Rental Housing and Crime: The Role of Property Ownership and Management

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Abstract: This paper examines how residential rental property ownership characteristics affect crime. It examines the incidence and frequency of disturbances, assaults, and drug possession and distribution using police incident report data for privately owned rental properties. Results show that a small percentage of rental properties generate incident reports. Count model regressions indicate that the distance that the owner resides from the rental property, size of rental property holdings, tenant Section 8 voucher use, and neighborhood owner-occupied housing rates are associated with reported violations. The paper concludes with recommendations about local government policies that could help to reduce crime in rental housing.

Keywords: *crime, rental housing, management, count model*

JEL Classification: K42, R29

1. Intro

In towns and cities across the country, the so-called “absentee” landlord and urban “slumlord” is viewed as a major source of problems, such as crime and neighborhood blight, that plague distressed neighborhoods. According to conventional wisdom, non-resident landlords are less likely to screen their tenants, to manage and maintain properties properly, and to have an interest in the wellbeing of the surrounding community (Dymowski 2001; Mayer 1981). The growth in external ownership and the problems associated with it have also been identified as sources of middle class flight from cities (Dymowski 2001).

Given the preponderance of strong feelings on the issue, there is a surprising lack of empirical evidence to support the contention that rental property ownership and management characteristics influence property conditions and crime. A number of studies link homeownership and various types of positive outcomes (Dietz and Haurin 2003). These outcomes include lower crime (Glaeser and Sacerdote 1999; Rephann 1999; Alba, Logan, and Bellair 1994), higher property values (Coulson, Hwang, and Imai 2003; Rohe and Stewart 1996), better building maintenance (Mayer 1981), more civic-minded neighbors (Rohe, Van Zandt, and McCarthy 2002; DiPasquale and Glaeser 1999; Rohe and Stewart 1996), and better educated and well-adjusted children (Harkness and Newman 2002; Rohe, Van Zandt, and McCarthy 2002). Moreover, the prevalence of abandoned property has been found to be associated with greater crime (Spelman 1993). Therefore, it would seem plausible that rental ownership qualities such as the physical proximity of a landlord or property manager can influence crime in a rental setting as well.

Additional attention to this issue is merited for at least three reasons. First, there is a public perception that non-local landlords and poor property management cause many local crime problems. Even within the social sciences, there is a growing recognition that researchers should “pay closer attention to the economics of property ownership and the management of places” (Eck and Wartell 1998). Second, evidence suggests that the “absentee owned” share of the national rental inventory is increasing (Apgar 2004). With the growth of Internet real estate marketing, it has become much easier for amateur investors to research, purchase, and rent apartments without ever actually visiting them. Third, high rates of tenancy can often be found in neighborhoods with higher crime levels. Therefore, understanding the characteristics of these properties could help in crafting policies to revitalize neighborhoods.

This study seeks to contribute to our knowledge of how residential rental property ownership and management qualities affect crime. It examines the incidence and frequency of certain types of crimes that occur in privately owned rental properties, including disturbances, assaults, and drug possession and distribution. These crimes were selected because they are frequently found in a residential setting and are considered important measures or indicators of neighborhood "quality of life." Characteristics of rental properties are examined with the aid of count regression models that incorporate landlord, tenant, and neighborhood variables including residence of owner, size of landlord property holdings, tenant HUD Section 8 voucher use, and neighborhood socioeconomic characteristics. It is hypothesized that problem properties are more likely to be found when the owner resides further away from the property, when the owner owns multiple units, when tenants receive public housing assistance, and when neighborhood measures of residential mobility and disadvantage are greater.

The next section contains a review of literature that draws on Routine Activities Theory to explain intra-metropolitan or intra-urban variation in criminal activity. The third section describes the study region and data used. The fourth section details the research hypotheses that motivate this study. The fifth section explains the count regression techniques used. The sixth section presents and discusses the empirical results. The paper concludes with a summary and policy recommendations.

2. Literature Review

Whether stated explicitly or not, many studies of the geographical distribution of crime are motivated by Routine Activities Theory. Rather than examining the economic or psychological aspects of the individual's decision to commit a crime, Routine Activities Theory focuses on the "criminology of places," that is to say the situational aspects such as the physical, locational, functional, and management characteristics of the properties themselves (Cohen and Felson 1979). The theory recognizes three factors that contribute to crime occurrence: (a) a motivated offender, (b) an attractive target, and (c) level of guardianship for the target. Assuming the supply of motivated offenders is constant, geographical variation in crime occurs because of differences in the availability of targets and differences in levels of target guardianship.

Places differ in terms of the presence of factors that contribute to crime commission. For instance, shopping centers are likely to be viewed as more attractive targets for larceny than residences because of the abundance of new merchandise. Places also differ with respect to the level of guardianship – for example, some stores employ better security measures (e.g., alarms, surveillance cameras, and security personnel). Furthermore, the available supply of motivated offenders, typically young males drawn from disadvantaged socioeconomic backgrounds, may differ from locale to locale.

The social science literature has identified several key place-based factors that help measure target attractiveness, levels of guardianship, and supply of motivated offenders. These variables include certain aspects of the local built environment such as ease of access (Hakim, Rengert, and Shachmurove 2001; Fishman, Hakim, and Shachmurove 1998), urban physical design features and property layout (Zelinka and Brennan 2001; Mazerolle and Terrill 1997), presence of security features (Hakim, Rengert, and Shachmurove 2001; Fishman, Hakim, and Shachmurove 1998; Hakim and Shachmurove 1996), commercial land uses (Olligschlaeger 1997; Hakim and Shachmurove 1996; Roncek and Maier 1991; Sherman, Gartin and Buerger 1989), local law enforcement or legal system characteristics (Hakim et al. 1979), and neighborhood socioeconomic characteristics (McNulty and Holloway 2000; Olligschlaeger 1997; Alba, Logan, and Bellair 1994; Roncek and Maier 1991).

