Crime and Local Inequality in South Africa

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Abstract –We examine the effects of local inequality on property and violent crime in South Africa. The findings are consistent with economic theories relating inequality to *property* crime and also with sociological theories that imply that inequality leads to crime in general. Burglary rates are 20-30% higher in police station jurisdictions that are the wealthiest among their neighbors, suggesting that criminals travel to neighborhoods where the expected returns from burglary are highest. Finally, we do not find evidence that inequality between racial groups fosters interpersonal conflict at the local level.

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I. Introduction

Crime is among the most difficult of the many challenges facing South Africa in the post-apartheid era. The country's crime rates are among the highest in the world and no South African is insulated from its effects. Beyond the pain and loss suffered by crime victims, crime also has less direct costs. The threat of crime diverts resources to protection efforts, exacts health costs through increased stress, and generally creates an environment unconducive to productive activity. Additionally, the widespread emigration of South African professionals in recent years is attributable in part to their desire to escape a high crime environment.[1] All of these effects are likely to discourage investment and stifle long-term growth in South Africa. Consequently, it is important to understand the factors that contribute to crime.

Both economic and sociological theory has linked the distribution of welfare to criminal activity. Economists have suggested that inequality may capture the differential returns to criminal activity and thereby have an association with crime rates. If criminals travel, not only the welfare distribution in the local area, but that of neighboring areas as well, may be linked to local crime levels. Sociologists have hypothesized that inequality and social welfare in general may have effects on crime through other channels. Inequality may be associated with lack of social capital, lack of upward mobility, or social disorganization, all of which may cause higher levels of crime. Furthermore,

[1] According to a survey conducted by the South African Migration Project, blacks and whites both "…rated security and safety as the most significant push factor, reinforcing the national importance of addressing the crime problem as a deterrent to the brain drain" Dodson (2002).

economic inequalities between groups may engender conflict in a society by consolidating and reinforcing ethnic and class differences (Blau & Blau, 1982).

In this paper, using data on crime and estimates of welfare measures by police station jurisdiction in South Africa, we consider three questions. First, we examine the extent to which economic versus sociological theories explain the variation in crime rates, by comparing the implications of various theories for violent crime and property crime separately. Next, we consider how the relative position of a community among neighboring areas may be associated with crime. Finally, we examine whether crime is particularly prevalent in areas with high inequality between racial groups.

The next section discusses the reasons why there might be an association between economic welfare and crime at the community level. Section III summarizes the empirical literature on inequality and crime and explains the contribution of this paper. Section IV briefly outlines the empirical approach and describes our data sources. Section V presents the regression results for various types of crime and Section VI concludes.

II. Crime and Economic Welfare

There are a number of reasons why the local distribution of economic welfare might be associated with the prevalence of crime. Various arguments have been made by economists, sociologists, and public health specialists.

First, community welfare measures may be associated with crime levels via a relationship with the returns from crime and non-crime activities. In his seminal work, Becker (1968) proposes an occupational choice model in which the incentives for individuals to commit crime are determined by the differential returns from legitimate and illegitimate pursuits. At an aggregate level, researchers have suggested various approaches to approximate these returns. For example, Machin and Meghir (2000) argue that criminals are more likely to come from the bottom end of the wage distribution, and they measure the returns to legitimate activities with the 25th percentile wage. Ehrlich (1973) postulates that the payoffs to activities such as robbery, burglary and theft depend on the level of transferable assets and can be proxied by median income in the community.

Under certain conditions, a Becker-type economic model can generate a relationship between property crime and local inequality. Suppose, for example, that the expected returns from illegitimate activities are determined by the mean income of households in the community. Also suppose that the returns from crime for potential criminals are equal to the incomes of those at the lower end of the local income distribution. Then the relative benefits of crime will be determined by the spread between the community mean and the incomes of the relatively poor. This implies that the expected level of crime will be greater in a community with higher inequality. Using variations on this argument, Ehrlich (1973), Chiu and Madden (1998) and Bourguignon (2001) all suggest that economic incentives for crimes are higher in areas with greater inequality in the community. A Beckerian model does not imply that inequality per se causes crime but rather that empirically inequality may capture the incentives for criminal activity. This leaves no reason to suspect that crime should be correlated with inequality if the costs and benefits of crime are controlled for.

Second, local economic welfare may also be associated with the level of protection from crime. Private crime protection measures may include guard dogs, bars on windows, electric fences, and alarm systems with armed security response. Chiu and Madden (1998) provide a model that allows for richer neighborhoods to have lower crime rates, partly because they may employ effective defense strategies against crime. Wealthier people may also have better access to legal protection (Black, 1983). Inequality may also be positively correlated with crime if, as Pradhan and Ravallion (1998) suggest, concern for public safety at the household level is a concave function of income, thereby creating a negative correlation between public concern for safety and inequality at the aggregate level. The provision of protection from crime through collective action such as neighborhood watch programs may also be low in communities with low social capital. Lederman et al. (2001) suggest that social capital may decrease crime rates by lowering the cost of social transactions and attenuating free-rider problems of collective action. If inequality is correlated with lack of social capital in a community, then one expects to observe a positive correlation between inequality and crime.

Third, lack of upward mobility in the society may be linked to the prevalence of crime. Coser (1968, cited by Blau & Blau, 1982, p. 119) argues that people who perceive their poverty as permanent may be driven by hostile impulses rather than rational pursuit of their interests. Wilson and Daly (1997) hypothesize that sensitivity to inequality, especially by those at the bottom, leads to higher risk tactics, such as crime, when the expected payoffs from low-risk tactics are poor. If income inequality, a static measure, is correlated with social mobility, a dynamic concept, then these theories imply a higher prevalence of criminal behavior in more unequal areas.

Fourth, closely related to theories involving social mobility are those related to social disorganization and crime. In an influential paper, Merton (1938) proposes that "…when a system of cultural values emphasizes, virtually above all else, certain *common* symbols of success *for the population at large* while its social structure rigorously restricts or completely eliminates access to approved modes of acquiring these symbols *for a considerable part of the same population*, that antisocial behavior ensues on a considerable scale". Hence, the lack of upward mobility in a society, combined with a high premium on economic affluence results in anomie, a breakdown of standards and values. According to Merton, poverty or even "poverty in the midst of plenty" alone is not sufficient to induce high levels of crime. Only when their interaction with other interdependent social and cultural variables is considered, one can explain the association between crime and poverty.

Finally, people may be particularly sensitive to inequalities across ethnic, racial, or religious groups, or across geographical areas.[2] Blau and Blau (1982) argue that three concepts are central to theories on social relations in a population: heterogeneity, inequality, and the extent to which two or more dimensions of social differences are correlated and consolidate status distinctions. For example, racial heterogeneity and income inequality, both correlated with status in the community, could inhibit marriage between persons in different positions or spell potential for violence. They suggest, "… great economic inequalities generally foster conflict and violence, but ascriptive

[2] Kanbur (2002) argues that "…spatial units may develop special identities even without the basis of ethnicity, race or religion."

inequalities do so particularly." Their theory suggests inequality between racial groups is an especially strong force behind high crime rates.

A point of departure from the literature in this paper is the incorporation of the effects of characteristics of neighboring communities on crime. With respect to the sociological theories of crime, such as Merton (1938), Coser (1968), and Wilson and Daly (1997), it is not clear whether it is inequality within the community or within a larger geographical unit that should matter in relation to crime. Next consider the Beckerian economic theory of crime. For ease of exposition, we define "criminal catchment area" for a neighborhood to include the neighborhood itself and all bordering neighborhoods, while we use "own neighborhood" to refer to only the neighborhood itself. Because individuals may travel from surrounding communities to commit crimes, or to neighboring areas to work, the relevant returns to legitimate activities for potential criminals (those who could commit crimes reported in own neighborhood) are the returns available in the criminal catchment area. The relevant returns to crime, however, are those in own neighborhood alone.

Suppose two adjoining neighborhoods are identical and have identical income distributions, except that in one neighborhood households have incomes and transferable assets worth twice those of households in the other neighborhood. Consequently, inequality is equal within each of the two neighborhoods. Further suppose that individuals can observe the mean income (or assets) of households in a neighborhood, but not the welfare levels of individual households. In economic theories of crime, such as Ehrlich (1973), where crime rates are a positive function of the absolute differential returns from crime and a negative function of punishment, it is not clear why crime levels should be higher in the richer neighborhood. When travel between neighborhoods is not considered and punishment is by imprisonment only, then the effect of the difference in mean incomes between the two neighborhoods could be zero as the returns from legitimate and illegitimate activities, and, hence, the opportunity cost of crime are all higher by the same proportion in the richer neighborhood.[3] On the other hand, if individuals can freely travel between the two neighborhoods at negligible cost, every individual who allocates some time to property crime will prefer to conduct their activity in the richer neighborhood, where the expected returns are twice as high. Thus, if criminals can travel, economic theory predicts that crime will be higher in wealthier neighborhoods, even controlling for inequality.

Crime rates may also be partially determined by the wealth of own neighborhood relative to other neighborhoods in the catchment area. As above, consider a criminal catchment area that consists of multiple neighborhoods instead of just two, where the neighborhoods differ only in their mean level of income and assets. Then, criminals will conduct all of their illegitimate activity in the richest neighborhood. Property crimes may still take place in the poorer areas if travel is costly, the amount of protection from crime varies across neighborhoods, or criminals have better information on returns from crime in their immediate neighborhood.

The relationship between community welfare and property crime may vary with the specific type of crime. The travel story seems best suited to explain residential

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[3] Ehrlich (1973) argues that the changes in optimal time allocation between legitimate and criminal activities due to such a "pure wealth effect" depends on the offender's relative risk aversion.

burglary, because the benefits–the value of transferable assets–are most clearly linked to local household wealth. The travel scenario is less applicable to other property crime such as vehicle theft or robbery, because the crime may take place while the victim is away from his or her neighborhood. Consequently, wealth in the area in which the theft is reported may not be linked to the return from crime.

In summary, a variety of theories suggest that higher inequality may be associated with crime. Standard economic theories, which seem most applicable to property crime, imply that inequality may be positively correlated with crime through its effect on the differential returns from criminal activity versus legitimate pursuits. This would suggest that there would be no relationship between crime and inequality, controlling for the benefits and costs of crime participation. However, sociological theories of crime imply that inequality also has a direct effect on crime. These theories suggest that inequality leads to higher levels of both property crime and violent crime, independent of the net returns to such crimes. Higher inequality might also lead to more crime through lower levels of protection from crime if inequality suppresses collective action or concern for public safety at the aggregate level.

The theoretical literature on crime does not generally address the relationship between aggregate income levels and crime. We have argued above that if mean level of income adequately captures the level of transferable assets in the community and individuals travel to commit crimes, then all else equal *property* crime should be positively correlated with mean income. At the same time, higher incomes may lead to lower property crime levels through more effective protection. There is no obvious reason to expect *violent* crime levels to be associated with mean income levels.

III. Evidence from the Literature

The empirical evidence on the crime-inequality relationship, mainly based on comparisons across countries, or states and cities in the U.S., generally shows a positive correlation between inequality and crime. A meta-analysis of 34 aggregate data studies (Hsieh & Pugh, 1993) shows that 97% of bivariate correlation coefficients for violent crime with either poverty or inequality were positive, with 80% of the coefficients above 0.25. Ehrlich (1973) finds a positive relationship between relative poverty (percent of population under half the median income in the state) and crime, with higher elasticities for property crime than violent crime. Ehrlich also finds median income in a state to be positively associated with property crime. Machin and Meghir (2000) argue that higher wages at the bottom end of the wage distribution reduce crime, while criminal activity is positively correlated with returns from crime in the United Kingdom. Gould, Weinberg, and Mustard (2002) also find mean wages of non-college educated men and unemployment rate to be significantly related to crime, but find no consistent relationship between mean income and crime rates across U.S. counties. Kelly (2000) finds a strong relationship between income inequality and violent crime across US counties, but finds no such relationship for property crime. Kelly does not control for mean or median income. Blau and Blau (1982) find that both between-race and within–race economic inequality are associated with criminal violence across U.S. states. Lederman et al. (2001) argue that increases in income inequality and lower growth rates lead to increases in violent crime across countries. Using panel data for approximately 39 countries, Fajnzylber et al. (2001) report similar findings for homicide and robbery rates across countries. Lederman et al. (2001) also argue that higher social capital, measured using levels of trust in each country, leads to lower rates of homicides. Kennedy, et al. (1998), using data on 39 U.S. states, find that inequality affects violent crime mostly through its effect on social capital.

There are several important limitations worth mentioning in this literature. First, the unit of observation for which crime is examined is relatively large. The work cited above refers mostly to cross-country studies and analyses of states and large metropolitan areas in the U.S. It is unlikely that the underlying process that produces crime is the same across countries. Various authors (Kelly, 2000; Chiu and Madden, 1998; Wilson and Daly, 1997) suggest that the appropriate geographical unit to study might well be much smaller, such as a neighborhood, rather than a state, county, or a large metropolitan area. A recent paper by Fafchamps and Moser (2002) looks at crime levels and its correlates in more than 1000 communes in Madagascar but does not address the issue of inequality and crime.

