Property Crime and Inequality: The Case of South Africa

Haroon Bhorat, Adaiah Lilenstein, Jabulile Monnakgotla, Amy Thornton, Kirsten van der Zee

Abstract

It is well established in the literature that property crime rates increase with increasing levels of inequality. However, most research in this area comes from contexts of low-to-moderate crime and inequality rates. This paper explores whether this relationship holds in a context of extreme levels of crime and inequality, using South Africa as a case study. We use cross-sectional precinct-level property crime rates from 2011 combined with census data. We perform non-parametric, semi-parametric, and parametric analyses to uncover the nature of the property crime-inequality relationship and find strong evidence of a positive linear relationship between property crime and an interaction term of income with inequality, but strong evidence of a negative relationship between property crime and inequality on its own. This result is robust to various measures of inequality. One explanation for this finding could be that inequality acts as a signal to relatively richer residents in an area (local elites) that they are more at risk of falling victim to crime. As a consequence of this mechanism, local elites start investing in protective measures which could dampen crime rates.

1. Introduction

Led by the seminal papers of Becker (1968) and Ehrlich (1973), economists have been empirically testing the relationship between crime and inequality for about 40 years. It has been generally accepted that crime increases with inequality in a linear fashion. This relationship has been confirmed by a rich literature that differentiates by level of aggregation (e.g. cities, provinces, countries), data format (e.g. panel or cross-sectional), crime type (e.g. homicide, violent, property) and measure of inequality used (for meta-analyses see: Hsieh & Pugh, 1993; Rufrancos et al., 2013; Kelly, 2000). However, the vast majority of studies on property crime have been conducted using North American and European country data, notably countries with moderate levels of inequality, and while there are studies in high inequality contexts (specifically in Latin America), these focus on violent crime. Our aim is to revisit the topic of crime and inequality specifically in a high crime-high inequality setting to determine whether a positive relationship still holds at extreme levels of both variables, by using property crime in South Africa as a case study. One reason why we may question whether a positive relationship between crime and inequality would hold in a high-inequality setting is because of how inequality could impact on the fear of crime and the behavioural responses it elicits.

Although there is a perennial difficulty in comparing country-level crime rates due to differences in national reporting rates and recording practices, South Africa is considered to have exceptionally high crime rates (Heiskanen, 2010). Figure 1 places South Africa in the international context of crime and inequality. We compare South Africa to a relevant comparator group of Low and Middle Income Countries (LMICs) in an attempt to parse out the effect of higher quality recording rates in High Income Countries.

What is immediately apparent from Figure 1 is that South Africa is a global outlier in terms of inequality. The Gini coefficient here is over 0.6 and the highest in the sample. In a study of 108 economies, South Africa yielded the highest Gini coefficient, 0.62, when calculated as an average over the years between 1960 and 1992 – a period covering apartheid rule (Deininger & Squire, 1996). Post-apartheid estimates suggest that inequality has in fact increased: The Gini coefficient has risen from 0.66 in 1993, to 0.70 in 2008 according to analysis by Leibbrandt et al. (2012). In 2014, the Gini was estimated to be 0.69 (World Bank, 2018).

From Figure 1 we also see a positive correlation between inequality and crime. South Africa ranks second of the 13 selected countries for both property crime and murder. Murder is included here as it is not subject to the same reporting issues as most other categories of crime[1]. Heiskanen (2010) describes South Africa as having high rates of house-breaking or burglary in a global sample, some of the highest rates of motor vehicle theft when the rates are adjusted for the number of automobiles in the country, and ranked South Africa in the highest quartile for robbery. Furthermore, South Africa has substantially higher property crime rates than the countries with comparatively high inequality, namely Brazil, Colombia and Botswana.