Property ownership and management characteristics have also received some consideration. Roncek and Maier (1991) note that commercial bar establishments with management and security deficiencies experience more crime. In a residential setting, homeownership may help insulate against crime (Glaeser and Sacerdote 1999; Rephann 1999; Alba, Logan, and Bellair 1994).

There are several reasons that homeowners might be both less likely to be victimized as well as less likely to commit crime. First, homeowners are less mobile than tenants (Dietz and Haurin 2003; Rohe and Stewart 1996). They are less likely to move because of the transaction costs associated with buying and selling. As a result, they may have a heightened awareness of any changes in their surroundings and have established better neighborhood social networks (Rohe, Van Zandt, and McCarthy 2002; DiPasquale and Glaeser 1999; Rohe and Stewart 1996). Second, homeowners are more likely to be sensitive to decreases in property values and changes in underlying quality of life factors such as crime that might detract from these values. Their interest in preserving the value of properties creates a "vested interest in neighborhood conditions" (Rohe and Stewart 1996) and a greater likelihood of investing in property maintenance and security (Dietz and Haurin 2003; Rohe and Stewart 1996). Third, homeownership has been connected to better child outcomes (Dietz and Haurin 2003; Rohe, Van Zandt, and McCarthy 2002; Harkness and Newman 2002). This relationship may exist in part because homeowners exhibit lower household mobility which in turn fosters a more stable home environment. Therefore, homeowners may produce children who are less likely to engage in juvenile crime. Fourth, homeownership has been linked to better physical and mental health outcomes (Dietz and Haurin 2003; Rohe, Van Zandt, and McCarthy 2002). Therefore, homeowners may be more resilient in stressful situations and less likely to react violently or unpredictably.

Rental properties often have more criminal activity than owner-occupied dwellings, but differences also exist among rental properties. For example, public ownership has been found to be associated with more crime (McNulty and Holloway 2000; Roncek, Bell, and Francik 1981). This finding may simply reflect other factors correlated with public housing such as tenant socioeconomic disadvantage and social isolation (McNulty and Holloway 2000), certain aspects of the built environment (Mazerolle and Terrill 1997) or apartment complex scale (Santiago, Galster, and Pettit 2003; Roncek, Bell, and Francik 1981).

Proper rental property management may also be important in controlling crime. Eck and Wartell (1998) find that "drug dealers select places that have weak management." Weak management is often distinguished by lower levels of property maintenance, less frequent visits by the owners and managers to the property, and fewer efforts to screen tenants. Clarke and Bichler-Robertson (1998) suggest that management reduces rental property crime by applicant screening, eviction and improved security.

Management quality is not directly observable and that presents a difficulty for empirical hypothesis testing. Since poorly managed properties receive less maintenance and often exhibit signs of greater physical deterioration, the exterior appearance may provide a visual clue. Ownership characteristics may also be important indicators. Apgar (2004) notes that many part-time “mom-and-pop” rental property investors lack the skills to manage and maintain rental housing. The challenges of managing these properties may grow as the size of holdings expand. Physical distance may also serve as a managerial impediment. More remote owners may find it difficult to monitor the conditions that exist at their properties or communicate with tenants. On the other hand, nearby owners will have both a greater stake in property conditions because of its effect on their own living space (Mayer 1981) or surrounding neighborhood.

3. Data

The study area is the city of Cumberland (population 21,518) located in the economically lagging Appalachian region of Western Maryland. The city has experienced a significant increase in the crime rate during the past 20 years. This trend stands in marked contrast to the state and U.S., which have experienced substantial reductions in crime rates. As a result, the crime rate now stands significantly higher than state and national averages and the reputation of the area as being a safe rural community has begun to be called into question.

Compared to the U.S. and Maryland, the City of Cumberland has a relatively low rate of owner occupancy that has changed very little in the past 40 years. According to the 2000 Census, approximately 58% of occupied housing units are owner occupied compared to 67.7% for Maryland and 66.2% for the U.S (U.S. Census 2000). Much of the rental stock is located in the central older areas of town. Those who reside outside city limits own over half of the units. Fewer than one in five property owners lives on the same premises as the rental unit; this compares with one in four in a national survey (Savage 1998).

Data for this study were combined from the following sources:

City of Cumberland Police Department Incident Report Database. This database records incident reports filed by city police in 2005. It contains information on approximately 25,000 incident reports based on emergency hotline calls and police observations including criminal incidents, traffic reports, and service calls. Each incident report record contains an address, brief description of the nature of the call, time of call, investigating officer, and disposition of the case (e.g., closed, open, arrest).

City of Cumberland Rental Unit Database. This data contains information on 3,134 privately owned registered rental units representing 1,480 properties within the City of Cumberland in 2005. Rental registration is required by city ordinance. Comparisons of database records with 2000 Census counts of renter-occupied units suggest a very high rate of compliance. Registered units are subject to an annual fee and must be inspected when an apartment unit changes tenants. Some city rental units are not covered by the ordinance and thereby not represented in this database. These include publicly owned rental units, privately owned units rented with Section 8 vouchers, and units that are rented/leased by agencies through programs that are sponsored by the state. These units are exempted because they are subject to other housing agency inspections.

City of Cumberland HUD Section 8 Voucher Database. This database contains approximately 436 addresses where HUD Section 8 vouchers were used in 2005. The Section 8 program is administered differently than the rental unit database and records are filed separately.