Second, comparability of definitions of crime categories and welfare indicators poses serious problems for most cross-country studies, as does aligning data for various countries for the same time period. For example, Fajnzylber et al (1998) use the Deininger-Squire (1996) inequality data, the problems for which are well documented (Atkinson and Brandolini, 2000).

Third, most studies treat crime markets as closed, meaning that only the characteristics of own area, and not those of neighboring areas, are allowed to influence the crime rates. This may be a justifiable assumption when the unit of observation is a country or a state but quickly loses appeal when geographical units are such that travel for legitimate or illegitimate activities between them is plausible. Even the theoretical work on the determinants of crime has not addressed this issue despite the fact that it is not constrained by the availability of data for small geographical units.[4]

Fourth, few studies highlight the differences between the determinants of property crime and violent crime. One exception is Kelly (2000), who argues that economic theory is better suited to explaining property crime.

Finally, very few studies address the relative importance of economic inequality between groups (e.g. racial or geographical groups), rather than within groups, as a determinant of crime. One study that attempts to address this issue (Blau and Blau, 1982) does not utilize a direct measure of within-group inequality.

In this paper, we address the limitations summarized above. The geographical unit used in the analysis is the police station jurisdiction, which is smaller than the units employed in empirical work that we have encountered in the literature.[5] Using geographical information for each of the police station jurisdictions, we are able to allow explicitly for spatial effects in the analysis. The data further provides us with a detailed breakdown of different types of crimes, defined in the same manner for all of South Africa.[6] Finally, utilizing well-known inequality decomposition techniques, we analyze

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[4] Chiu and Madden (1998) model residential burglaries with an implicit focus on small neighborhoods, but ignore the issue of possible spatial effects by citing empirical work that suggests burglars do not travel too far to commit crime.

[5] The median population for a police station jurisdiction is 18,297 while the median area is approximately 227 square miles. These figures are much smaller in urban areas.

[6] There may be differences in interpretation and reporting across police stations.

the relationship between crime and inequality within and between racial groups in South Africa.

IV. Empirical Strategy

Empirically, we first establish the simple correlation between inequality and various types of crime in South Africa across police station jurisdictions. Next, we consider whether the observed relationships are more consistent with the economic or sociological theories of crime, by controlling for costs and benefits of crime and by comparing the results for violent and property crimes. We also examine the effect on crime of the relative position of a community among neighboring communities in terms of its wealth. Finally, we analyze whether inequalities between racial groups are more relevant in explaining crime levels than inequalities within racial groups.

The dependent variable for the analysis is the number of crimes reported by police station jurisdiction. We regress crime counts by jurisdiction on inequality and a varying set of regressors, always including jurisdiction population as a control, along with dummy variables for each of the nine provinces in South Africa. Because crime counts are discrete and there are zeros and small values in a non-negligible number of police station jurisdictions, we utilize a negative binomial regression model.[7]

Data

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7 See Greene (1997), pages. 931 – 940 for a fuller discussion of models for count data. Goodness of fit tests (as implemented in STATA) has indicated overdispersion, so we have opted to utilize a negative binomial model, of which the Poisson model is a special case.

The data employed for the analysis comes from three main sources. First each household in the 1996 Population Census of South Africa was matched to its local police station jurisdiction, to generate information on household composition, race, education, primary occupation, housing characteristics and access to services for each police station jurisdiction. Second, crime data for 1996 were obtained from the South African Police Service (SAPS). The crime information is a comprehensive database of crimes reported for the entire country by police station jurisdiction. Third, mean per capita expenditure and per capita expenditure inequality were estimated for each police station jurisdiction by applying a recently developed small area estimation technique to the South Africa 1996 Population Census, along with the 1995 October Household Survey and Income and Expenditure Survey. The estimation method is described in Appendix A.

Dependent variables

We analyze six categories of property crime: residential burglary, vehicle theft, armed robbery with aggravated circumstances, rape, serious assault, and murder. Summary statistics for these crimes are presented in Table 1. Because theory has different implications for property crime and violent crime, we select crimes that fall, as much as possible, exclusively into one category or the other. Burglary and vehicle theft are property crimes that are generally non-violent, while serious assaults and rapes are violent crimes with no apparent direct pecuniary benefit to perpetrators.[8] We also examine two additional crimes that do not fall cleanly into one category but are often studied in the literature: murder and armed robbery. Although both are crimes that are

[8] Vehicle thefts exclude carjackings.

violent in nature, robberies—and sometimes murders—are primarily motivated by material gain.

Welfare indicators

The measure of inequality employed in the analysis is the mean log deviation (Generalized Entropy inequality measure with c = 0).[9] Mean log deviation takes the following form:

$$I_0 = -\sum_i f_i \log(\frac{y_i}{m}),$$

where f_i refers to the population share of household i, y_i is the household's per capita expenditure, and m is mean per capita expenditure for the area in question.

To control for the returns from crime, we use mean expenditure in own jurisdiction, as this will likely be highly correlated with transferable assets. One would also like to control for the legitimate earnings opportunities for individuals who are likely to commit crimes. We use unemployment rate in the catchment area as a proxy for the opportunity cost of crime.[10] We also introduce a dummy variable that indicates whether the jurisdiction is the richest in the criminal catchment area.

[9] We will use the median expenditure, GE(1), and the Gini Index in a future draft of this paper to test the robustness of the results to the choice of the welfare indicators.

[10] Gould et al. (2002) suggest that wages may be a better measure for labor markets prospects of potential criminals, because, they argue, unemployment is often short-lived and cyclical. However, duration of unemployment in South Africa is significantly higher. According to

We decompose our inequality measure to examine inequalities within and between racial groups in relation to crime.[11] Generalized Entropy inequality measures can be additively decomposed into a between and within-group component along the following lines:

$$I_0 = [g_j \log(\frac{m}{m_j})] + \sum_j I_j g_j$$

where *j* refers to sub-groups, g_j refers to the population share of group *j* and I_j refers to inequality in group j. The between-group component of inequality is captured by the first term to the right of the equality sign. It can be interpreted as measuring what would be the level of inequality in the population if everyone within the group had the same (the group- average) consumption level μ_j. The second term on the right reflects what would be the overall inequality level if there were no differences in mean consumption across groups but each group had its actual within-group inequality I_j.

Other explanatory variables

We test the sensitivity of the results by introducing additional control variables that may be associated with crime levels. Population density may be an important

Rama (2001), 38% of the unemployed stayed out of a job for more than three years in 1999. In any event, data on wages is not available for police station jurisdictions in South Africa.

[11] In South Africa, the census allows for five "population groups": African, White, Colored, Asian/Indian, and "other". Due to data availability limitations, we collapse these into three separate categories—African, White, and other—which we refer to throughout the paper as "racial groups."

determinant of crime, either by increasing the supply of potential victims who do not know the criminal, or by reducing the chances of apprehension (Kelly, 2000). Population density is defined as the number of persons per square kilometer. We also employ the percentage of households headed by a female, which has been used as an indicator of instability, disorientation, and conflict in personal relations in the sociological literature (for example, Blau and Blau, 1982). Finally, it has been suggested that youth may be more prone to crime (Cohen and Land, 1987). We have created a variable that is equal to the percentage of population aged 21-40 for use in the empirical models.[12]

Finally, we include race as a control variable. Kelly (2000) argues that race is a predictor of crime through social isolation and feelings of hopelessness in black communities in the U.S. Race may also be associated with other factors linked to crime. For example, our analysis of the South Africa's 1998 Victims of Crime Survey shows race to be a strong correlate of private and public protection. Blacks are less likely than those in other racial groups to have private forms of protection (alarms, high walls, fences, armed security, guns) and also collective action (neighborhood watch).[13]

V. Results

Main Results

Figures 1-4 show log-log scatter plots of per capita crime levels versus inequality. There is a positive correlation for all four crimes shown. The same relationship is seen in

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[12] Analysis with alternative definitions of this variable, using different age groups or only males, produced results similar to those presented in this paper.

[13] Detailed information available from the authors.

the regression results using the most basic specification, shown in Table 2. These are negative binomial regressions with crime counts as the dependent variable and inequality, population, and province dummies on the right hand side. Because all non-dummy variables are in log form, the coefficients can be interpreted as elasticities. The elasticities range from 0.53 for rape to 1.17 for burglary.

The bivariate correlations between mean per capita expenditure and crime rates are shown in Figures 5-8. Absent any additional controls, property crimes are strongly and positively associated with average estimated expenditure in the police station jurisdiction. The correlation between violent crimes and mean expenditure is weaker and has somewhat of an inverted U-shape.

In the analysis shown in Table 3, we regress crime rates on inequality and mean per capita expenditure. Adding mean expenditure greatly increase the explanatory power of the property crime regressions, but has negligible impact on the pseudo-R-squared for the violent crime regressions. Once mean expenditure is controlled for, the correlation between inequality and vehicle theft completely disappears, while the coefficients on inequality for other crimes fall substantially but remain positive and significant. The coefficients on mean expenditure show strong relationships with property crime and a weaker association with violent crime. The elasticities on mean expenditure for burglary and vehicle theft, which are 0.97 and 1.77 respectively, are high relative to those for violent crime. This is consistent with our assertion that mean expenditure per capita may proxy the returns to property crime.

Table 4 presents results from analysis that includes an additional control for unemployment in each jurisdiction's criminal catchment area. In the absence of earnings data for potential criminals, we suggest that the employment rate may capture the opportunity cost of crime. The coefficients on inequality and mean expenditure are virtually unchanged in this specification, while we find no association between unemployment and crime, other than the small negative coefficient on vehicle theft, significant only at the 10% level. These results represent our best effort to control separately for the costs and benefits of crime for potential criminals. Clearly, the mean expenditure and unemployment variables may have other, more complicated relationships to crime rates. For example, unemployment may capture not only opportunity costs for potential criminals, but also part of the value of transferable assets, and thus the benefits of crime. An insignificant or weak negative relationship between unemployment and crime is not an uncommon finding in the literature (Kelly, 2000; Ehrlich, 1973) and we revisit the issue later in the paper (see Table 9).

Next we consider the impact of the rank of a jurisdiction's wealth among its neighbors. In Table 5, we include a dummy variable equal to one if the jurisdiction has the highest per capita expenditure among jurisdictions in its criminal catchment area. Controlling for inequality and mean expenditure in own jurisdiction, and unemployment in the catchment area, burglary rates are 20% higher in jurisdictions that are the wealthiest among their neighbors. This is consistent with the hypothesis that burglars travel to neighboring areas where the expected returns are highest. The coefficient on the richest jurisdiction dummy is insignificant for other crimes. The fact that we find a significant link between a jurisdiction's relative rank and burglary, but not other crimes, is not surprising. There is no theoretical reason to suppose that violent crime should be associated with a jurisdiction's wealth, while vehicle thefts are much less clearly linked to the characteristics of the area in which the crime is reported.

Next we examine the relationship between crime and inequality within and between racial groups. Table 6 presents the results of the decomposition of overall inequality in each police station jurisdiction into its within and between racial group components. Table 6 shows that, on average, 36% of inequality in a police station jurisdiction can be attributed to differences in mean levels of expenditure between racial groups.

Table 7 repeats the analysis shown in Table 5, but reports parameter estimates for within and between-group inequality, instead of overall inequality. The motivation here is to shed some light on the hypothesis that economic inequalities between racial groups are particularly important in the generation of crime, especially violent crime. The results are surprising. Almost all of the association between inequality and levels of crime can be attributed to inequality within racial groups. While within-group inequality has a large and positive correlation with burglaries, assaults, and rapes, between-group inequality has a very small correlation with burglaries and no association with any other crimes. It is inequality among Africans, Whites, or others, and not inequality across these groups that is most related to violent crime levels. Decomposing inequality into within and between-group components does not substantially affect the other parameter estimates.

Misreporting in Crime

Underreporting is a potentially serious but frequently neglected problem in the crime literature. There is often the danger that the observed relationships between crime and other variables reflect correlations with crime misreporting. It is generally difficult to deal with this problem due to the absence of independent data on crime reporting.[14] In South Africa, however, the nationally representative Victims of Crime Survey (VCS) was conducted in 1998, in which households were asked whether crimes they experienced were reported to the police. Summary statistics for selected crimes are presented in Table 8. The definitions of the crime categories in the VCS differ from those in the SAPS data, and hence the figures in this table are meant to be only suggestive of possible underreporting. According to the VCS data, underreporting is a particularly serious problem for robbery and is least serious for theft of vehicles.

Measurement error in the dependent variable is a problem in regression analysis to the extent that it is correlated with some of the regressors in the model. In the case of crime misreporting, if, for example, only wealthy people reported crime or the police only filed official reports for complaints by the rich, then one would find a correlation between wealth and *reported* crime regardless of the true relationship between wealth and crimes committed.