South Africans are also highly aware of the country's high crime rate and the fear of falling victim to crime is foremost in their minds, to the extent that fear of crime in South Africa has been likened to 'hysteria' (Gie, 2009; Shaw & Gastrow, 2001). South Africans have specific – but not unique – behavioural responses to their fear of crime which may impact on actual crime rates. These responses include, for example, retreat from public spaces; a proliferation of gated communities; building of high walls and security fences, and use of private security companies (Lemanski, 2004; Roberts, 2008; Pillay, 2008). Whilst the construction of 'fortified enclaves' such as gated communities exists mainly in more affluent areas, efforts to improve residential protection has been observed among all socio-economic groups (Lemanski, 2004).

[1] Police-recorded crime data is not equivalent to "all" crime, but only that which has been reported and documented, and can therefore be viewed as a somewhat indirect measure of true crime (Heiskanen, 2010). The reliability of property crime data is especially tricky in this respect; recording rates often correlate with a country's level of development, which can be linked in part to reporting being a requirement for insurance (Heiskanen, 2010). Much research on crime has focused on homicide as a consequence of this concern as it is considered the most reliably reported crime type and least susceptible to obscuration by reporting rates (Malby, 2010). For this reason, we report both property crime and murder in Figure 1.

Figure 1. Income Inequality and Crime, 2011

Notes: Crime statistics from the UNODC (2018); Gini coefficient from the World Bank (2018). Property crime defined as the sum of the per 100 000 population rates for non-residential burglary, residential burglary and motor vehicle theft. Countries with asterisks (*) lacked one of these elements, either because two categories were combined or because one category was not collected. The sample consists of selected low and middle income (LMIC) countries with data available for property crime and Gini coefficient for 2011. LMIC status defined according to the World Bank categorization.

This context therefore makes South Africa an interesting case for the study of crime and inequality: Both inequality and crime are high, whilst individuals evidently react to these high crime rates given the probability of being a victim of a crime. We begin with a discussion of the theory behind the relationship between crime and inequality, highlighting the probable form that the theory assumes the relationship will take. In Section 3 we provide an overview of the data used and methodology followed. Thereafter, we test the relationship between crime and inequality at a relatively detailed geographical unit, for South Africa, in Section 4. Section 5 concludes.

2. Theories of Crime and Inequality

Rufrancos et al. (2013) explain that it is well-established that the relationship between inequality and crime exists, however, the mechanism itself is far less understood. There are a few competing theories from both sociology and economics which attempt to model the relationship between crime and inequality. From economics, Becker's (1968) classic theory is an example of a rational choice model where agents are driven by income maximisation. Merton's (1938) 'strain theory' is a sociological theory of crime which proposes that society puts pressure on its members to achieve certain materialistic goals in order to be socially accepted. This theory emphasises feelings of injustice and resentment that motivate crime amongst those who feel relatively deprived. Individuals may commit crime in an effort to attain the materialistic goals that they see reflected in society. Similarly, Runciman's (1966) theory of relative deprivation suggests that income inequality increases feelings of dispossession and unfairness, which leads poorer individuals to reduce perceived economic injustice through crime. Kelly (2000) suggests that these theories are all ultimately about Becker's (1968) income maximization motive, with variations on how individual decisions are modulated.

Becker (1968) characterises the choice to commit crime as a gamble faced by a rational agent, the outcome of which is dependent on the costs and benefits associated with either committing a crime or not. The benefit of committing a crime is either monetary (e.g. burglary) or psychological gain (e.g. assault), while the expected cost of the crime is a function of the probability of apprehension and the severity of punishment if apprehended. The expected benefit of not committing a crime (which is also the opportunity cost of crime) is the probability of employment and the expected wage in employment. There is no cost to abstaining from crime other than the opportunity cost of the crime itself. Hence, the individual chooses to commit a crime if the following condition holds:

$$(1 - p_1).U_{C1} + p_1.U_{C2} > (1 - p_2).U_{NC1} + p_2.U_{NC2}$$

Where, on the left hand side, p_1 is the probability of apprehension, U_{C1} is the utility associated with committing a crime and not being caught, and U_{C2} is the utility associated with committing a crime conditional on being caught, p_1. On the right hand side, p_2 is the probability of employment, U_{NC1} is the utility associated with not committing a crime and not being employed, and U_{NC2} is the utility associated with not committing a crime and being employed. In high unemployment and inequality settings, p_2 and U_{NC2} are low, tipping the equation in favour of criminal activity. High levels of unemployment make p_2 low whilst high levels of inequality make U_{NC2} low. When inequality increases, the payoff to legitimate employment decreases.