Maryland Office of Planning Property View data. This database compiles information from the Maryland Department of Assessments and Taxation on all real property for 2005. It includes information on various characteristics of the property including street location, physical location in terms of latitudinal and longitudinal coordinates, Census Block Group identification code, lot size, dwelling age, enclosed area, structure condition code, assessable value, and owner's address.

U.S. Census 2000 of Population and Housing. This data contains Census Block Group level data on various population and housing characteristics for 2000 that were used to generate neighborhood indicators of socioeconomic level and housing quality.

4. Research Hypotheses

The Uniform Crime Reports distinguishes between property and violent crimes. This distinction is useful in as much as it highlights the severity of the crime as well as suggests possibly differing explanatory models. Another distinction is sometimes made between "predatory or exploitive crimes" and "crimes that are mutualistic, competitive and individualistic" (Roncek and Maier 1991). Arguments between familiar parties such as assaults would constitute "competitive" crimes whereas burglary would be considered "exploitative."

The role of place is likely to differ depending on the type of crime. Sherman, Gartin and Buerger (1989) argue that "predatory stranger" crimes are much more dependent on place than "competitive" crimes. The presence of competitive crimes like domestic assaults and disturbances at certain residences "may simply indicate that certain buildings are receptors for the kind of people most likely to experience, or at least call police about, domestic problems; such calls might occur at the same rate no matter where they lived." (p. 47)

Eck and Wartell (1998) suggest that place characteristics such as property management may help explain variation in these kinds of problems as well. When residents are more likely to engage in disruptive behavior, poor property management may be an accessory factor. If disturbances and criminal activity originate in a particular rental unit and no attempt is made to notify the occupant that the conditions are disruptive to the neighborhood, one can conclude that the property has weak management.

In the case of owner-occupied residential properties, management is clear – the owner-occupant lives in the property and assumes principal responsibly for its maintenance and the conduct of its residents. For rental properties, management is often more diffuse, ambiguous, and difficult to engage. Leases may vary in terms of the management responsibilities assumed by the tenant (e.g., cutting the grass, sub-letting, allowance of smoking or pets). Moreover, landlords may also live outside the community, making communication more challenging. Legal ownership forms such as partnerships and corporations may also hamper management contact.

Rental property management quality may vary in other ways. Non-local landlords should have fewer opportunities and greater costs for inspecting and monitoring their rental properties. Property management may also differ based on the number of properties that are owned. The part-time landlord may more effectively manage two properties than twenty. Length of property ownership could also be important with more experienced landlords making better property managers. Finally, the motivation for owning rental properties may influence the quality of management. The landlord who invests in rental property to ensure a steady rental income may be a more attentive manager than the property speculator who invests to achieve short-term capital gains.

Since management quality is not directly observable, this paper tests for several hypothetical correlates of property management (see table 4.1). It is hypothesized that local owners that reside on the property (***LEVEL1***) are likely to be more effective property managers than those who live further away (***LEVEL2-LEVEL7***). Moreover, because of the higher transactions costs associated with management from a distance, management quality is hypothesized to weaken with each increment in distance from the property. In addition, it is hypothesized that there are diseconomies of scale in property management. As the number of units registered by the landlord (***OWNUNITS***) increases, property management quality decreases.

Additional property, tenant, and neighborhood variables are introduced to control for other explanations for residential crime (see table 4.1). The number of apartment units (***UNITS***) in a dwelling would be expected to increase the likelihood of crime occurrence there because of the greater number of households at risk. It may also increase the likelihood of detection because of the close proximity of other tenants. The only tenant level indicator available for this study is a dummy variable indicating whether a tenant of the property uses a HUD section 8 voucher to pay for rent (***HUDUNIT***). This variable is used to control for tenant socioeconomic status. A disadvantaged individual has a greater likelihood of engaging in criminal activity. Therefore, the coefficient for this variable would be expected to be positive.

Based on the criminal literature review, selected neighborhood variables are used as control variables. In defining the boundaries of neighborhoods, this study uses Census Block Groups from the 2000 U.S. Census. The neighborhood variables include measures of residential stability (***RESSTAB***) and home ownership (***OWNOCC***) which are expected to be negatively associated with rental unit crime, measures of socioeconomic deprivation such as the percentage of households headed by female householders with children (***FFHH***), poverty rate (***POVRATE***), minority population percentage (***MINPOP***), unemployment rate (***UNEMP***), percentage of households receiving public assistant (***PUBASS***), and median household income (***HHINC***), and demographic factors which indicate populations with varied propensities to criminal activity such as the percentage of residents that is young males (***MALEPOP***), percentage of teenagers that is 'drifters' (***YOUNGUN***), and percentage of residents that is college educated (***COLLPOP***).

The units of observation used in this study are individual properties with dwellings. Usually, these properties are single-family homes, but in some instances they are attached structures such as residential duplexes, row houses, and condominium/apartment units within buildings.

The dependent variables used in this study are the number of incident reports filed for individual properties for three separate categories of criminal incidents during the 2005 calendar year: disturbances, assault (including domestic assault), and use or distribution of controlled dangerous substances such as cocaine, opiates, marijuana and barbiturates.

Typically, a very small percentage of properties accounts for a relatively high percentage of crimes. For instance, Sherman, Gartin, and Buerger (1989) find that in Minneapolis over half of the police calls are generated by 3.3 percent of addresses. Moreover, domestic disturbance and assault calls are even more concentrated – all disturbance calls occur at nine percent and all assaults at seven percent of places. The data here show similar patterns. Figure 4.1 shows the relative frequency of incident report counts for the three types of incidents. Twenty-one percent of rental residences generate all of the disturbance incidence reports. Thirteen percent of rental residences accounts for all of the assault reports and five percent accounts for all drug reports.