To examine the extent to which misreporting effects the results presented in Tables 2-7, we repeat the analysis using adjusted crime statistics. We conduct the analysis exclusively for residential burglary, which, unlike other crimes, both appears frequently in the victims survey and has nearly identical definitions in the VCS and SAPS

[14] Glaeser and Sacerdote (1999) adjust reported crime rates in the Uniform Crime Reports using independent data on reporting from the National Crime Victimization Survey in the U.S.

data. For respondents in the VCS, who said they were victims of burglary in the five years previous to the survey, we estimate a probit regression for whether the crime was reported to the police. We use the same explanatory variables, at the police station jurisdiction level, as in our earlier analysis: inequality, per capita expenditure, unemployment, and the richest jurisdiction dummy. The results of this regression are shown in the first column of Table 9. Unemployment in the criminal catchment area is negatively correlated with the probability of a residential burglary being reported by a household, while per capita expenditure has a positive parameter estimate that is only significant at the 10% level. We use the coefficient estimates from this regression to predict, for each jurisdiction, the probability p that a burglary was reported to the police. We then calculate an adjusted count of burglaries for each police station by multiplying the reported number of crimes by $1/p$. Columns 2-5 in Table 9 present the results from analysis using the adjusted burglary counts as the dependent variable for four regression models previously estimated in Tables 2-6. Column 6 redisplays earlier results from the full specification (same as column 5) using unadjusted counts as the dependent variable. Compared with the earlier results the elasticities of inequality and per capita expenditure are still positive and significant but somewhat attenuated. As underreporting is more likely in areas with higher unemployment, the adjustment causes the elasticity of unemployment to also become positive and significant –suggesting that unemployment does capture the opportunity cost of crime for potential criminals to a certain extent. This analysis also confirms that misreporting in crime may bias parameter estimates. Nonetheless, the results we derive for residential burglary remain broadly the same:

burglaries are more likely to take place in wealthier areas, which are unequal, and in particular those that have the highest mean expenditure among their neighbors.

Are the results robust to the inclusion of other explanatory variables?

Researchers have suggested that many factors other than economic welfare may be related to the prevalence of crime in a community. In this subsection, we examine whether these variables are consistently associated with crime in South Africa, and assess whether the parameter estimates for the welfare indicators are sensitive to their inclusion.[15]

Tables 10-13 present the results for each of the four crime types included in the analysis. Percentage of individuals aged 21-40 in the jurisdiction is strongly correlated with all types of crime, with a consistently large elasticity for all types of crime. Population density is also significantly correlated with property crime levels, albeit the elasticity is small. Race (measured by percentage of African households in jurisdiction) and percentage of female-headed households have no consistent correlation with crime levels.

The parameter estimates for the welfare indicators are generally robust to the inclusion of these variables in the regression models. The qualitative results are identical for residential burglaries, i.e. they are positively correlated with mean expenditure, inequality in the jurisdiction, and with the dummy variable for the richest community in the criminal catchment area. With additional controls, inequality and being the richest community have a positive but not consistently significant correlation with vehicle thefts.

[15] Tables of pairwise correlations for these variables are shown in Appendix Table 1.

Mean expenditure levels remain the strongest correlate of vehicle thefts in a community. Regarding violent crimes, the coefficient on mean expenditure for either crime type is unstable, once covariates are introduced. The effect of inequality in jurisdiction remains positive and significant for both assaults and rapes, and being the richest jurisdiction locally has no correlation with violent crime levels.

Are the results robust to the specification of functional form?

We have used a count model for the regression analysis of crime *levels*, with a control for population. However, some researchers have utilized OLS regressions for similar analysis of crime *rates* (typically, crimes per 100,000 individuals). To test the sensitivity of the results to the regression specification and to better compare the results to others in the literature, we reestimate the models using an OLS specification, regressing log crime rates on logs of the same explanatory variables.

Table 14 presents the results for our most basic specification, in which only inequality is considered. Inequality is still strongly associated with all crimes, but the elasticities are consistently higher using OLS regressions. Table 15 shows that, conditional on mean per capita expenditure, inequality is positively associated with all crimes except vehicle thefts with the elasticities again substantially larger than those from the negative binomial regressions. The association between mean expenditure and property crime is the same as before, while the small positive association in the earlier models between mean expenditure and serious assault disappears. Furthermore, adding unemployment in the criminal catchment area and a richest jurisdiction dummy to the regression model (see Tables 16 & 17) generates no more differences in the results.

Lastly, Table 18 presents the results of the specification where we examine the association between crime and inequality within and between groups. Inequality within racial groups is strongly correlated with all types of crime with consistently large elasticities, while inequality between groups is positively correlated with burglary, assault, and rape but the elasticities are small—all less than 0.15.

In summary, the OLS results are broadly similar to those from the negative binomial regressions. Mean expenditure levels are strongly correlated with property crimes, while inequality is positively correlated with all crimes with the exception of vehicle thefts. Jurisdictions that are the wealthiest in their criminal catchment area are more likely to experience residential burglaries than their neighbors. The association between inequality and crime is mostly due to inequality within racial groups, although between-group inequality may have a small association with crime as well.

Murder and Robbery

Many studies on crime examine murders and robberies. Murder is often studied because it is thought to suffer least from reporting problems and is one of the most violent crimes. Robberies are usually referred to as violent crimes as well despite the fact that the primary motivation of a robbery is largely economic. In this subsection, we demonstrate that while murders fit well within the general picture of violent crimes, robberies fit much better with property crimes.

Table 19 shows the results of negative binomial regressions for murder and armed robbery. The results for murder are similar to those for assault and rape. Murder levels have a small positive association with mean expenditure levels and are positively correlated with inequality. The elasticity of murder with respect to inequality within or between racial groups is insignificant. Robbery, on the other hand, exhibits the common characteristic of property crimes – it is highly correlated with mean expenditure in the jurisdiction.

VI. Conclusions

Both theoretical and empirical papers in the crime literature have called for an analysis of crime at a smaller level of geographical disaggregation than countries, states or large metropolitan areas. When the unit of analysis is large, not only is there loss of information regarding relative welfare levels across neighborhoods, but also the fact that individuals may travel to conduct criminal activities is ignored. In this paper, utilizing data on crime and welfare in all police station jurisdictions in South Africa, we have analyzed the effect of local inequality on crime. Although, the contribution of this paper is mainly empirical, we have also suggested a pathway for the generation of property crimes in a jurisdiction that takes into account the distribution of welfare in the surrounding area, and not just within its own borders.

Starting with property crimes, the empirical results indicate that inequality is highly correlated with both burglary and vehicle theft, but once mean expenditure in own jurisdiction and unemployment in the catchment area are controlled for, this correlation becomes smaller for burglary and disappears completely for vehicle theft. Property crime is strongly correlated with mean expenditure in the jurisdiction, indicating that returns from crime are major determinants of property crimes. If wealthier communities have more effective protection from crime, the elasticity of residential burglaries with respect to mean expenditure, controlling for protection, may be even higher. Considering the welfare levels in neighboring jurisdictions, we show that jurisdictions that are the wealthiest jurisdiction in their criminal catchment areas have higher levels of burglary. That the locally wealthiest neighborhoods are hotspots for residential burglary is consistent with the story that burglars travel based on information on welfare levels of different neighborhoods. At the same time, that burglaries do not occur exclusively in such areas suggests that there are travel costs, that burglars have more idiosyncratic information regarding houses in their own neighborhood, or that the level of protection varies between jurisdictions.

Violent crimes, our results indicate, are more likely to happen in areas with high expenditure inequality but are not consistently correlated with mean expenditure levels. Controlling for unemployment, mean expenditure and other covariates does not substantially reduce the correlation between inequality and violent crime. Most of the correlation between overall inequality and violent crimes is attributable to inequality within racial groups, although between-group inequality also has a significant but very small correlation with crime. This finding is at odds with the suggestion that "…economic inequalities matter, but ascribed inequalities do so particularly". (Blau and Blau, 1982)

The results support the sociological theories of crime, especially with respect to violent crimes. Beckerian economic theory of crime does not predict any correlation between inequality and crime other than via a correlation with the differential returns from such crimes. That we find a conditional correlation of inequality with burglaries and violent crimes lends support to theories that suggest that inequality may lead to higher crime levels through other, non-economic, channels.

Some economic and sociological theories of crime suggest that there may be a positive relationship between poverty and crime levels. We have not explored this in our empirical analysis, mainly because mean expenditure and poverty are very highly and negatively correlated in our data set – the correlation coefficient is -0.87.[16] The results are robust to the inclusion of other covariates that may also be important factors in explaining the variation in crime levels. They are also robust to the specification of functional form. The parameter estimates for burglaries change somewhat when we introduce a correction for underreporting, suggesting that misreporting in crime may bias results in similar studies. However, the basic results stand. Unemployment in the criminal catchment area, a proxy for the opportunity cost of crime, becomes positively correlated with burglaries once crime counts are adjusted for underreporting.

We hesitate to draw policy implications from analysis using cross-sectional data without a strong identification strategy, especially given that a direct indicator of the most visible policy tool, public expenditures on crime prevention, is missing from the empirical analysis. Nonetheless, we note the following. First, regarding prevention efforts for various property and violent crimes, policymakers may want to focus on

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[16] When poverty rate, measured by the headcount index, is included in the regression models for burglary with inequality as the only other regressor, it has an elasticity of -0.56 that is statistically significant. Controlling for only mean expenditure, it has a positive and significant elasticity of 0.21. When all three welfare measures are included in the regression model, poverty has no correlation with burglary.

different elements, as it is likely that different mechanisms are responsible for the generation of each type of crime. Second, increasing the public supply of resources for prevention in high property crime areas would be regressive, because these crimes are most likely to occur in richer neighborhoods. Governments may care as much about equitable distribution of public resources as marginal benefit of the extra resources spent (Behrman & Craig, 1987). Third, policies that help reduce economic inequalities between neighborhoods within a local administration may also help reduce property crime levels, particularly residential burglaries. Finally, policy-makers would do well to worry about the distribution of income when devising strategies for economic growth, as the welfare benefits from growth may be attenuated by decreased safety if such growth is accompanied by increased inequality.