A theory that links both sociological and economic ideas comes from Pradhan and Ravallion (2003) who argue that concern for public safety is a concave function of household income. Consequently, there is a negative relation between inequality and public concern for safety, leading to a positive correlation between crime and inequality. This is a relevant theory in country contexts with low social cohesion and high fear of crime. In an environment where social groups are increasingly polarized, individuals become increasingly preoccupied with protecting their own interests (Lemanski, 2004).

Chiu and Madden (1998) provide a clear micro-theoretical framework for why we would expect property crime to increase with inequality, based on Becker's original formulation. The Chiu and Madden (1998) model has since been supported by other empirical studies (Kelly, 2000; Demombynes & Ozler, 2005). The model consists of victims and potential burglars in a closed neighbourhood. Burglars aim to maximise income from crime and therefore aim to target richer residents. Wealth is discerned via the imperfect signal of housing quality—which similarly modulates a criminals' judgement of relative deprivation and inequality in the area. When inequality increases, crime becomes more attractive to lower income residents because (a) the returns from the alternative to crime go down and (b) the gains from crime go up. Furthermore, Chiu and Madden (1998) explicitly allow for rich neighbourhoods to have low crime rates partly due to their ability to invest in protective measures against crime.

Following Chiu and Madden (1998), if crime occurs within neighbourhoods, we can similarly imagine rich and poor neighbourhoods with low inequality having low crime rates, since neighbours are equally rich in the first case and equally poor in the second. We can also imagine a poor neighbourhood with high inequality. In this case, the relatively deprived may still prey on the relatively well-off within the neighbourhood, leading to higher crime rates. The relatively well-off in this neighbourhood are no doubt aware of their status and that they are likely targets (in the Chiu & Madden [1998] model this is conveyed by the signal of housing quality). This could prompt the local elites to take steps to protect themselves (for example, a lock or a dog) even if they are poor in the overall national income distribution. Regardless of income, local elites could try to invest in private security measures when they recognize that inequality is so severe in their neighbourhood that they are at a critical risk of falling victim to crime. Inequality, like income but independently, could act as a signal to potential victims about how at risk they are of being robbed or burgled.

In sum, there is a strong theoretical base for modeling crime as an increasing function of inequality. There is also theory to support a non-linear crime-inequality relationship, in the form of an inverted-U. The remainder of the paper comprises our empirical investigation of what the observed relationship between property crime and inequality looks like in this extreme context of South Africa.

3. Data and Methodology

3.1 Data

The dataset used to test our hypothesis combines the South African Police Service's (SAPS) official Crime Statistics (SAPS, 2011)[2] and the 2011 South African Census Community Profiles (Statistics South Africa, 2011). The SAPS Crime Statistics provides the crime reported in each police precinct, grouped into 27 spatial categories. The Census Community Profiles are derived from the 2011 South African census, where census data are aggregated to the small area layer (SAL) level. The Census Community Profiles data provides population and aggregated demographic and socio-economic information for each SAL, for example, employment, household size and proportion of males and females.

To combine the data sets, each of the 85 000 SALs from the Census Community Profiles Data are allocated to one of the 1 124 police precincts according to their geographic boundaries, through geospatial mapping[3]. Thus, every South African in the 2011 Community Profiles data was allocated to a police precinct based on the SAL they were surveyed in, and the already aggregated demographic and socio-economic data from the Community Profiles dataset was then aggregated further to the police precinct level, since the police precinct is our unit of observation. For example, the average age for every SAL within each precinct was averaged, resulting in a mean age for each of the 1 124 precincts. The combined dataset includes precinct level demographic and socio-economic information, population, area in squared kilometers, and crime rates. The dataset thus includes all of the 52 million South Africans surveyed in the 2011 census, separated into the 1 124 police precincts[4].