5. Model

The dependent variable is a count that is best modeled using count regression models that take into account the discreteness, non-negativity, and non-linearity of the data generating process. These models have advantages over linear regression because they conform more closely to the pattern of data generation observed and produce non-negative predictions (Walters 2007; Cameron and Trivedi 2006; Grogger 1990). Moreover, they offer the possibility of estimation and inference improvements over the linear regression model. The use of OLS with count data violates two fundamental assumptions of the Classical Linear Regression model. When the appropriate model is non-linear, as is suggested by count data, bias is introduced. In addition, application of OLS with count data results in error variance differences that violate the assumption of homoskedasticity (Walters 2007). The possible alternative of transforming count data to dichotomous form and using non-linear bi-variate regression models such as logit or probit is not recommended because it results in a loss of information (Walters 2007).

The reference point for developing count models is the Poisson distribution (Cameron and Trivedi 2006). The Poisson distribution represents the probability of a count (*y*) of discrete events occurring during a designated time period as follows:

$$\Pr_1(y) = \frac{e^{-\mu}\mu^{y}}{y!} \quad y = 0,1,2,\ldots\mathrm{N}. \tag{1}$$

In order to incorporate independent explanatory factors, Poisson regression allows μ to vary with each observation. Independent variables are invoked to explain the variation in μ_i. This can be represented as follows:

$$\mu_i = E(y_i \mid x_i) = e^{\mathbf{x}_i \beta} = e^{\beta_1 + \beta_2 x_{2i} + \ldots \beta_k x_{ki}} \qquad (2)$$

The Poisson regression model (PRM) is somewhat restrictive because it has the property that both the mean and variance are the same – E(y)=V(y)=μ – a condition referred to as equidispersion. Relatedly, Poisson count regressions also often result in lower predictions of zero counts than are realized in the data. Choice of other count regression models that allow the variance to exceed the mean (a condition referred to as overdispersion) can rectify this problem.

Three such models are presented here based on Cameron and Trivedi (2006) and Long and Freese (2006). The first, the Negative Binomial Regression (NBRM), adjusts the Poisson model by introducing a random error (ε_i) that is independent of the independent variables ($\boldsymbol{x}_i$). That is to say:

$$\mu_i = E(y_i \mid x_i) = e^{x_i \beta} = e^{\beta_1 + \beta_2 x_{2i} + \ldots \beta_k x_{ki} + \varepsilon} \qquad (3)$$

Assuming that E(e^{ε_i}) is equal to one (equivalent to the assumption that the expected value of the error term equals zero in the linear regression model) and that e^{ε_i} is drawn from a gamma distribution (Γ(.)) leads to a negative binominal distribution:

$$\Pr_2(y) = \frac{\Gamma(y + \alpha^{-1})}{y!\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu} \right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu} \right)^{y} \qquad (4)$$

where V(e^{ε_i})≡α. This results in E[y]=μ and V[y]= μ (1+ α μ). So, α influences the degree of dispersion – and if α=0 the model is equivalent to the Poisson regression model.

The zero-inflated count (ZIP) model and zero-inflated negative binomial model (ZINB) achieve overdisperson by in effect mixing bi-variate and count models. One assumes that observations can be divided into two latent groups. The first group has no probability of event occurrence, perhaps because of some intrinsic qualities of the observation (e.g., in the example provided by this study, a rental dwelling is empty). The other group has a probability of events occurring with frequency greater or equal to zero.

Probabilities for the model are computed as a weighted average of estimated probabilities of occurrence according to a bi-variate regression (e.g., logit or probit) and estimated probability of the number of occurrences according to the Poisson and Negative Binomial count regression models described earlier. These models can more formally be represented as follows:

$$\Pr(y) = \begin{cases} \Pr(0) + (1 - \Pr(0))\Pr_i(0) & \text{if } y = 0 \\ (1 - \Pr(0))\Pr_i(k) & \text{if } y \geq 1 \end{cases} \quad (5)$$

where Pr(0) is the bi-variate model computed probability of zero occurrences and $\Pr_i(0)$ and $\Pr_i(k)$ are the count model computed probabilities of zero occurrences and k occurrences respectively. For i=1 (where the count model is the Poisson), the model corresponds to the ZIP and for i=2 (where the count model is the Negative Binomial) the model is the ZINB. The variables used in estimating the bi-variate regression may differ from those used in the count regression.

6. Results

Regressions and diagnostic tests were conducted using STATA software's count model procedures ***POISSON***, ***NBREG***, ***ZIP***, ***ZINB***, additional count model diagnostic programs ***LISTCOEF*** and ***COUNFIT*** (Long and Freese 2006), and collinearity diagnostic routine ***COLDIAG2*** (Hendrickx 2004). In order to form a more parsimonious set of explanatory variables, linear regression diagnostics such as the condition index, variance inflation factor (VIF), and pairwise correlations were examined for values that were unusually high. Five variables were culled from the analysis including **POVRATE**, **RENT**, **RESTAB**, **HHINC**, and **UNEMP** resulting in a condition index of 25, a maximum VIF of less than two, and pairwise correlations below .53 in absolute value.

Table 6.1 presents the results of the four different count regression models, Poisson, Negative Binomial, Zero Inflated Poisson, and Zero Inflated Negative Binomial for disturbance counts. The table shows the estimated coefficients, t test statistics, and exponentiated coefficients[1] for each of the models. Since ZIP and ZINB are mixed models as explained above, they estimate two equations. The second estimated equation represents the overall probability of a zero count; the first represents the probability for a non-zero count. The same set of independent variables is used in estimating each equation.