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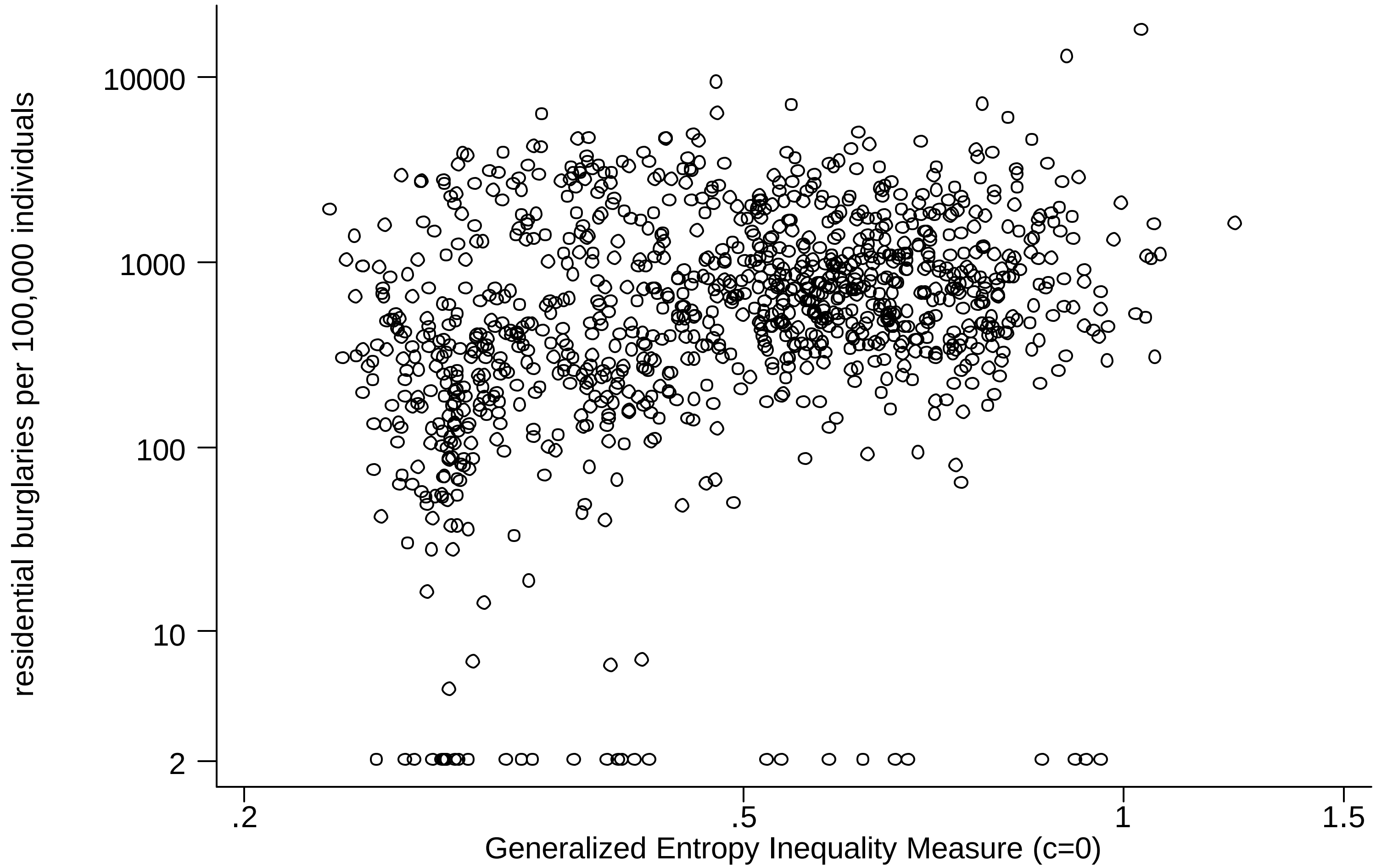
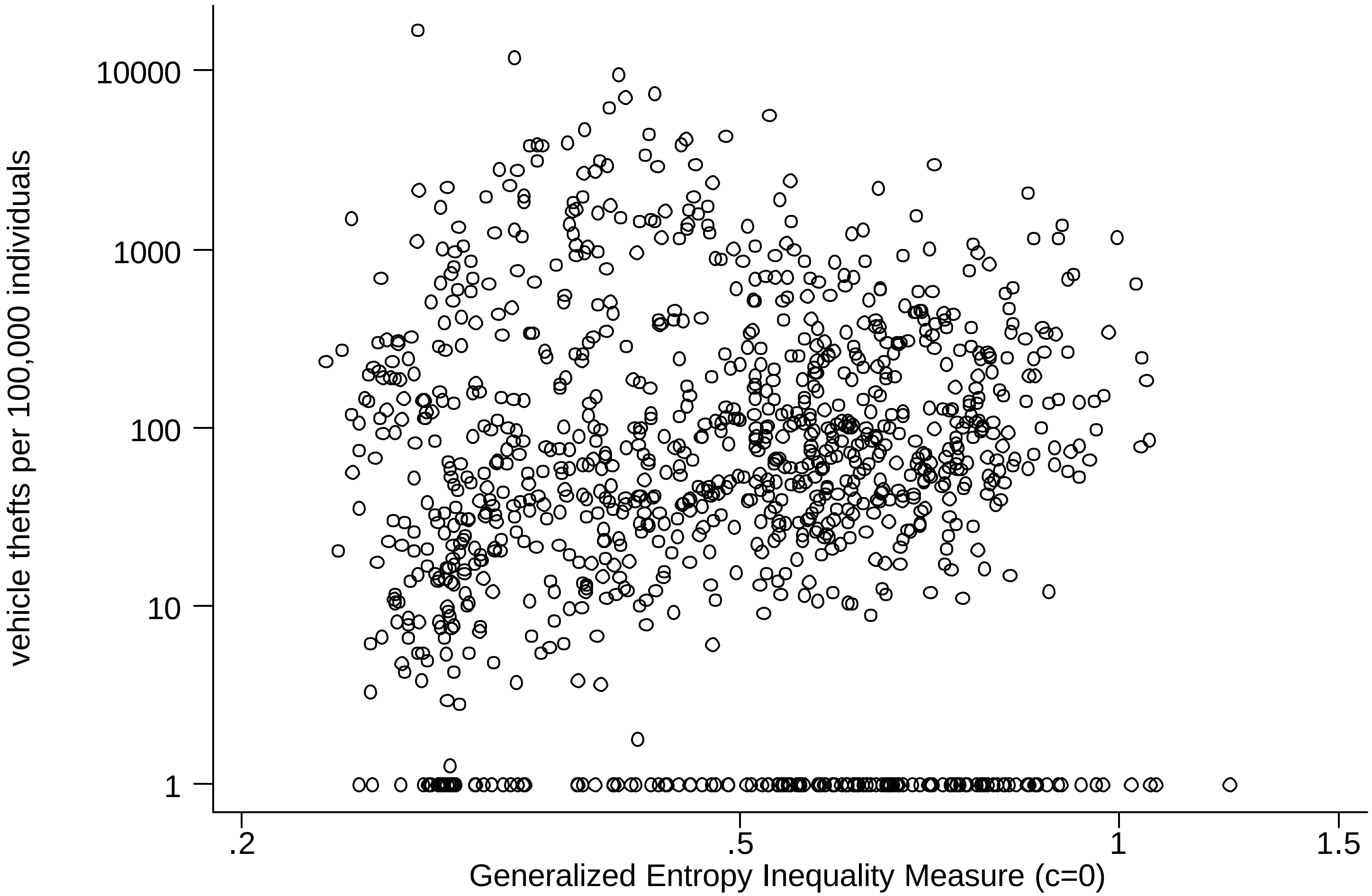
Figure 1: Inequality and Residential Burglaries per Capita



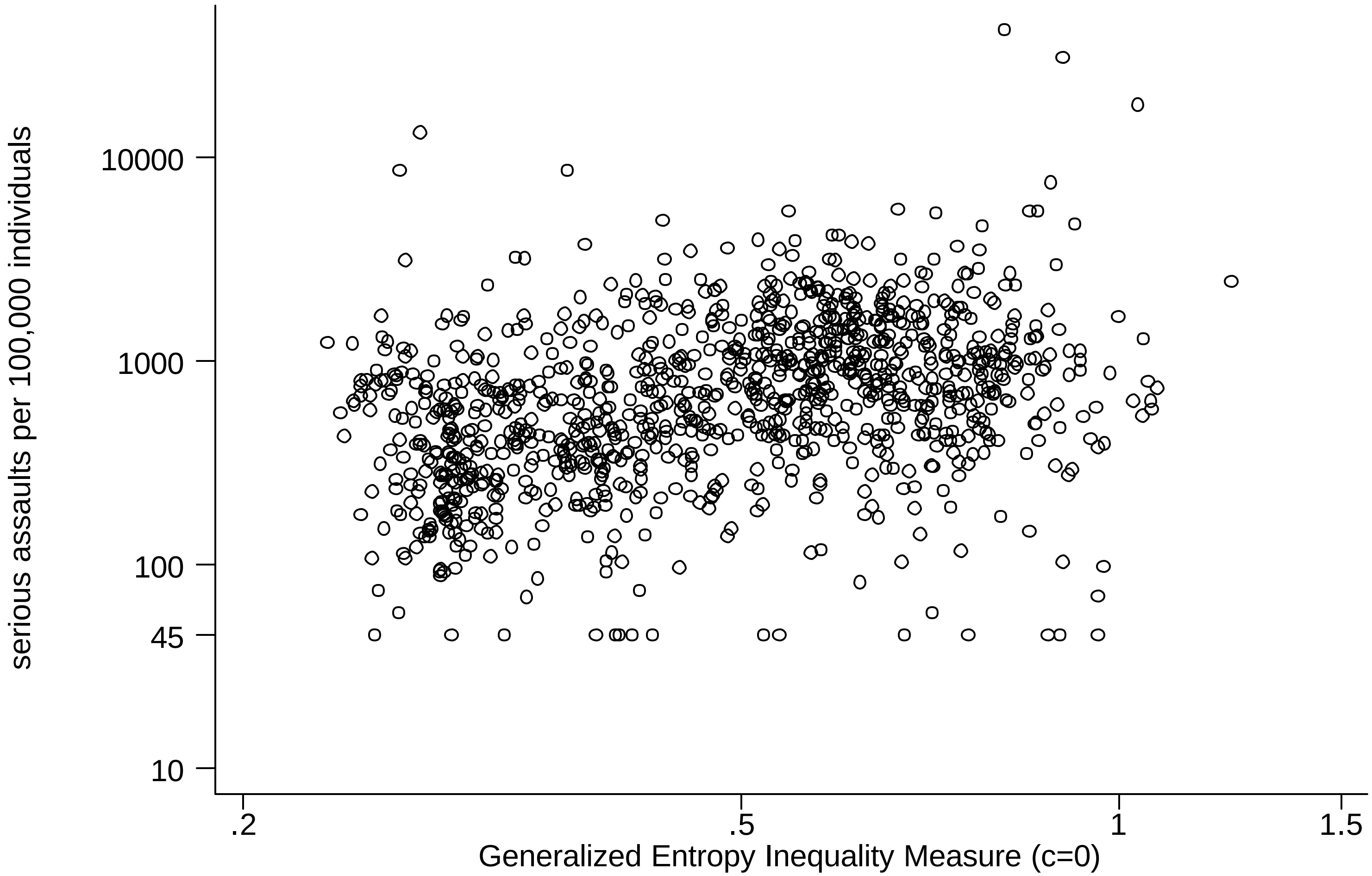
Both variables are in logarithms. Observations where residential burglaries were equal to zero have been replaced by the smallest values in the sample.

Figure 2: Inequality and Vehicle Thefts per Capita



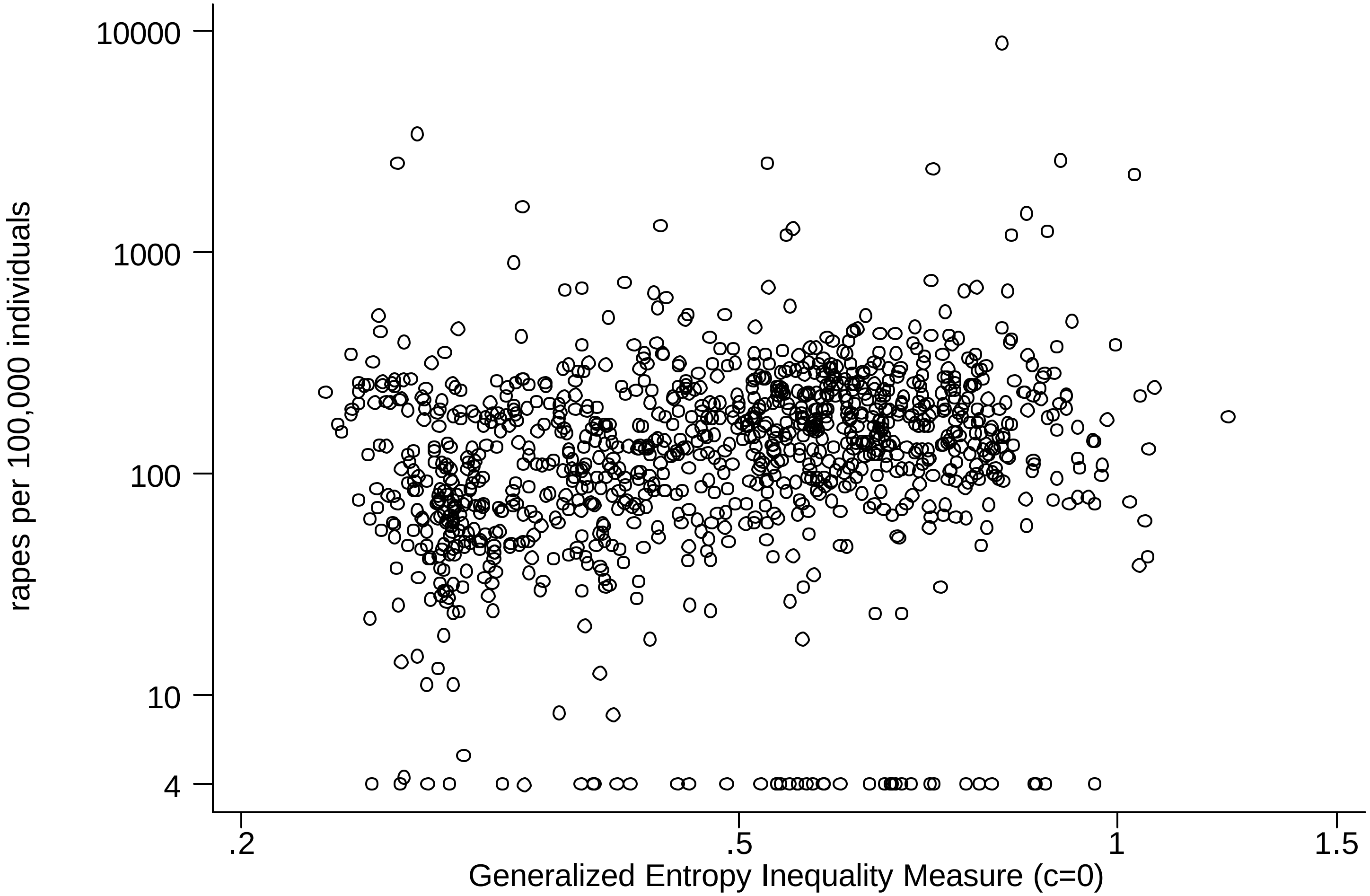
Both variables are in logarithms. Observations where vehicle thefts were equal to zero have been replaced by the smallest values in the sample.