This study focuses on property crime only. According to the SAPS, property crime is defined as crimes that involve the removal (theft) of property, where these crimes do not involve force or threat of harm to the victim. Property crime is therefore in line with Becker's (1968) income maximization and Chiu and Madden's (1998) model of why crime occurs. Although violent crime can also involve the removal of property for financial gain, which sits within our theoretical framework, violent crime can also be committed for psychological gain which does not fall under the same model. For this reason, we exclude violent crime and focus only on property crime. The types of crime that are included in our property crime definition are burglary at non-residential premises, burglary at residential premises, theft of motor vehicles and motorcycles, theft out of or from motor vehicles, and stock theft. The largest sub-categories of property crime are burglary at residential premises and theft out of a motor vehicle.

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[2] Since we are using administrative data we are dealing with reported crime rates, which are likely to be an underestimate of the actual number of crimes that occur. Reporting rates may be close to reality in the case of property crime, where reporting is necessary for insurance claims. This is particularly relevant the top end of the income distribution where more people are insured, while they may be more underreporting of crime at the bottom end of the income distribution.

[3] We utilised the SAL boundary geographic information system (GIS) data and generated a random point in the polygon algorithm that fell within each SAL's boundary. These were then mapped to the 2015 police station boundary data. Using a random point does not guarantee that the majority of the SAL would be in the same precinct as the random point itself. However, given that the irregular shape of the SALs can often lead to a central point or centroid falling completely outside of the SALs boundary, the random point minimises the error potential.

[4] By using the 2011 crime data, as opposed to more recent crime statistics, we avoid the bias that would arise from using population growth estimates that would have to be applied to the Community Profiles data and demographic information collected four years prior. Since we used the 2011 crime statistics, we lost 14 police precincts, which, although they existed in the 2015 SAPS boundaries, had police stations that were only built after 2011. We therefore have a total of 1 124 police precincts in our dataset rather than the 1 140 that exist in the 2015 SAPS data.

3.2 Methodology

The empirical strategy used here starts simple and becomes gradually more involved. We begin by presenting non-parametric results to assess the crude relationship between crime and inequality. We calculate inequality using a number of different measures. We then move on to semi-parametric estimations, which allow us to control for covariates but not dictate the shape of the crime-inequality relationship. From this we move on to OLS-regression analyses, which investigate the significance of different model specifications. In all cases we also investigate the existence and form of any relationships that exist between crime and income, as well as crime and an interaction term of income and inequality. Given the closeness between income and inequality, and their potential to interact, we believe a thorough understanding of both variables in necessary in order to understand the effect of inequality on crime.

Inequality Measures

When testing the relationship between inequality and crime it is important to ensure that the results are not driven by the choice of inequality measure used. The most common measure of inequality is the Gini, but other popular measures include Generalised Entropy measures with $\boldsymbol{\theta}$=0, 1, 2 (referred to hereafter as GE0, GE1 and GE2); or Atkinson's measures with ε =½, 1, 2 (referred to as ATK½, ATK1 and ATK2).

The most widely used single measure of inequality is the Gini coefficient, which ranges from 0 (perfect equality) to 1 (perfect inequality). It is based on the Lorenz curve, a cumulative frequency curve that compares the distribution of a specific variable (e.g. income) with the uniform distribution that represents equality.

The values of GE measures vary between 0 and ∞, with zero representing an equal distribution and higher values representing a higher level of inequality. The weighting parameter, $\boldsymbol{\theta}$, in the GE class represents the weight given to distances between incomes at different parts of the income distribution, and can take any real value. Measures from the GE class are sensitive to changes at the lower end of the distribution for α close to zero, equally sensitive to changes across the distribution for $\boldsymbol{\theta}$ equal to one, and sensitive to changes at the higher end of the distribution for higher value. The most common values of $\boldsymbol{\theta}$ used are 0,1 and 2. GE(0) is the mean log deviation, or Thiel's L, GE(1) is the Thiel's index, or Thiel's T, and GE(2) is half the squared coefficient of variation.