The results for the different estimation methods show certain similarities. The coefficients for ***LEVEL2-LEVEL7*** generally grow in magnitude indicating that crime increases as the property owner lives further away from a given rental property. This finding provides support for the hypothesis that management qualities differ between local and non-local landlords. Larger rental property holdings (***OWNUNITS***) are also associated with higher counts suggesting diseconomies of scale in managing rental properties. Non-ownership factors are statistically significant as well. Having tenants in a rental property who use Section 8 vouchers (***HUDUNIT***) is associated with a greater frequency of incident reports as are neighborhoods with a lower percentage of owner-occupied units (***OWNOCC***). Disturbances may be exacerbated in neighborhoods where there are lower levels of residential stability and fewer stakeholders. Alternatively, problem properties may be concentrated in neighborhoods with low owner occupancy.

Several diagnostic tests recommend the Negative Binomial regression model over the alternatives. A likelihood ratio test rejects the null hypothesis that $\alpha=0$ and provides evidence that the data is overdispersed, thereby disqualifying the Poisson model. A visual inspection of Figure 6.1 shows that the mean predicted probability of the Negative Binomial model provides a better fit to the observed data than the other models. This is further supported by the average residual of observed and average predicted counts (Mean |Diff|).[2] The Bayesian Information Criterion (BIC) model selection test statistic also supports the choice of the Negative Binomial regression model.

Table 6.2 shows the results of Negative Binomial regressions for disturbances, assaults, and drugs. For all three types of incidents, the magnitudes of the estimated coefficients grow with the owner's remoteness from the rental property. This "ownership distance gradient" for crime is illustrated in Figure 6.2. Section 8 voucher use at rental properties is also associated with more incident reports in each category. In two of the three regressions (disturbances and drugs), neighborhood owner-occupied housing rates are associated with lower activity.

There are also notable differences among the results. In contrast to disturbances, the size of landlord rental property holdings is not associated with more assault and drug incident reports. In addition, for assaults and drugs, other neighborhood correlates are observed – percentage of college educated residents (***COLLPOP***) for assaults and minority population and young males (***YOUNGUN***) for drugs. These results suggest, perhaps, that the exacerbating neighborhood conditions differ depending on the nature of the crime.

One way of viewing the contribution of absentee ownership to disorderly properties is to predict the number of criminal incidents emanating from private rental dwellings assuming that all the rental properties have a landlord living on the site. In this situation, the landlord is more likely to be selective of tenants, less accommodating to behavior and lifestyles which disturb the peace and harmony of the neighborhood, and more attentive to security. By setting the LEVEL2-7 variables equal to zero (i.e., landlord lives in rental dwelling), one finds that the total number of disturbances drops from 776 to 512 (a 34% decrease), the number of assaults goes from 313 to 159 (a 49% decrease), and the number of drug incidents declines from 79 to 54 (a 32% decrease).

7. Summary and Conclusions

This study investigates how residential rental property ownership and management qualities affect crime. For three types of incidents (disturbances, assaults, and drugs), landlord remoteness from properties is positively associated with reported criminal activity. This association may be caused by management quality deterioration due to the increased costs of conducting business from a distance or a remote landlord's ability to ignore some of the external costs imposed by tenant misbehavior on neighbors. Non-resident landlords may be less selective in choice of tenants, more accommodating of behavior and lifestyles that they would not accept if located 'next door' to their own residence, and less likely to employ effective surveillance and security measures.

In instances such as this, there may be a role for local government to provide better information, education, and enforcement to improve landlord property management capabilities. These might include code enforcement activities to identify poorly managed properties, notification letters sent by the police department to landlords when criminal activity is detected in a rental dwelling, and mandatory landlord training to enhance management capabilities. Other approaches might include establishing landlord licensing to disqualify inattentive landlords from operating rental properties and supporting the construction of professionally managed workforce or affordable housing projects to increase the availability of properly managed rental properties.

The results here suggest a role for local government stewardship as well. Section 8 voucher recipients agree to certain restrictions when they accept subsidized housing. In situations where enforcement is lax, Local Housing Authorities may leverage their position as a subsidy provider to improve tenant behavior. Better enforcement would involve greater coordination between local police departments and housing assistance offices to identify disorderly and criminal tenants.

Neighborhood based correlates of criminal activity are much less amenable to local government control than the aforementioned variables. But, the results here suggest that neighborhood homeownership may decrease crime. Promoting homeownership, especially among residents who lack the financial assets, credit history, income, or life skills is a challenge. Moreover, homeownership may not be for everybody, such as frequent movers. However, most renters would prefer to own and see renting as a negative experience (Fannie Mae 2001, 2003). Therefore, programs designed to improve tenant transition to homeownership may deserve more resources.

Endnotes

[1] The exponentiated coefficient ($e^{\beta_k \delta}$) is equal to the factor increase in the expected count when x_k increases by δ, holding all other variables constant. That is to say,

$$\frac{E(y \mid \mathbf{x}, x_k + \delta)}{E(y \mid \mathbf{x}, x_k)} = e^{\beta_k \delta}$$

[2] $$\text{Mean} \mid \text{Diff} \mid = \frac{\sum_{i=0}^{M} \left| (\Pr_{Observed}(y = i) - \frac{1}{N} \sum_{j=1}^{N} \Pr_{\Pr edicted}(y_j = i) \right|}{M + 1}$$

where $Pr_{Observed}$ is the observed probability, $Pr_{Predicted}$ is the estimated probability, N is the number of observations, and M is the maximum count.