Figure 3: Inequality and Serious Assaults per Capita



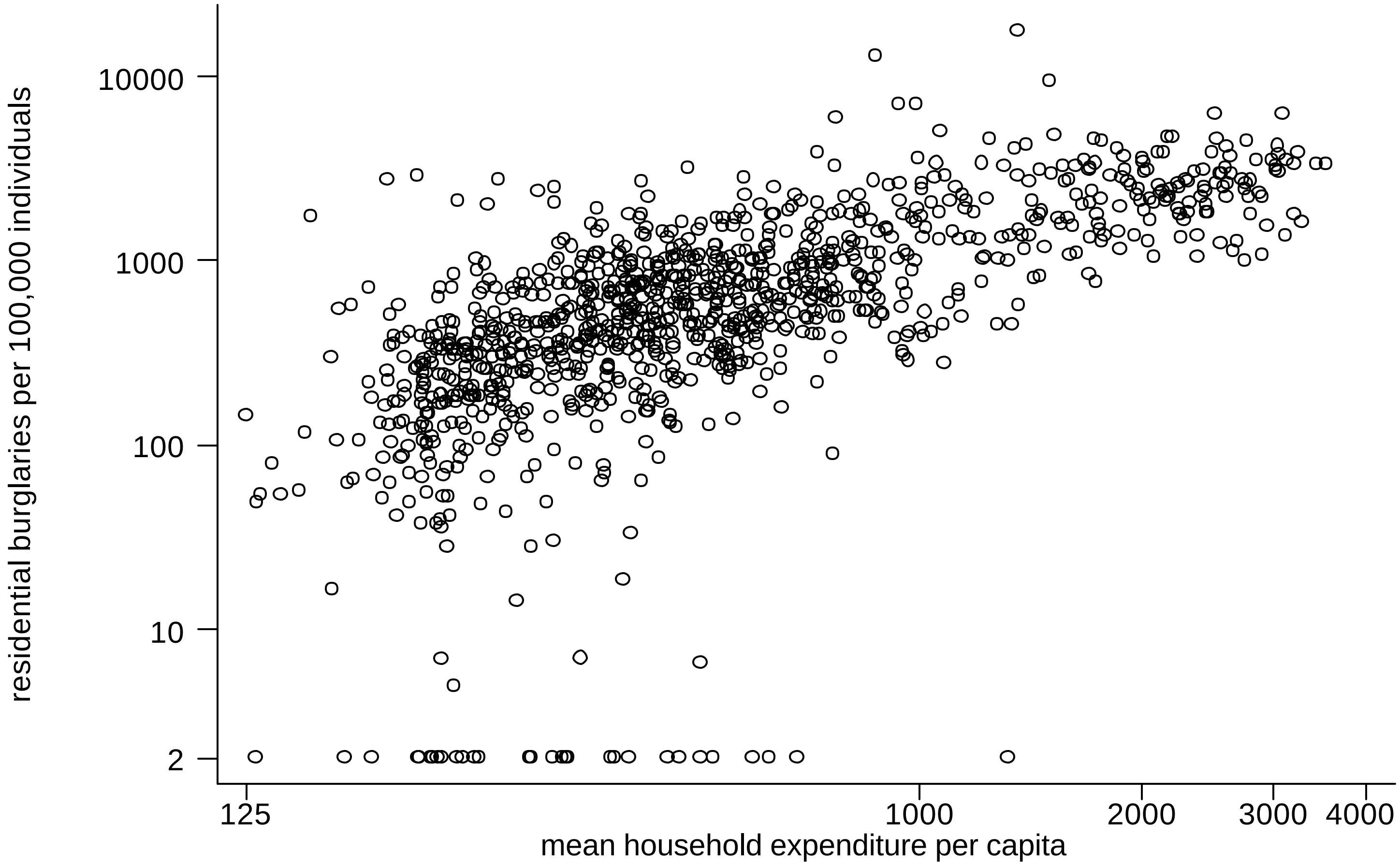
Both variables are in logarithms. Observations where serious assaults were equal to zero have been replaced by the smallest values in the sample.

Figure 4: Inequality and Rapes per Capita



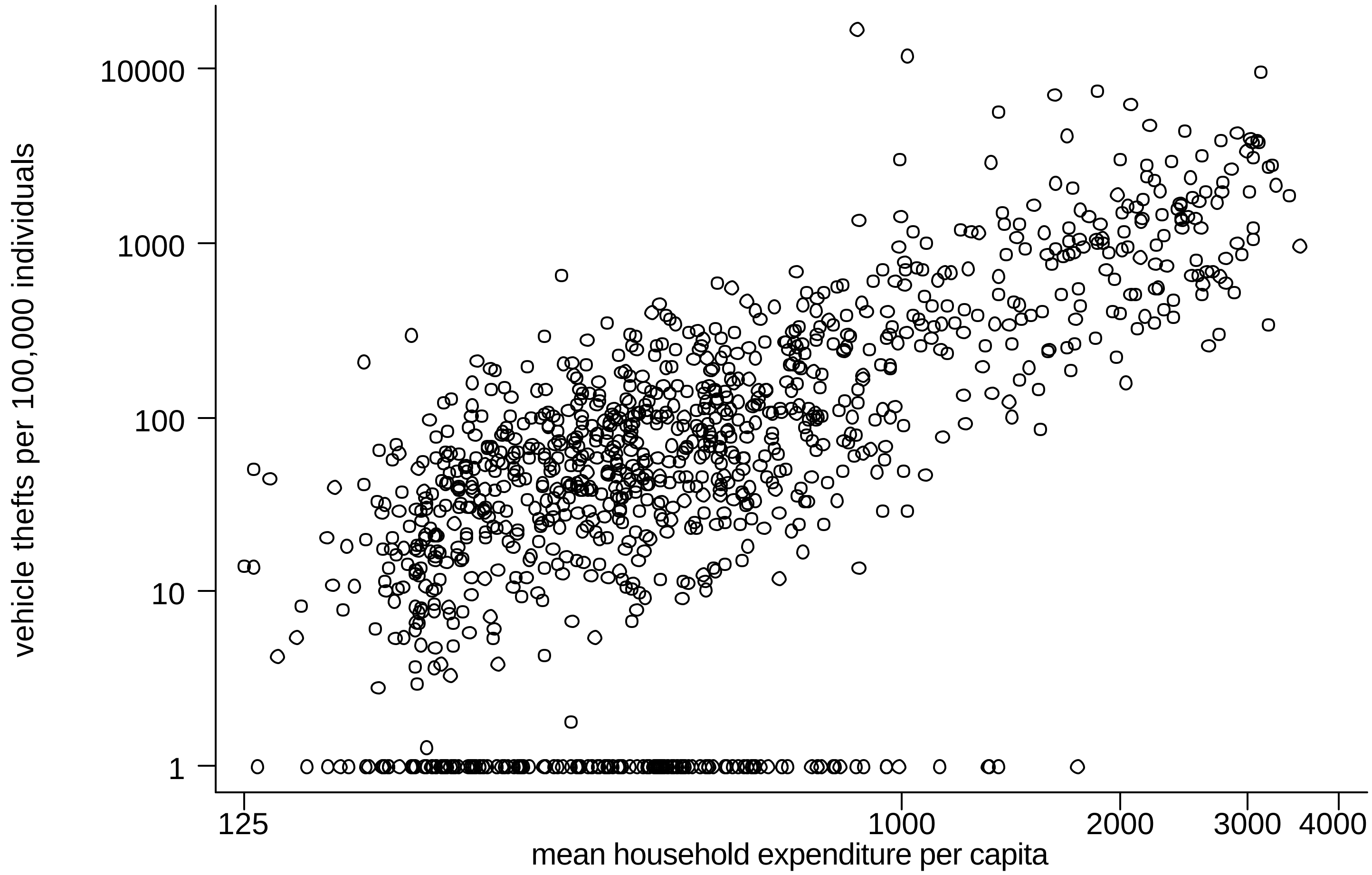
Both variables are in logarithms. Observations where rapes were equal to zero have been replaced by the smallest values in the sample.

Figure 5: Average Expenditure and Residential Burglaries per Capita



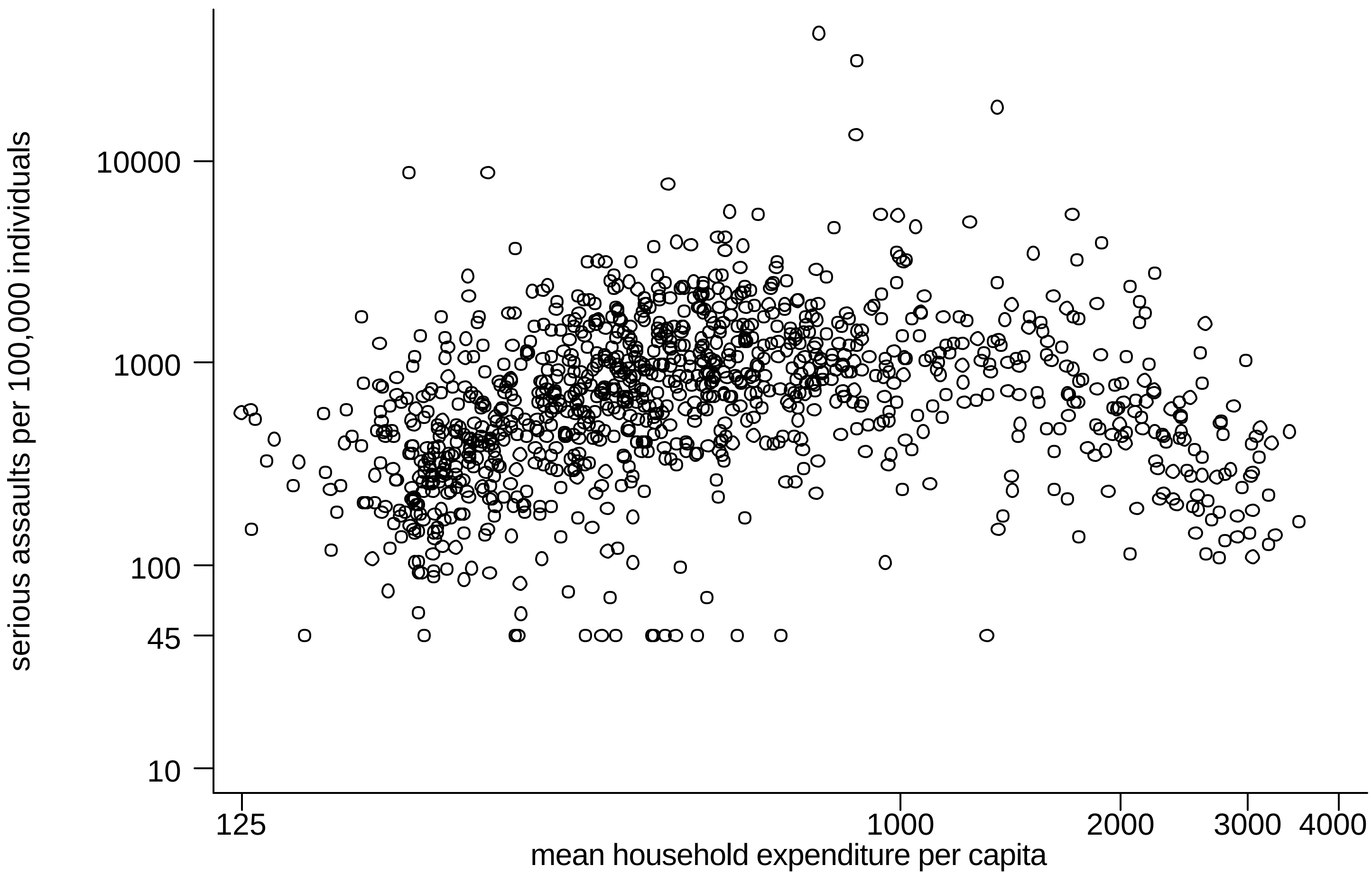
Both variables are in logarithms. Observations where residential burglaries were equal to zero have been replaced by the smallest values in the sample.