Atkinson has proposed another class of inequality measures which has similar theoretical properties to the Gini index. Like GE, this class also has a weighting parameter, ε, which measures aversion to inequality. The Atkinson index becomes more sensitive to changes at the lower end of the income distribution as ε approaches 1. Conversely, as the level of inequality aversion falls (that is, as ε approaches 0) the Atkinson index becomes more sensitive to changes in the upper end of the income distribution.

The analyses that follow use all seven measures of inequality and assess the level of agreement or disagreement among them.

OLS Model Specification

In this section, we outline the basic model specification for the OLS regressions, as well as the choice and construction of the variables used. The detail provided here also applies to the semi-parametric analysis. The general specification used for the OLS regression analysis is as follows:

$$\ell\text{n}(\text{crime}_i)=B_0 + \boldsymbol{\gamma}\text{Inequality}_{\boldsymbol{i}} + \boldsymbol{B}_1\ell\text{n}(\text{Income}_{\boldsymbol{i}}) + \boldsymbol{B}_2\mathbf{X}_{\boldsymbol{i}} + \varepsilon_{\boldsymbol{i}} \qquad (1)$$

In the equation, $crime_i$ represents the property crime rate (number of crimes per 100 000 residents) in precinct i in 2011. We take the natural logarithm of the crime rate as this normalises the distribution of crime, and thus the error term, ε_i. This transformation would convert zero crime rates into missing data – however, as there are no precincts without zero reported property crime, this does not affect our analysis.

$Inequality_i$ represents our inequality measure, and $Income_i$ is our measure for income at the precinct level. Both $Income_i$ and $Inequality_i$ were created using the annual household income reported in the Census Community Profiles data. This data was collected at the household level in 12 income bands. This predefined variable structure unfortunately collapses most variation in the income data. We use the midpoint of each bracket and apply this to all households in the same bracket;

this is used to calculate the logged per capita average income for each precinct, $\ell n(Income_i)$. We manipulate the data into a household level (as opposed to precinct-level) file for each precinct to calculate the different inequality measures.

The vector $\boldsymbol{X_i}$ includes controls for precinct level demographic characteristics, namely the unemployment rate, average age, the proportion of the precinct population who are youth (15-30 years), the proportion of males, proportion of various education levels, proportion of each race group[5], a measure of racial homogeneity[6], and the proportion of non-citizens. $\boldsymbol{X_i}$ also includes household and precinct level characteristics, namely the average household size, geographical composition (the proportion of urban, tribal authority areas and farm land), provincial dummies, and the geographical area of each precinct, measured in squared kilometers.

4. Results

4.1 Descriptive Statistics

Our sample consists of 1 124 police precincts, and all of the summary statistics presented in Table 1 are at this level. In the Census Community Profiles data, there are about 51 million individuals and 14 million households who have been allocated into these 1 124 police precincts. On average, there are about 45 000 people per police precinct living in an average of around 12 000 households. However, population per police precinct varies sharply. The largest police precinct has a population of 324 863, while the smallest has only 170 people.

Based on the data, we see that there were 471 property crimes on average in a precinct in 2011, which was equivalent to 1 196 crimes per 100 000 people. The distribution is right-skewed with the median of both the frequency and the crime rate per 100 000 people less than the respective mean. In other words, there is a small segment of the precinct population that has exceptionally high crime rates, compared to the majority.

The average per capita annual income was roughly \$3 527[7] in 2011 dollars. The mean is greater than the median indicating a right-handed skewness to the distribution, which is characteristic of the country's high levels of income inequality. Leibbrandt et. al. (2012) found the national population Gini was 0.66 in 2011. In the same period, our data indicates that the average of the Gini coefficient for police precincts was 0.68. The median of the Gini according to our data was 0.47, which implies a largely consistent distribution around the mean and median, with only a handful of police precincts with Gini coefficients over 0.7. Police precincts with exceptionally high inequality levels were a mixed collection of entirely urban areas and entirely rural areas, as well as a mixture of different provinces.

