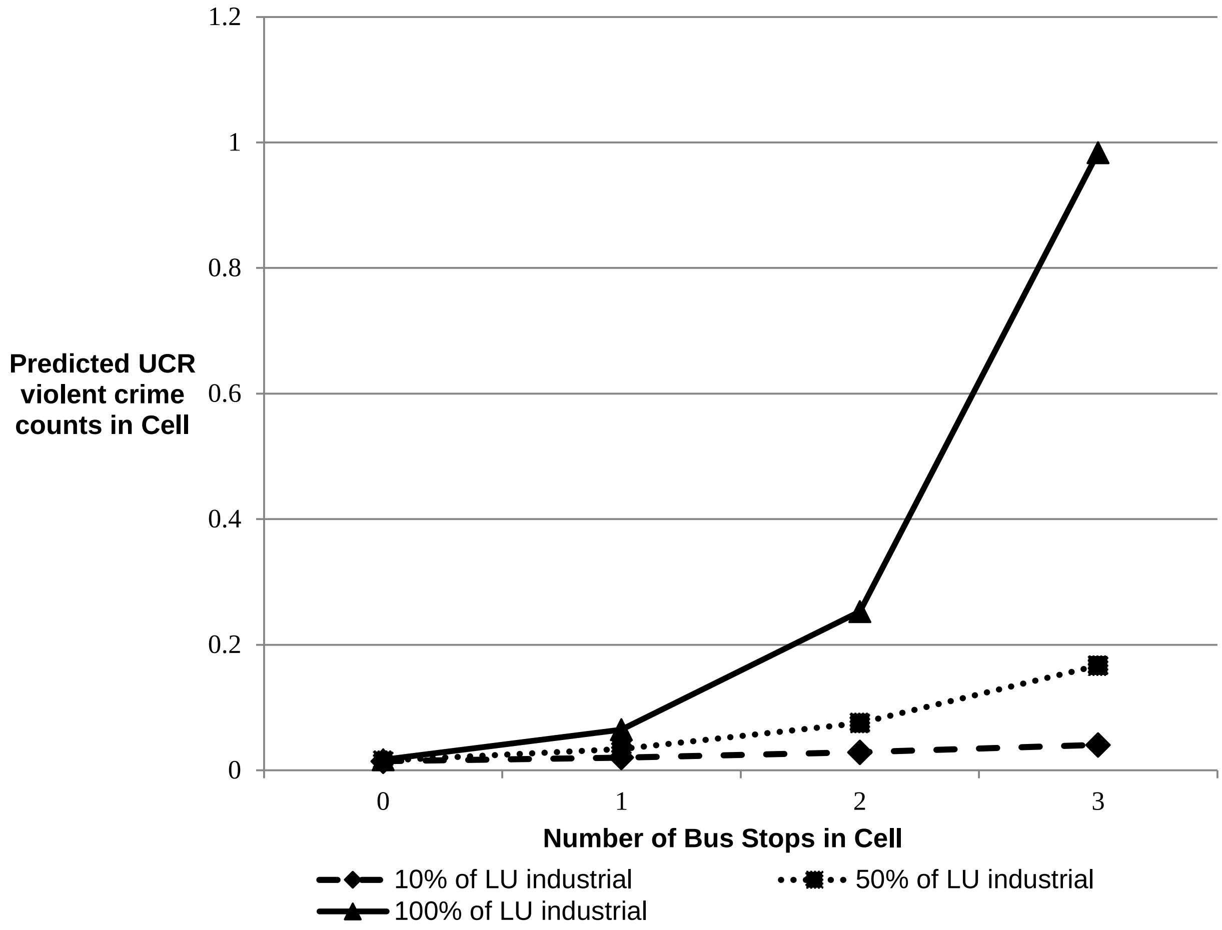


Figure 4. Predicted UCR Violent Crime Counts by Number of Bus Stops and Industrial Land Use



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## Appendix A. Details on Modeling Strategy Employed in Study.

As noted above, the modeling strategy here employs negative binomial models because crime counts in cells cannot be negative and many cells have zero reported UCR crimes. Such a variable more closely matches a Poisson distribution. Because the negative binomial model allows the variance to be larger than the mean (unlike the Poisson distribution, which assumes they are equal), we estimate negative binomial models.