Figure 6: Average Expenditure and Vehicle Thefts per Capita



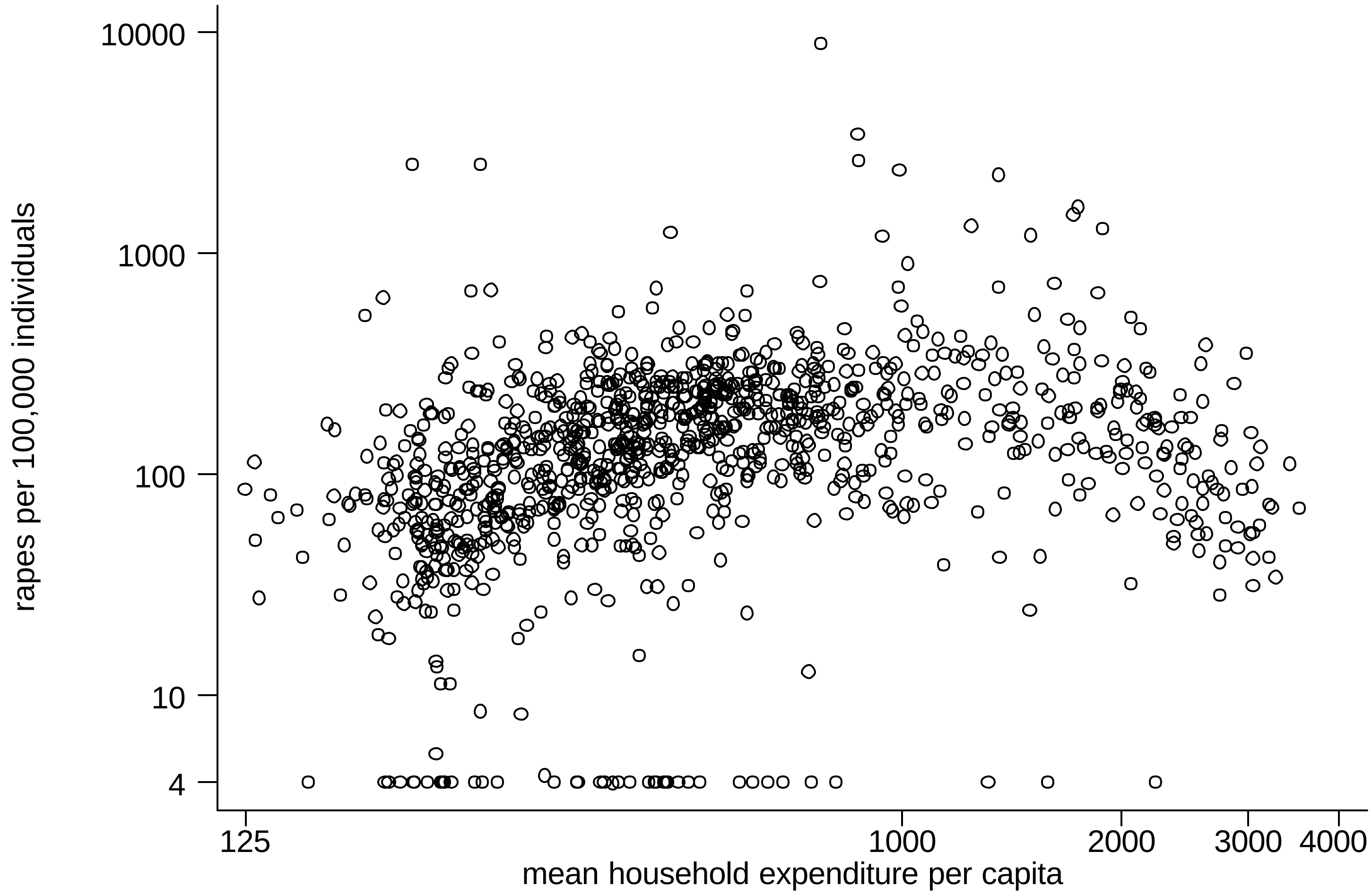
Both variables are in logarithms. Observations where vehicle thefts were equal to zero have been replaced by the smallest values in the sample.

Figure 7: Average Expenditure and Serious Assaults per Capita



Both variables are in logarithms. Observations where serious assaults were equal to zero have been replaced by the smallest values in the sample.

Figure 8: Average Expenditure and Rapes per Capita



Both variables are in logarithms. Observations where rapes were equal to zero have been replaced by the smallest values in the sample.

Table 1: Summary Statistics by Type of Crime

Variable	Mean	Minimum	Maximum
Residential burglary	963	0	17,834
Vehicle Theft	319	0	16,553
Serious assault	1,002	0	41,848
Rape	185	0	8,696
Murder	89	0	3,804
Robbery with aggravated circumstances	155	0	7,781

Crime variables are reported per 100,000 inhabitants for the year 1996. The figures are for 1,066 police station jurisdictions. The means reported here are simple means, i.e. not weighted by population size.

Table 2: Crime and Inequality

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	1.17 (0.09)**	0.74 (0.15)**	0.57 (0.08)**	0.53 (0.08)**
Population	0.86 (0.02)**	0.95 (0.04)**	0.79 (0.02)**	0.86 (0.02)**
Province Dummies				
Eastern Cape	-0.88 (0.10)**	-1.02 (0.16)**	-0.18 (0.09)*	-0.21 (0.08)*
Northern Cape	-1.21 (0.13)**	-1.94 (0.23)**	-0.03 (0.11)	-0.25 (0.11)*
Free State	-0.93 (0.12)**	-1.03 (0.20)**	-0.50 (0.10)**	-0.26 (0.10)**
Kwazulu-Natal	-0.51 (0.10)**	0.50 (0.16)**	-0.72 (0.09)**	-0.16 (0.08)*
Northwest Province	-1.03 (0.13)**	-0.94 (0.21)**	-0.30 (0.11)**	-0.05 (0.10)
Gauteng	0.69 (0.11)**	1.76 (0.18)**	0.03 (0.10)	0.45 (0.09)**
Mpumalanga	-0.39 (0.12)**	-0.11 (0.20)	-0.28 (0.10)**	-0.07 (0.10)
Northern Province	-0.99 (0.13)**	-1.07 (0.22)**	-0.02 (0.11)	-0.25 (0.11)*
Constant	-2.06 (0.23)**	-4.83 (0.40)**	-2.03 (0.18)**	-4.57 (0.19)**
Pseudo R^2	.075	.081	.076	.123
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 3: Crime, Inequality and Mean Expenditure

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	0.56 (0.08)**	-0.05 (0.10)	0.43 (0.09)**	0.30 (0.08)**
Mean Expenditure in Police Station	0.97 (0.04)**	1.77 (0.05)**	0.21 (0.05)**	0.28 (0.04)**
Population	0.82 (0.02)**	0.95 (0.03)**	0.78 (0.02)**	0.84 (0.02)**
Province Dummies				
Eastern Cape	-0.03 (0.08)	0.84 (0.12)**	-0.08 (0.09)	-0.03 (0.08)
Northern Cape	-0.31 (0.11)**	0.17 (0.17)	0.08 (0.11)	-0.05 (0.11)
Free State	0.13 (0.10)	1.16 (0.15)**	-0.33 (0.11)**	0.01 (0.11)
Kwazulu-Natal	0.11 (0.08)	1.31 (0.12)**	-0.66 (0.09)**	-0.04 (0.08)
Northwest Province	-0.09 (0.10)	1.09 (0.15)**	-0.18 (0.11)	0.15 (0.10)
Gauteng	0.25 (0.09)**	1.43 (0.12)**	-0.08 (0.10)	0.34 (0.09)**
Mpumalanga	0.30 (0.10)**	1.46 (0.14)**	-0.22 (0.10)*	0.05 (0.10)
Northern Province	-0.19 (0.10)	0.67 (0.15)**	0.06 (0.11)	-0.09 (0.11)
Constant	-8.94 (0.32)**	-18.39 (0.49)**	-3.44 (0.36)**	-6.48 (0.34)**
Pseudo R^2	0.118	0.170	0.078	0.127
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 4: Crime, Inequality, Mean Expenditure and Unemployment

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	0.56 (0.08)**	-0.02 (0.10)	0.43 (0.09)**	0.30 (0.08)**
Mean Expenditure in Police Station	0.97 (0.04)**	1.69 (0.06)**	0.18 (0.05)**	0.28 (0.05)**
Unemployment in Criminal Catchment Area	-0.01 (0.06)	-0.18 (0.09)*	-0.07 (0.07)	-0.01 (0.06)
Population	0.82 (0.02)**	0.97 (0.03)**	0.79 (0.02)**	0.85 (0.02)**
<u>Province Dummies</u>				
Eastern Cape	-0.02 (0.10)	1.00 (0.15)**	-0.02 (0.11)	-0.03 (0.10)
Northern Cape	-0.30 (0.11)**	0.27 (0.17)	0.13 (0.12)	-0.05 (0.12)
Free State	0.14 (0.11)	1.22 (0.15)**	-0.30 (0.11)**	0.02 (0.11)
Kwazulu-Natal	0.12 (0.10)	1.44 (0.13)**	-0.60 (0.11)**	-0.04 (0.10)
Northwest Province	-0.08 (0.11)	1.18 (0.16)**	-0.13 (0.12)	0.16 (0.11)
Gauteng	0.26 (0.09)**	1.52 (0.13)**	-0.03 (0.11)	0.34 (0.10)**
Mpumalanga	0.31 (0.11)**	1.56 (0.15)**	-0.17 (0.12)	0.05 (0.11)
Northern Province	-0.18 (0.12)	0.83 (0.17)**	0.13 (0.13)	-0.08 (0.12)
Constant	-8.94 (0.32)**	-18.41 (0.49)**	-3.46 (0.36)**	-6.48 (0.34)**
Pseudo R^2	.118	.170	.078	.127
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 5: Crime and the Distribution of Welfare in Criminal Catchment Area

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	0.55 (0.08)**	-0.02 (0.10)	0.42 (0.09)**	0.30 (0.08)**
Mean Expenditure in Police Station	0.92 (0.05)**	1.67 (0.07)**	0.16 (0.06)**	0.27 (0.05)**
Unemployment in Criminal Catchment Area	-0.04 (0.06)	-0.21 (0.09)*	-0.09 (0.07)	-0.01 (0.07)
Richest Jurisdiction in Criminal Catchment Area	0.20 (0.07)**	0.09 (0.10)	0.10 (0.08)	0.04 (0.07)
Population	0.82 (0.02)**	0.97 (0.03)**	0.78 (0.02)**	0.84 (0.02)**
Province Dummies				
Eastern Cape	-0.02 (0.10)	1.01 (0.15)**	-0.01 (0.11)	-0.02 (0.10)
Northern Cape	-0.30 (0.11)**	0.27 (0.17)	0.13 (0.12)	-0.05 (0.12)
Free State	0.12 (0.11)	1.21 (0.16)**	-0.30 (0.11)**	0.02 (0.11)
Kwazulu-Natal	0.13 (0.10)	1.44 (0.13)**	-0.59 (0.11)**	-0.03 (0.10)
Northwest Province	-0.07 (0.11)	1.18 (0.16)**	-0.12 (0.12)	0.16 (0.11)
Gauteng	0.31 (0.10)**	1.54 (0.13)**	-0.01 (0.11)	0.35 (0.10)**
Mpumalanga	0.31 (0.11)**	1.57 (0.15)**	-0.17 (0.12)	0.05 (0.11)
Northern Province	-0.17 (0.12)	0.84 (0.17)**	0.15 (0.13)	-0.07 (0.12)
Constant	-8.69 (0.33)**	-18.31 (0.50)**	-3.34 (0.38)**	-6.44 (0.35)**
Pseudo R^2	.119	.170	.078	.127
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 6: Inequality within and between Racial Groups

	Mean	Minimum	Maximum
Overall Inequality	0.514	0.234	1.228
Within-Group Inequality	0.324	0.198	0.839
Between-Group Inequality	0.189	0	0.785
Share of Between-Group Inequality in Overall Inequality	36.8%	0%	63.9%
Percentage of communities where one racial group accounts for more than 95% of jurisdiction population	32.2	0	1
Index of Racial Heterogeneity	0.264	0	0.666

In South Africa, the population census allows for four specific population groups (African, White, Colored, Asian/Indian) and a fifth category "other". For reasons related to the availability of data, the inequality and racial heterogeneity measures presented here refer to three population groups: African, White, and other. Index of Racial Heterogeneity is equal to one minus the sum of squared shares of each racial group. It can be interpreted as the probability of two households selected at random belonging to different racial groups.

Table 7: Crime and Inequality between Racial Groups

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
***Within*-Racial Group Inequality in Police Station**	0.87 (0.16)**	0.30 (0.22)	1.38 (0.19)**	1.01 (0.18)**
***Between*-Racial Group Inequality in Police Station**	0.07 (0.01)**	0.03 (0.01)	0.02 (0.01)	0.01 (0.01)
Mean Expenditure in Police Station	0.83 (0.05)**	1.60 (0.07)**	0.06 (0.06)	0.21 (0.05)**
Unemployment in Criminal Catchment Area	-0.04 (0.06)	-0.24 (0.09)*	-0.15 (0.07)*	-0.06 (0.07)
Richest Jurisdiction in Criminal Catchment Area	0.19 (0.07)**	0.07 (0.10)	0.08 (0.08)	0.02 (0.07)
Population	0.81 (0.02)**	0.99 (0.03)**	0.73 (0.02)**	0.81 (0.02)**
Province Dummies				
Eastern Cape	-0.22 (0.11)	0.88 (0.16)**	-0.45 (0.12)**	-0.35 (0.12)**
Northern Cape	-0.36 (0.11)**	0.17 (0.17)	0.03 (0.12)	-0.10 (0.11)
Free State	0.05 (0.11)	1.06 (0.15)**	-0.46 (0.11)**	-0.08 (0.11)
Kwazulu-Natal	-0.07 (0.11)	1.35 (0.14)**	-0.89 (0.11)**	-0.25 (0.11)*
Northwest Province	-0.21 (0.12)	1.05 (0.16)**	-0.45 (0.13)**	-0.07 (0.12)
Gauteng	0.27 (0.09)**	1.55 (0.13)**	-0.03 (0.11)	0.33 (0.10)**
Mpumalanga	0.21 (0.11)	1.48 (0.15)**	-0.36 (0.12)**	-0.07 (0.11)
Northern Province	-0.30 (0.14)*	0.72 (0.19)**	-0.32 (0.16)*	-0.42 (0.14)**
Constant	-7.19 (0.49)**	-17.55 (0.70)**	-0.70 (0.56)	-4.68 (0.51)**
Pseudo R^2	.123	.171	.082	.133
Observations	1064	1064	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 8: Reporting in Selected Crime Categories

Crime Category	% Reported to the Police
Theft of Cars, Vans, Trucks or Bakkies	95.0 (2.0)
Housebreaking and Burglary	59.1 (2.2)
Deliberate Killing or Murder	84.2 (3.7)
Robbery Involving Force Against the Person	41.8 (4.8)

All the numbers are authors' own calculations using the Victims of Crime Survey (VCS), 1998, Statistics South Africa. There are 3899 observations in the VCS. The percentages and the standard errors (in parentheses) reflect the complex sample design of the survey, including household weights, stratification, and clustering. The definitions of the crime categories in the VCS are somewhat different than those in the data from SAPS, and hence the figures in this table are meant to be only suggestive of possible underreporting in the SAPS data.