[5] Given South Africa's long and recent history of racial oppression and segregation, including race indicators is vital in any socioeconomic research in this context.
[6] Measured as the sum of the squared proportion of each racial category within an area
[7] Using a Dollar-Rand exchange rate of 8.13, which corresponds to the exchange rate on 30 November 2011.

Table 1. Summary Statistics of Police Precincts

	Mean	Median	Std. Dev.
Property Crime			
Frequency	471	224	638
Rate per 100 000	1 196	840	1 248
Inequality			
Gini Coefficient	0.68	0.69	0.05
Individual			
Prop. Males	0.49	0.49	0.03
Prop. Youth (15-30 years)	0.46	0.46	0.08
No Schooling	0.07	0.06	0.07
Primary or less	0.30	0.32	0.09
Secondary Education	0.43	0.42	0.09
Higher Education	0.07	0.04	0.08
Household			
Avg HH Size	3.70	3.58	0.88
Avg Annual PC Income ($)	3 527	2 116	4 206
Geographical			
Prop. Urban	0.59	0.76	0.40
Labour Market			
Prop. Unemployed	0.25	0.25	0.11

Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). N = 1124. Dollar-Rand exchange rate of 8.13 from 30 November 2011 used.

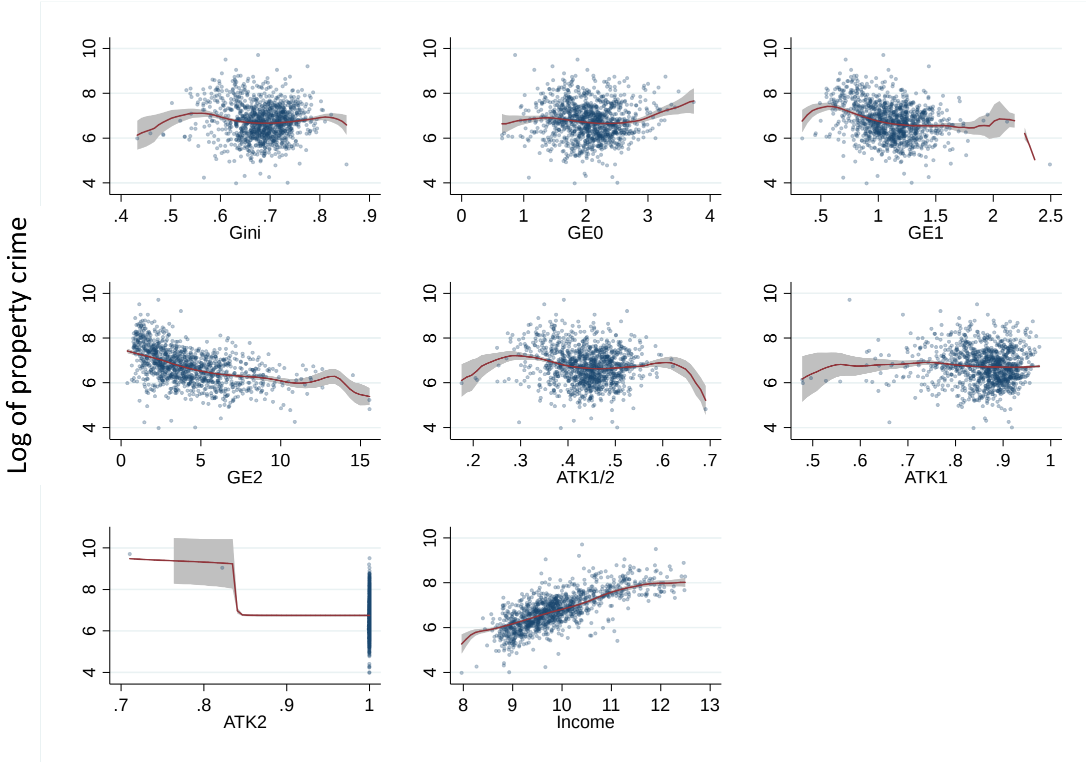
4.2 Non-Parametric Analysis of Crime and Inequality

In the non-parametric analysis below we can see the crude relationship between crime and different measures of inequality. Figure 2 displays these relationships for the Gini, GE0, GE1, GE2, Atkinson's ½, 1 and 2 (ATK½; ATK1; ATK2). Since inequality is derived from income, the final graph in the series displays this relationship as well.