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Table 4.1 Variable Definitions

Variable	Description
Independent	
DISTURB	Number of reports filed for disturbances[a]
ASSAULT	Number of reports filed for assault[a]
DRUG	Number of reports filed for drug possession or distribution[a]
Tenant characteristics	
HUDUNIT	Dwelling tenant uses Section 8 voucher[b]
Rental dwelling characteristics	
UNITS	Number of registered rental units in dwelling[b,c]
Ownership characteristics	
LEVEL1	Owner lives in same dwelling[d]
LEVEL2	Owner lives beyond LEVEL1 but in same neighborhood[d]
LEVEL3	Owner lives beyond LEVEL2 but in city[d]
LEVEL4	Owner lives beyond LEVEL3 but in same zipcode [d]
LEVEL5	Owner lives beyond LEVEL4 but within 60 miles of city[d]
LEVEL6	Owner lives beyond LEVEL5 but within 500 miles of city[d]
LEVEL7	Owner lives at least 500 miles from city[d]
OWNUNITS	Total number of units owned by landlord[b,c,d]
Neighborhood Characteristics	
FFHH	Percentage of households that is female headed with children[e]
RESSTAB	Percentage of residents 5 years and older who lives in same house as in 1995[e]
MINPOP	Percentage of residents that is black[e]
MALEPOP	Percentage of residents that is male 18-24 years of age[e]

COLLPOP	Percentage of residents 25 years and older that is college educated[e]
YOUNGUN	Percentage of 16-19 year old residents that is not in school, not a high school graduate, and unemployed[e]
UNEMP	Unemployment rate[e]
PUBASS	Percentage of households receiving public assistance income[e]
POVRATE	Poverty rate[e]
OWNOCC	Percentage of housing units owner-occupied[e]
HHINC	Median household income[e]
RENT	Median contract rent[e]

Source: [a]City of Cumberland Police Department Incident Report data (2005), [b] City of Cumberland Community Development Department Section 8 rental property database (2005), [c] City of Cumberland Community Development Department rental property database, [d] Property View, Maryland Office of Planning (2005), [e] U.S. Census (2000).