Table 9: Correcting for Misreporting in Residential Burglary

	Probit Results using	Negative Binomial Regression Results using				
	Household reporting of Burglaries	**Adjusted** Burglaries				**Unadjusted** Burglaries
Inequality in Police Station	0.20 (0.19)	0.88 (0.09)**	0.34 (0.08)**	0.35 (0.08)**	0.33 (0.08)**	0.55 (0.08)**
Mean Expenditure in Police Station	0.22 (0.13)		0.77 (0.04)**	0.85 (0.05)**	0.77 (0.05)**	0.92 (0.05)**
Unemployment in Criminal Catchment Area	-0.42 (0.16)**			0.24 (0.06)**	0.19 (0.06)**	-0.04 (0.06)
Richest Jurisdiction in Criminal Catchment Area	-0.14 (0.21)				0.31 (0.08)**	0.20 (0.07)**
<u>Province Dummies</u>						
Eastern Cape		-0.43 (0.10)**	0.29 (0.09)**	0.10 (0.11)	0.10 (0.10)	-0.02 (0.10)
Northern Cape		-1.00 (0.13)**	-0.29 (0.11)**	-0.41 (0.12)**	-0.41 (0.12)**	-0.30 (0.11)**
Free State		-0.74 (0.12)**	0.13 (0.11)	0.04 (0.11)	0.02 (0.11)	0.12 (0.11)
Kwazulu-Natal		-0.21 (0.10)*	0.33 (0.09)**	0.14 (0.11)	0.15 (0.10)	0.13 (0.10)
Northwest Province		-0.17 (0.12)	0.65 (0.11)**	0.51 (0.12)**	0.53 (0.11)**	-0.07 (0.11)
Gauteng		0.72 (0.11)**	0.38 (0.10)**	0.27 (0.10)**	0.37 (0.10)**	0.31 (0.10)**
Mpumalanga		-0.02 (0.12)	0.54 (0.10)**	0.39 (0.11)**	0.40 (0.11)**	0.31 (0.11)**
Northern Province		-0.30 (0.12)*	0.35 (0.11)**	0.14 (0.12)	0.17 (0.12)	-0.17 (0.12)
Population		0.85 (0.02)**	0.81 (0.02)**	0.80 (0.02)**	0.80 (0.02)**	0.82 (0.02)**
Constant	-1.46 (0.72)*	-1.94 (0.22)**	-7.39 (0.33)**	-7.38 (0.33)**	-6.98 (0.34)**	-8.69 (0.33)**
Pseudo R^2	0.077	0.071	0.095	0.096	0.098	0.119
Observations	627	1066	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Probit regressions are at the household level using data on reporting of residential burglary to the police from the Victims of Crime Survey. Adjust number of burglaries in a police station jurisdiction is the number of actual burglaries reported divided by the probability of a burglary being reported in that jurisdiction.

Table 10: Using Other Covariates for Residential Burglaries

	Basic Model	Other Covariates Added One at a Time				All Other Covariates
Inequality in Police Station	0.55 (0.08)**	0.94 (0.09)**	0.56 (0.08)**	0.46 (0.08)**	0.51 (0.08)**	0.77 (0.11)**
Mean Expenditure in Police Station	0.92 (0.05)**	0.77 (0.05)**	0.92 (0.05)**	0.78 (0.05)**	0.96 (0.05)**	0.73 (0.06)**
Unemployment in Criminal Catchment Area	-0.04 (0.06)	-0.04 (0.06)	-0.04 (0.06)	-0.01 (0.06)	-0.07 (0.06)	-0.03 (0.06)
Richest Jurisdiction in Criminal Catchment Area	0.20 (0.07)**	0.23 (0.07)**	0.20 (0.07)**	0.25 (0.07)**	0.20 (0.07)**	0.26 (0.07)**
Population Density		0.13 (0.02)**				0.08 (0.02)**
Female-headed households			0.01 (0.08)			0.18 (0.09)*
Percentage aged 21-40				0.97 (0.15)**		0.87 (0.18)**
Percentage African					0.08 (0.03)**	0.02 (0.03)
Population	0.82 (0.02)**	0.71 (0.02)**	0.82 (0.02)**	0.81 (0.02)**	0.80 (0.02)**	0.72 (0.03)**
Constant	-8.69 (0.33)**	-6.87 (0.41)**	-8.67 (0.35)**	-6.67 (0.45)**	-8.70 (0.33)**	-5.42 (0.54)**
Province Dummies	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.119	0.122	0.119	0.122	0.119	0.124
Observations	1066	1066	1066	1066	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 11: Using Other Covariates for Vehicle Thefts

	Basic Model	Other Covariates Added One at a Time				All Other Covariates
Inequality in Police Station	-0.02 (0.10)	0.71 (0.12)**	0.07 (0.11)	-0.10 (0.10)	-0.10 (0.10)	0.48 (0.13)**
Mean Expenditure in Police Station	1.67 (0.07)**	1.38 (0.07)**	1.70 (0.07)**	1.43 (0.07)**	1.81 (0.07)**	1.39 (0.08)**
Unemployment in Criminal Catchment Area	-0.21 (0.09)*	-0.15 (0.09)	-0.20 (0.09)*	-0.06 (0.09)	-0.22 (0.09)*	-0.03 (0.09)
Richest Jurisdiction in Criminal Catchment Area	0.09 (0.10)	0.18 (0.09)	0.09 (0.10)	0.17 (0.09)	0.09 (0.10)	0.21 (0.09)*
Population Density		0.25 (0.03)**				0.14 (0.03)**
Female-headed households			0.25 (0.11)*			0.50 (0.11)**
Percentage aged 21-40				1.88 (0.18)**		1.70 (0.22)**
Percentage African					0.23 (0.05)**	0.05 (0.05)
Population	0.97 (0.03)**	0.75 (0.04)**	0.95 (0.03)**	0.98 (0.03)**	0.96 (0.03)**	0.81 (0.04)**
Constant	-18.31 (0.50)**	-14.62 (0.59)**	-17.85 (0.54)**	-14.54 (0.60)**	-18.62 (0.50)**	-12.08 (0.71)**
Province Dummies	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.170	0.179	0.171	0.180	0.172	0.186
Observations	1066	1066	1066	1066	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 12: Using Other Covariates for Assaults

	Basic Model	Other Covariates Added One at a Time				All Other Covariates
Inequality in Police Station	0.42 (0.09)**	0.84 (0.11)**	0.37 (0.09)**	0.33 (0.08)**	0.40 (0.09)**	0.51 (0.12)**
Mean Expenditure in Police Station	0.16 (0.06)**	0.02 (0.06)	0.14 (0.06)*	-0.14 (0.06)*	0.19 (0.06)**	-0.16 (0.06)**
Unemployment in Criminal Catchment Area	-0.09 (0.07)	-0.07 (0.07)	-0.07 (0.07)	0.07 (0.07)	-0.10 (0.07)	0.08 (0.07)
Richest Jurisdiction in Criminal Catchment Area	0.10 (0.08)	0.12 (0.08)	0.10 (0.08)	0.17 (0.08)*	0.10 (0.08)	0.17 (0.07)*
Population Density		0.12 (0.02)**				0.02 (0.02)
Female-headed households			-0.13 (0.09)			0.31 (0.09)**
Percentage aged 21-40				1.89 (0.15)**		2.08 (0.19)**
Percentage African					0.06 (0.03)	-0.05 (0.03)
Population	0.78 (0.02)**	0.68 (0.03)**	0.79 (0.02)**	0.78 (0.02)**	0.78 (0.02)**	0.74 (0.03)**
Constant	-3.34 (0.38)**	-1.45 (0.47)**	-3.52 (0.40)**	0.95 (0.48)	-3.37 (0.38)**	2.13 (0.58)**
Province Dummies	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.078	0.081	0.078	0.089	0.078	0.089
Observations	1066	1066	1066	1066	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 13: Using Other Covariates for Rapes

	Basic Model	Other Covariates Added One at a Time				All Other Covariates
Inequality in Police Station	0.30 (0.08)**	0.87 (0.10)**	0.20 (0.09)*	0.13 (0.08)	0.24 (0.08)**	0.37 (0.10)**
Mean Expenditure in Police Station	0.27 (0.05)**	0.07 (0.05)	0.23 (0.05)**	-0.02 (0.05)	0.35 (0.05)**	-0.04 (0.05)
Unemployment in Criminal Catchment Area	-0.01 (0.07)	0.00 (0.06)	0.01 (0.07)	0.14 (0.06)*	-0.05 (0.07)	0.12 (0.06)*
Richest Jurisdiction in Criminal Catchment Area	0.04 (0.07)	0.09 (0.07)	0.04 (0.07)	0.13 (0.07)	0.03 (0.07)	0.14 (0.07)*
Population Density		0.17 (0.02)**				0.05 (0.02)**
Female-headed households			-0.27 (0.08)**			0.15 (0.09)
Percentage aged 21-40				2.09 (0.13)**		1.97 (0.17)**
Percentage African					0.14 (0.03)**	0.03 (0.03)
Population	0.84 (0.02)**	0.69 (0.03)**	0.87 (0.02)**	0.82 (0.02)**	0.83 (0.02)**	0.76 (0.03)**
Constant	-6.44 (0.35)**	-3.81 (0.42)**	-6.86 (0.37)**	-1.83 (0.43)**	-6.52 (0.35)**	-1.01 (0.52)
Province Dummies	YES	YES	YES	YES	YES	YES
Pseudo R^2	0.127	0.136	0.128	0.149	0.129	0.150
Observations	1066	1066	1066	1066	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%

Table 14: Crime and Inequality using OLS

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	1.77 (0.11)**	1.03 (0.17)**	0.97 (0.08)**	0.76 (0.09)**
Constant	-3.37 (0.14)**	-6.78 (0.21)**	-3.96 (0.09)**	-5.95 (0.11)**
Province Dummies	YES	YES	YES	YES
Adjusted-R^2	0.28	0.25	0.22	0.10
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Dependent variable is the log per capita crime rate. All explanatory variables are in logs. Crime rates equal to zero were replaced with the smallest value for that crime.

Table 15: Crime, Inequality and Mean Expenditure using OLS

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
Inequality in Police Station	1.08 (0.11)**	-0.23 (0.15)	0.93 (0.08)**	0.61 (0.10)**
Mean Expenditure in Police Station	1.05 (0.06)**	1.92 (0.08)**	0.06 (0.04)	0.23 (0.05)**
Constant	-11.05 (0.44)**	-20.77 (0.63)**	-4.39 (0.34)**	-7.66 (0.41)**
Province Dummies	YES	YES	YES	YES
Adjusted-R^2	0.45	0.50	0.22	0.12
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Dependent variable is the log per capita crime rate. All explanatory variables are in logs. Crime rates equal to zero were replaced with the smallest value for that crime.

Table 16: Crime, Inequality, Mean Expenditure and Unemployment using OLS

	Property Crimes		Violent Crimes	
	Residential Burglary	Vehicle Theft	Aggravated Assault	Rape
Inequality in Police Station	1.07 (0.11)**	-0.22 (0.15)	0.93 (0.08)**	0.61 (0.10)**
Mean Expenditure in Police Station	1.02 (0.07)**	1.95 (0.10)**	0.06 (0.05)	0.24 (0.06)**
Unemployment in Criminal Catchment Area	-0.08 (0.09)	0.10 (0.13)	0.02 (0.07)	0.03 (0.08)
Province Dummies	YES	YES	YES	YES
Constant	-11.03 (0.44)**	-20.80 (0.63)**	-4.40 (0.34)**	-7.66 (0.41)**
Adjusted-R^2	0.46	0.50	0.22	0.12
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Dependent variable is the log per capita crime rate. All explanatory variables are in logs. Crime rates equal to zero were replaced with the smallest value for that crime.