None of the figures below display a clear upward sloping relationship, as we have come to expect from the literature. The GE0 does appear upward sloping in the right tail but otherwise very little evidence of the standard relationship is observed. The Gini and ATK½ suggest a quadratic relationship but even this is contrary to the inverted-U discussed above, with just a U-shape evident instead. The GE1 and GE2 seem to be downward sloping and the ATK1 is flat. The ATK2 is far too driven by the left tail to make anything of the relationship. In contrast, income shows a steeply positive relationship, as expected.

While it is immediately obvious that the ATK2 is driven by the tails of the distribution, it is not the only one. On closer inspection, all measures actually seem to be unduly influenced by a very small number of observations, with the exception of income. For this reason, Figure 3 below presents the same results but with the top and bottom 1 percent of observations removed.

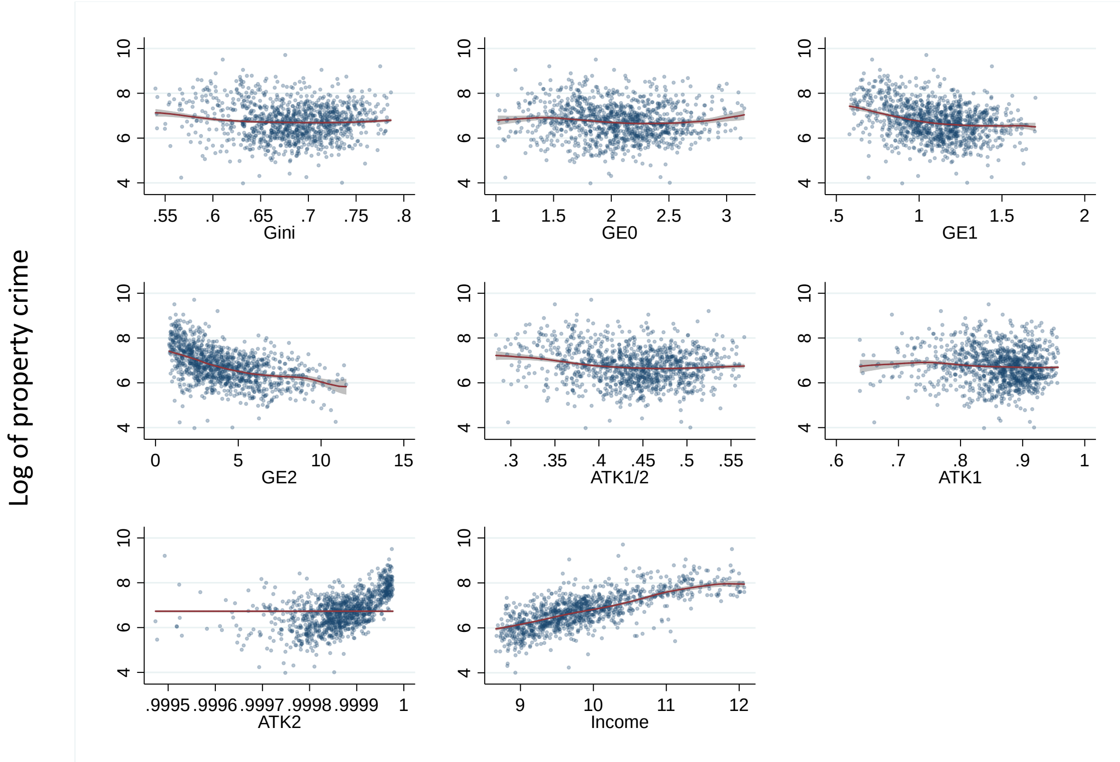
Figure 2. Non-Parametric Relationship between Precinct Inequality and Property Crime



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the range of inequality.