Figure 4.1 Observed Crime Counts

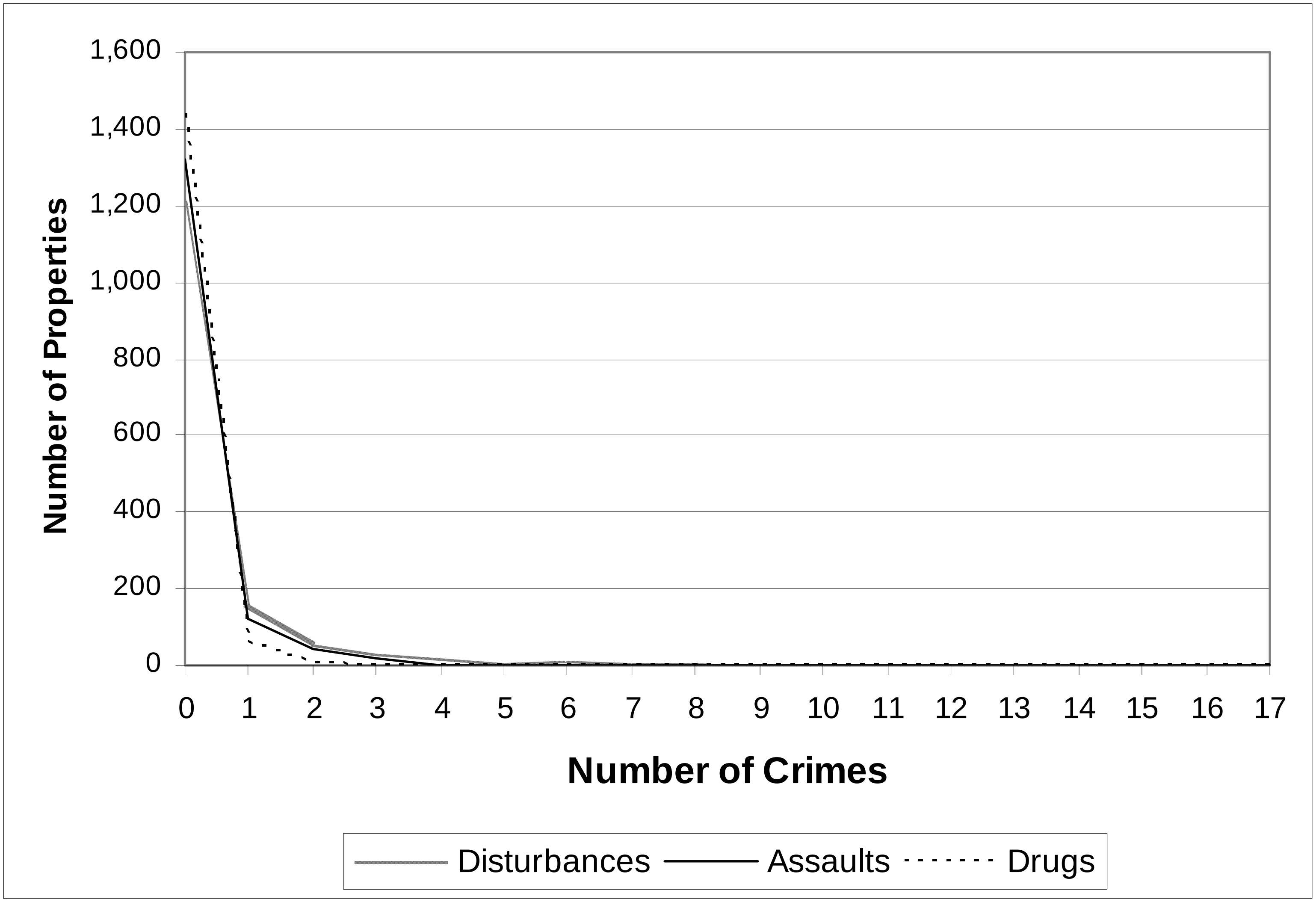

Table 6.1 Count Model Results for Disturbances

	PRM			NBRM		
	β	t	e^{β_k}	β	t	e^{β_k}
Ownership						
LEVEL2	-0.0575	-0.33	0.944	0.1171	0.42	1.124
LEVEL3	0.0286	0.19	1.029	0.2543	1.05	1.289
LEVEL4	0.3834	2.73***	1.467	0.3586	1.53	1.431
LEVEL5	0.5436	3.85***	1.722	0.6565	2.65***	1.928
LEVEL6	0.8278	5.75***	2.288	0.7898	2.93***	2.203
LEVEL7	0.5466	2.54**	1.727	0.6743	1.43	1.963
OWNUNITS	0.0150	4.58***	1.015	0.0190	2.38***	1.019
Tenant						
HUDUNIT	1.0525	13.89***	2.865	0.9561	5.44***	2.601
Rental dwelling						
UNITS	-0.0018	-0.38	0.998	0.0486	1.24	1.050
Neighborhood						
FFHH	0.0375	2.00**	1.038	0.4625	1.43	1.047
MINPOP	0.0483	2.86***	1.050	0.0356	1.05	1.036
YOUNGUN	0.0197	3.28***	1.020	0.0147	1.36	1.015
MALEPOP	-0.0365	-0.95	0.964	-0.0483	-0.69	0.953
COLLPOP	-0.0219	-2.86***	0.978	-0.01418	-1.26	0.986
OWNOCC	-0.0119	-3.87**	0.988	-0.01237	-2.32**	0.988
CONSTANT	-1.2685	-3.87***		-1.4592	-2.55**	
Mean |Diff|		0.019			0.001	
BIC		3447.839			2551.449	

***** α =.01, ** α=.05, * α=.01**

Table 6.1 Count Model Results for Disturbances continued

	ZIP			ZINB		
	β	t	e^{β_k}	β	t	e^{β_k}
LEVEL2	-0.0535	-0.25	0.948	0.3807	0.95	1.463
LEVEL3	-0.3315	-1.80*	0.718	-0.1810	-0.56	0.834
LEVEL4	-0.3594	-2.08**	0.698	-0.0381	-0.12	0.963
LEVEL5	0.1246	0.74	1.133	0.3645	1.12	1.440
LEVEL6	0.0707	0.41	1.073	0.5256	1.56	1.691
LEVEL7	0.2719	0.98	1.312	0.8326	1.65*	2.299
OWNUNITS	-0.0043	-0.81	0.996	-0.0061	-0.79	0.994
HUDUNIT	0.1163	1.13	1.123	0.7181	4.29***	2.051
UNITS	0.1416	8.06***	1.152	0.0006	0.04	1.001
FFHH	0.0507	2.15**	1.052	0.0479	1.15	1.049
MINPOP	0.0128	0.63	1.013	-0.0168	-0.46	0.983
YOUNGUN	0.0056	0.74	1.006	0.0004	0.03	1.000
MALEPOP	0.0053	0.11	1.005	0.0619	0.68	1.064
COLLPOP	0.0032	0.37	1.003	-0.0277	-1.98**	0.973
OWNOCC	-0.0082	-2.16**	0.992	-0.0109	-1.60	0.989
CONSTANT	0.1908	0.49		-0.1307	-0.19	
LEVEL2	0.1948	0.59	1.215	0.8084	1.55	2.244
LEVEL3	-0.5575	-1.98**	0.573	-0.7069	-1.28	0.493
LEVEL4	-0.8616	-3.18***	0.422	-0.5535	-1.18	0.575
LEVEL5	-0.6200	-2.31**	0.538	-0.4061	-0.85	0.666
LEVEL6	-0.7639	-2.59**	0.466	-0.3298	-0.62	0.719
LEVEL7	-0.3804	-0.74	0.684	1.0198	1.03	2.773
OWNUNITS	-0.0325	-3.03***	1.033	-0.1114	-2.81***	0.895
HUDUNIT	-1.0865	-6.21***	0.337	-0.3768	-0.62	0.686
UNITS	0.0321	1.89*	0.968	-0.4423	-2.33**	0.643
FFHH	0.0078	0.21	1.008	-0.0077	-0.10	0.992
MINPOP	-0.6325	-1.68*	0.939	-0.1337	-1.75*	0.875

YOUNGUN	-0.0168	-1.37	0.983	-0.0332	-1.35	0.967
MALEPOP	0.0715	0.91	1.074	0.2026	1.35	1.225
COLLPOP	0.0323	2.39**	1.033	-0.0090	-0.33	0.991
OWNOCC	-0.0005	-0.01	1.000	-0.0059	-0.55	0.994
CONSTANT	1.7674	2.68***		2.2566	1.72*	
Mean |Diff|		0.005			0.002	
BIC		2776.957			2596.039	