We also include a spatial lag variable which is the average of the crime counts for each specific crime in the eight surrounding cells in the 3X3 neighborhood of the instant cell. This approach controls for variation in the unobserved heterogeneity in the surrounding cells that might impact crime within the cell and creates a fairly conservative modeling approach. This also helps to control for spatial auto-correlation, which might be expected for cells that are adjacent to each other. We chose this approach to modeling the spatial lag because it is intuitive and due to the lack of a standard control for this issue in negative binomial models.

To control for the fact that higher numbers of crimes could be expected in cells with larger residential populations we include a population offset in the models. We control for population in the area by including the natural log of the estimated cell population.

The 2010 census population data was not available below the census tract level. Therefore, we used 2000 census data for blocks to produce an estimate of the population in the cell. The population was assumed to be evenly distributed throughout a block and therefore the proportion of the block within the cell was multiplied by the population for the block. Then, the values for each cell were summed to generate a cell population estimate. We argue that using 2000 census block data will produce more accurate estimates of the cell population than using 2010 census tract totals to estimate a cell value, which would require assuming that the population was evenly distributed over an entire census tract. Either approach requires that we make some assumptions about the population but we believe that the variation over time within a block is likely to be relatively limited compared to the variation of population within a census tract and therefore produces more accurate estimates of the population within the cell.

To allocate the socio-economic data to each cell, the cell centroid was intersected with the census tract data for Indianapolis. Therefore, cell values mirror the census tract containing the cell centroid. This is necessary because the relevant census data is no longer available for smaller units such as blocks, or block groups. This does force the assumption that census tract values are uniformly distributed throughout the census tract. There, is however, no other way to derive estimates for current socio-economic values for these small areas. We acknowledge that this is a potential limitation of the current study.

## APPENDIX B. BIVARIATE CORRELATION MATRIX (N=7,494)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Bus stops | 1.00 | .23* | .11* | .02 | -.04* | -.01 | .09* | .19* | -.07* | -.03* | -.01 | .44* | -.01 | .04* | .05* | .01 |
| 2. Violent crime | | 1.00 | .38* | .03* | .09* | .09* | .15* | .14* | -.11* | -.04* | -.05* | .14* | -.04* | -.01 | -.01 | -.05* |
| 3. VC lag | | | 1.00 | .05* | .15* | .18* | .26* | .11* | -.16* | -.07* | -.07* | .04* | -.05* | -.02 | -.02 | -.03* |
| 4. Pct. Black | | | | 1.00 | -.35* | .58* | -.04* | -.04* | -.13* | .01 | .09* | -.02 | .02 | -.01 | -.01 | .11* |
| 5. Pct. Hispanic | | | | | 1.00 | .06* | -.01 | .07* | .06* | -.01 | -.06* | -.04* | -.03* | -.03* | .02* | -.05* |
| 6. Disadvantage | | | | | | 1.00 | .05* | -.07* | .09* | .03* | .04* | .01 | .04* | -.04* | -.03* | .16* |
| 7. Hi dens res. | | | | | | | 1.00 | -.17* | -.24* | -.12* | -.09* | -.08* | -.02 | -.03* | -.03* | -.01 |
| 8. % commercial | | | | | | | | 1.00 | -.07* | -.04* | -.07* | .22* | -.02 | -.05* | .01 | -.01 |
| 9. % industry | | | | | | | | | 1.00 | -.01 | -.07* | .06 | -.01 | -.08* | -.03* | -.03* |
| 10. % water | | | | | | | | | | 1.00 | .01 | .05* | -.02 | .02 | -.02 | -.03* |
| 11. % park | | | | | | | | | | | 1.00 | .01 | .01 | .01 | -.01 | -.05* |
| 12. Busy road | | | | | | | | | | | | 1.00 | .03* | -.01 | .05* | .01 |
| 13. Cemetery | | | | | | | | | | | | | 1.00 | -.02 | .01 | .01 |
| 14. School | | | | | | | | | | | | | | 1.00 | .01 | -.05* |
| 15. Hospital | | | | | | | | | | | | | | | 1.00 | -.02 |
| 16. % vacant | | | | | | | | | | | | | | | | 1.00 |

* p < .05 (two-tailed test)