Table 17: Crime and the Distribution of Welfare in Catchment Area using OLS

	Property Crimes		Violent Crimes	
	Residential Burglary	Vehicle Theft	Aggravated Assault	Rape
Inequality in Police Station	1.06 (0.11)**	-0.22 (0.15)	0.93 (0.08)**	0.61 (0.10)**
Mean Expenditure in Police Station	0.96 (0.07)**	1.89 (0.10)**	0.03 (0.06)	0.25 (0.07)**
Unemployment in Criminal Catchment Area	-0.12 (0.09)	0.07 (0.13)	-0.00 (0.07)	0.03 (0.09)
Richest Jurisdiction in Criminal Catchment Area	0.27 (0.11)*	0.24 (0.16)	0.12 (0.09)	-0.02 (0.10)
Province Dummies	YES	YES	YES	YES
Constant	-10.70 (0.46)**	-20.51 (0.66)**	-4.25 (0.35)**	-7.68 (0.42)**
Adjusted-R^2	0.46	0.50	0.22	0.12
Observations	1066	1066	1066	1066

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Dependent variable is the log per capita crime rate. All explanatory variables are in logs. Crime rates equal to zero were replaced with the smallest value for that crime.

Table 18: Crime and Inequality between Racial Groups using OLS

	Property Crimes		Violent Crimes	
	Residential Burglary	**Vehicle Theft**	**Aggravated Assault**	**Rape**
***Within*-Racial Group Inequality in Police Station**	0.76 (0.23)**	1.87 (0.34)**	1.19 (0.18)**	1.48 (0.22)**
***Between*-Racial Group Inequality in Police Station**	0.14 (0.01)**	-0.01 (0.02)	0.09 (0.01)**	0.05 (0.01)**
Mean Expenditure in Police Station	0.89 (0.07)**	1.65 (0.11)**	-0.06 (0.06)	0.12 (0.07)
Unemployment in Criminal Catchment Area	-0.06 (0.09)	-0.02 (0.13)	-0.03 (0.07)	-0.04 (0.09)
Richest Jurisdiction in Criminal Catchment Area	0.25 (0.11)*	0.19 (0.16)	0.10 (0.09)	-0.05 (0.10)
Province Dummies	YES	YES	YES	YES
Constant	-9.62 (0.64)**	-16.31 (0.92)**	-2.63 (0.50)**	-5.33 (0.59)**
Adjusted-R^2	0.48	0.52	0.22	0.14
Observations	1064	1064	1064	1064

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Dependent variable is the log per capita crime rate. All explanatory variables are in logs. Crime rates equal to zero were replaced with the smallest value for that crime.

Table 19: Murder and Robbery

	Murder			Armed Robbery		
Inequality in Police Station	0.53 (0.08)**	0.33 (0.09)**		0.16 (0.13)	-0.56 (0.12)**	
Mean Expenditure		0.25 (0.05)**	0.24 (0.06)**		1.20 (0.07)**	1.15 (0.07)**
Unemployment in Criminal Catchment Area		0.11 (0.07)	0.12 (0.07)		0.49 (0.09)**	0.43 (0.10)**
Richest Police Station among Neighbors		0.05 (0.08)	0.05 (0.08)		-0.16 (0.11)	-0.17 (0.11)
Within-Group Inequality			0.29 (0.18)			0.14 (0.24)
Between-Group Inequality			0.03 (0.01)**			-0.06 (0.02)**
Population	0.92 (0.02)**	0.90 (0.02)**	0.88 (0.02)**	0.89 (0.03)**	0.88 (0.03)**	0.87 (0.03)**
<u>Province Dummies</u>						
Eastern Cape	-0.10 (0.08)	-0.06 (0.11)	-0.09 (0.12)	0.16 (0.14)	0.64 (0.15)**	0.43 (0.17)*
Northern Cape	-0.31 (0.12)**	-0.21 (0.13)	-0.20 (0.13)	-0.92 (0.21)**	-0.13 (0.20)	-0.28 (0.20)
Free State	-0.62 (0.11)**	-0.46 (0.12)**	-0.43 (0.12)**	0.08 (0.17)	1.13 (0.17)**	0.90 (0.17)**
Kwazulu-Natal	0.25 (0.08)**	0.26 (0.10)*	0.21 (0.11)	1.52 (0.14)**	1.83 (0.14)**	1.73 (0.15)**
Northwest Province	-0.42 (0.10)**	-0.34 (0.12)**	-0.35 (0.13)**	0.50 (0.17)**	1.28 (0.17)**	1.05 (0.18)**
Gauteng	0.33 (0.09)**	0.16 (0.10)	0.13 (0.10)	2.56 (0.15)**	2.04 (0.13)**	2.09 (0.13)**
Mpumalanga	-0.27 (0.10)**	-0.27 (0.11)*	-0.29 (0.12)*	1.12 (0.17)**	1.66 (0.16)**	1.53 (0.16)**
Northern Province	-1.01 (0.11)**	-0.97 (0.13)**	-0.97 (0.15)**	0.53 (0.18)**	1.02 (0.18)**	0.67 (0.21)**
Constant	-5.84 (0.22)**	-7.25 (0.36)**	-6.82 (0.54)**	-6.42 (0.32)**	-14.36 (0.54)**	-13.51 (0.76)**
Pseudo R^2	0.148	0.149	0.149	0.148	0.151	0.150
Observations	1066	1063	1061	1066	1063	1061

Standard errors in parentheses. * significant at 5%; ** significant at 1%. Within-Group and Between-Group Inequality refer to inequality within and between racial groups in each police station.

Appendix A

Table A-1: Correlations between Welfare Indicators

		1	2	3	4	5	6
1	Inequality in Police Station	1.0000					
2	Mean Expenditure in Police Station	0.102	1.0000				
3	Unemployment in Catchment Area	-0.114	-0.622	1.0000			
4	Richest Jurisdiction in Neighboring Area	0.113	0.297	-0.077	1.0000		
5	Inequality within Racial Groups	0.359	0.019	0.332	0.139	1.0000	
6	Inequality between Racial Groups	0.725	0.314	-0.392	0.116	-0.075	1.0000

All variables are in logarithms except the richest jurisdiction in neighboring area, which is a dummy variable

Table A-2: Correlations between Selected Variables

		1	2	3	4	5	6	7	8
1	Population	1.0000							
2	Mean Expenditure in Jurisdiction	0.0094	1.0000						
3	Inequality in Jurisdiction	-0.5053	0.1024	1.0000					
4	Population Density	0.7448	0.3034	-0.6285	1.0000				
5	Female-headed Households	0.4910	-0.4349	-0.4753	0.2956	1.0000			
6	Percentage aged 21-40	-0.0713	0.6340	0.2225	0.2159	-0.6479	1.0000		
7	Unemployment in Jurisdiction	0.4077	-0.6871	-0.3446	0.1507	0.7172	-0.5913	1.0000	
8	Percentage African	0.2305	-0.4549	-0.0188	0.1000	0.3785	-0.2554	0.4641	1.0000

Appendix B

Brief methodological description on small area estimation of welfare indicators

What follows is an overview of the methodology we employ to construct welfare indicators for small geographical areas, such as the police station jurisdictions in South Africa. We provide this section so that the reader is clear about the source of the welfare measures utilized as explanatory variables in the crime regressions throughout the rest of this paper. Please see Elbers, Lanjouw, and Lanjouw (2002) for a fuller discussion, and Babita, Demombynes, Makhatha, and Özler (2002) for details regarding the specific application to the South Africa data.

The basic methodology applied in linking surveys and census-type data sets is very similar to that of synthetic estimation used in small-area geography. Prediction models are derived for consumption or income as the endogenous variable, on the basis of the survey. The selection of right-hand side variables is restricted to those variables that can also be found in the census (or some other large data set). The parameter estimates are then applied to the census data and poverty and inequality statistics derived. Simple performance tests can be conducted which compare basic poverty or inequality statistics across the two data sets (at representative levels for the household survey). For Ecuador, Madagascar, and South Africa, Demombynes et al (2002) show that stratum level poverty estimates derived from consumption measured directly in the household survey, are very similar to those calculated on the basis of imputed household consumption in the census.

The calculation of poverty and inequality statistics using predicted income or consumption has to take into account that each individual household income or consumption value has been predicted and has standard errors associated with it. Elbers et al (2002) show that the approach yields estimates of the incidence of poverty and of inequality that are consistent, and that the standard errors are reasonably precise for small geographic units, such as parroquias in Ecuador. Furthermore, a recent case study from[17] demonstrates that these estimates are precise enough to permit meaningful pair-wise comparisons across 2nd and 3rd levels of administration.

As described above, the concept of imputing expenditures for each household in the census is simple to grasp, yet it requires great attention to detail, especially regarding the computation of standard errors. This also makes the exercise computationally quite intensive. It involves constructing an association model between per capita household expenditure and household characteristics that are common to both the census and the household survey. After carefully constructing the variables in the exact same manner in each data set, we estimate a regression model of logarithmic per capita household expenditure on the other constructed variables that consist of household composition, education, primary occupation, quality of housing, and access to services.

The basis of the approach is that per capita household expenditure for a household h in cluster c can be explained using a set of observable characteristics. These observable characteristics must be found as variables in both the survey and the census:[18]

(1) $$\ln y_{ch} = E[\ln y_{ch} | \mathbf{x}_{ch}] + u_{ch}.$$

[17] See Mistiaen et al (2002).

[18] The explanatory variables are observed values and thus need to have the same definitions and the same degree of accuracy across data sources. In Babita et al (2002), the criteria and approach used to select these explanatory variables are explained in detail. Finally, note that from a methodological standpoint it does not matter whether these variables are exogenous.

Using a linear approximation to the conditional expectation, the household's logarithmic per capita expenditure is modeled as

(2) $\ln y_{ch} = \mathbf{x}_{ch}'\boldsymbol{\beta} + u_{ch}$.

More explicitly, we model the disturbance term as

$$u_{ch} = h_c + e_{ch}$$

where h_c is the cluster component and e_{ch} is the household component. This complex error structure will not only allow for spatial autocorrelation, i.e. a "location effect" for households in the same area, but also for heteroskedasticity in the household component of the error. The two error components are independent of one another and uncorrelated with observable characteristics.

The model in (2) is estimated by Generalized Least Squares using the household survey data. The results from this first stage of the analysis are a set of estimated model parameters, including the beta vector, an associated variance-covariance matrix, and parameters describing the distribution of the disturbances.

To avoid forcing the parameter estimates to be the same for all areas in South Africa, we run the first stage regressions separately for each of the 9 provinces. The explanatory power of the nine regressions ranged from an adjusted-R^2 of 0.47 (Eastern Cape) to 0.72 (Free State), with the median adjusted-R^2 equal to 0.64[19].

In the second stage analysis we combine these parameter estimates based on the *survey data* with household characteristics from the *census data* to estimate welfare measures for subgroups of the census population. It is possible to produce these estimates for any subgroups that can be identified in the census. For the purposes of this paper, we perform the calculations at the police station jurisdiction levels.

Specifically, we combine the estimated first stage parameters with the observable characteristics of each household in the census to generate predicted log expenditures and relevant disturbances. We simulate a value of expenditure for each household, $\hat{y}_{ch}$, based on both predicted log expenditure, $\mathbf{x}_{ch}'\tilde{\mathbf{ß}}$, and the disturbance terms, $\tilde{h}_c$ and $\tilde{e}_{ch}$ using bootstrap methods:

(3) $$\hat{y}_{ch} = \exp\left(\mathbf{x}_{ch}'\tilde{\mathbf{ß}} + \tilde{h}_c + \tilde{e}_{ch}\right).$$

For each household, the two disturbance terms are drawn from distributions described by parameters estimated in the first stage[20]. The beta coefficients, $\tilde{\mathbf{ß}}$, are drawn from the multivariate normal distribution described by the first stage beta estimates and their associated variance-covariance matrix. We then use the full set of simulated $\hat{y}_{ch}$ values to calculate expected values of the average expenditure, poverty, and inequality measures for the two spatial subgroups described above.

We repeat this procedure 100 times, drawing a new set of beta coefficients and disturbances for each set of simulations. For each subgroup, we take the mean and standard deviation of the welfare indicators over all 100 simulations. For any given location, these means constitute the point estimates of the welfare indicators, while the standard deviations are the standard errors of these estimates.

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[19] The R-squared values that we report are from OLS models. We do this to give our readers a sense of the explanatory power of our regression models, as there is no precise counterpart to R-squared in a GLS model. See Greene (1997), p. 508 for details.

[20] Please note that these errors are not necessarily drawn from a normal distribution. For details, please refer to Babita et al (2002).

There are two principal sources of error in the welfare measure estimates produced by this method.[21] The first component, referred to as *model error* in Elbers et al (2002), is due to the fact that the parameters from the first-stage model in equation (2) are estimated. The second component, described as *idiosyncratic error*, is associated with the disturbance term in the same model, which implies that households' actual expenditures deviate from their expected values. While population size in a location does not affect the *model error*, the *idiosyncratic error* increases as the number of households in a target population decreases.

[21] A third potential source of error is associated with computation methods. Elbers et al (2002) found this component to be negligible with a sufficiently high number of simulation draws.