***** α =.01, ** α=.05, * α=.01**

Figure 6.1 Count Model Prediction Residuals

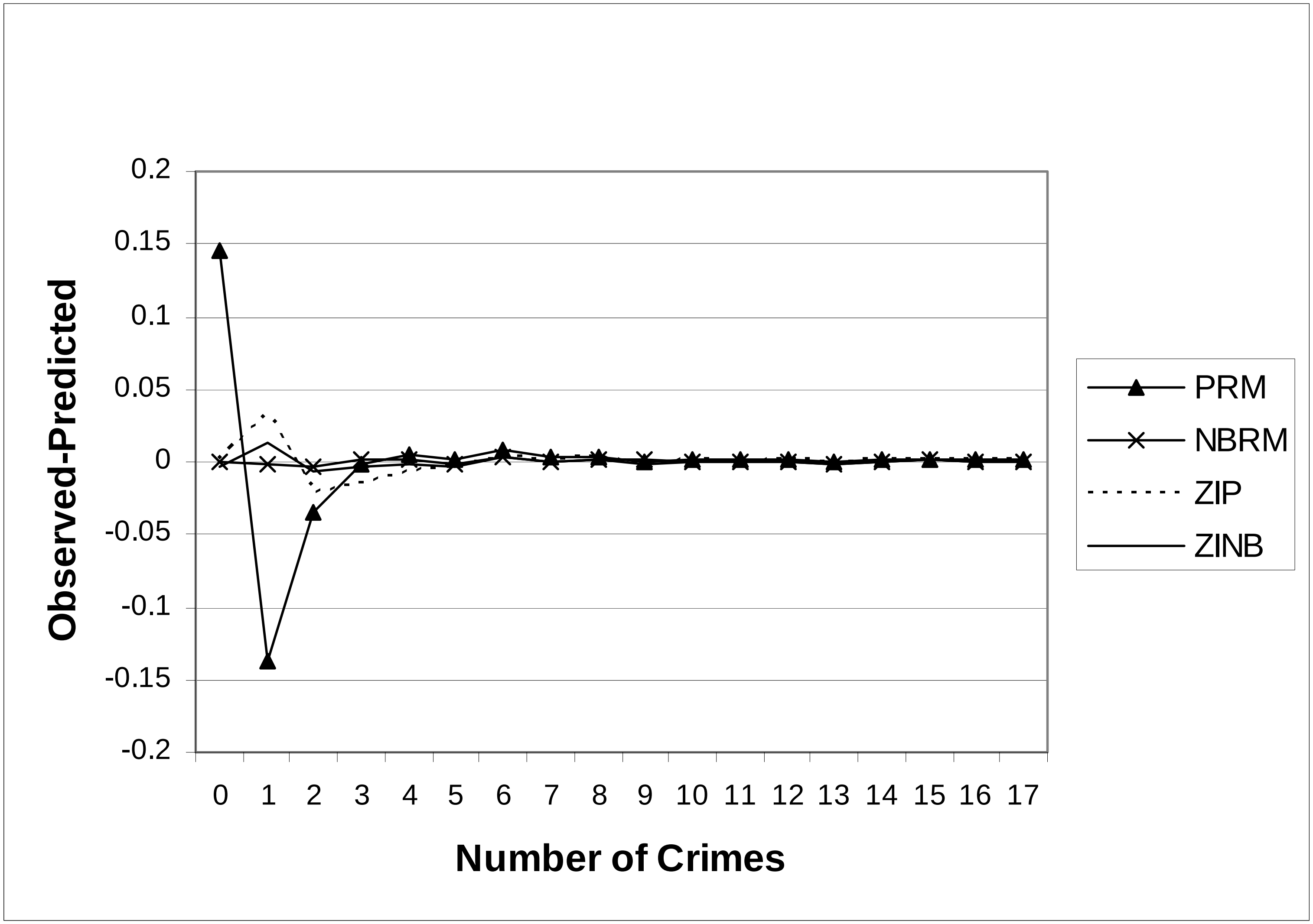

Table 6.2 Negative Binomial Regression Model Results

	DISTURB			ASSAULT			DRUG		
	β	t	e^{β_k}	β	t	e^{β_k}	β	t	e^{β_k}
Ownership									
LEVEL2	0.1171	0.42	1.124	0.4656	1.35	1.593	-0.1097	-0.19	0.860
LEVEL3	0.2543	1.05	1.290	0.6410	2.08**	1.898	0.1545	0.33	1.167
LEVEL4	0.3586	1.53	1.431	0.7853	2.65***	2.193	0.4969	1.14	1.620
LEVEL5	0.6565	2.65***	1.928	0.8466	2.73***	2.332	0.5698	1.29	1.762
LEVEL6	0.7898	2.93***	2.203	1.0311	3.10***	2.804	0.9258	2.05**	2.526
LEVEL7	0.6743	1.43	1.963	0.67051	1.23	1.955	0.5460	0.73	1.673
OWNUNITS	0.0190	2.38**	1.019	0.01304	1.61	1.013	0.0021	0.18	1.004
Rental dwelling									
UNITS	0.0486	1.24	1.050	-0.00909	-0.44	0.991	0.0114	0.66	1.011
Tenant									
HUDUNIT	0.9561	5.44***	2.601	1.2261	7.02***	3.408	1.2756	5.36***	3.647
Neighborhood									
FFHH	0.0463	1.43	1.047	0.0240	0.65	1.024	-0.6474	-0.81	0.951

MINPOP	0.0356	1.05	1.036	0.0444	1.15	1.045	0.1148	2.17**	1.117
YOUNGUN	0.0147	1.36	1.015	0.0046	0.38	1.005	0.0434	1.96**	1.041
MALEPOP	-0.0483	-0.69	0.953	-0.0062	-0.08	0.994	-0.1909	-1.23	0.847
COLLPOP	-0.0142	-1.26	0.986	-0.0283	-2.02**	0.972	-0.0414	-1.36	0.959
OWNOCC	-0.0123	-2.32**	0.988	-0.0003	-0.04	1.000	-0.0221	-2.10**	0.979
CONSTANT	-1.4592	-2.55**		-2.8741	-4.25***		-2.2091	-1.66*	
Pseudo R^2	0.0490			0.0597			0.1069		

***** α =.01, ** α=.05, * α=.01**

Figure 6.2 Crime Level Ownership Distance Gradients