Looking at Figure 3 it is clear that the tails of the distribution did drive much of the relationships seen previously. Now, most measures appear either flat or slightly downward sloping. The suggestion of a downward slope is unexpected and completely contrary to conventional wisdom. On the other hand, without the tails crime is still increasing steeply with income, with a weak suggestion of nonlinearity toward the right-end.

Figure 3. Non-Parametric Relationship between Precinct Inequality and Property Crime without Tails



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the range of inequality.

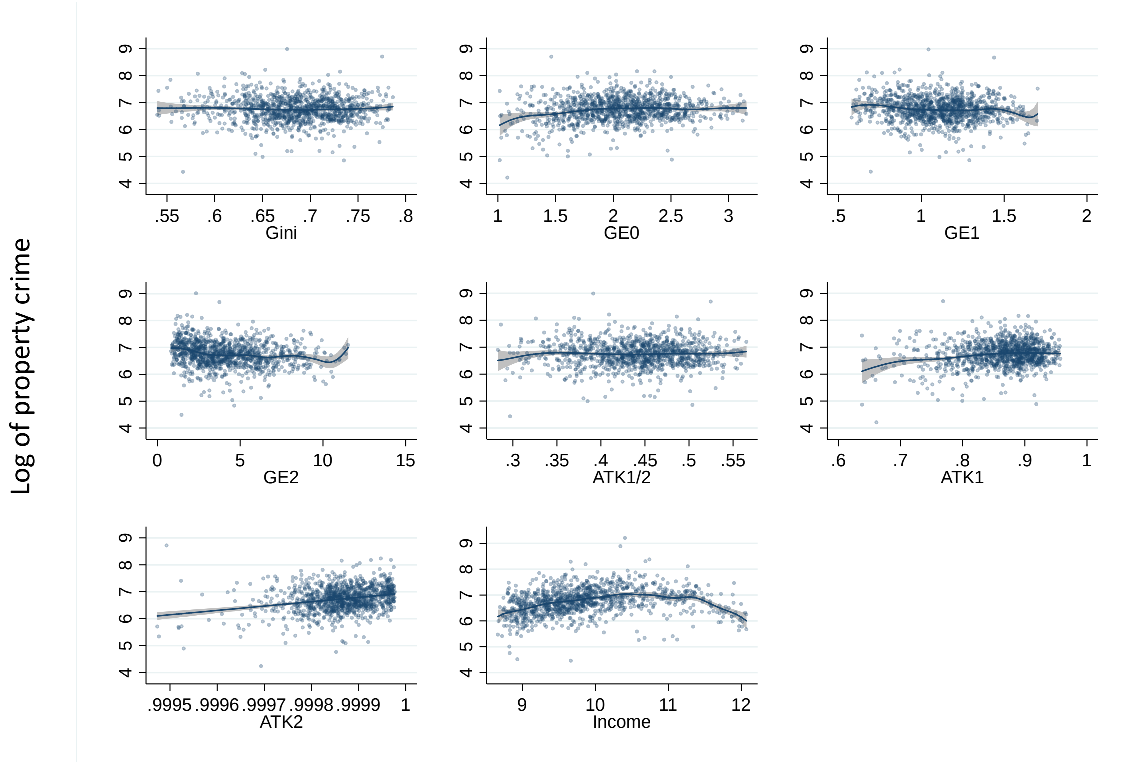
4.3 Semi-Parametric Analysis of Crime and Inequality

The suggestion of a negative relationship between crime and inequality seen above is novel and deserves greater investigation. In this section we control for a range of covariates (list available in Section 3.2, Methodology) while still allowing a non-parametric sense of the relationship between crime and inequality to emerge.

What we see below, in Figure 4, is essentially a disagreement between the different measures of inequality in terms of how they relate to crime. The Gini still appears flat while now the GE0 and the three Atkinson's measures are increasing. The GE1 and GE2 suggest decreasing relationships. The relationship between crime and income has also changed – a clear quadratic, inverted-U shape, is observed.

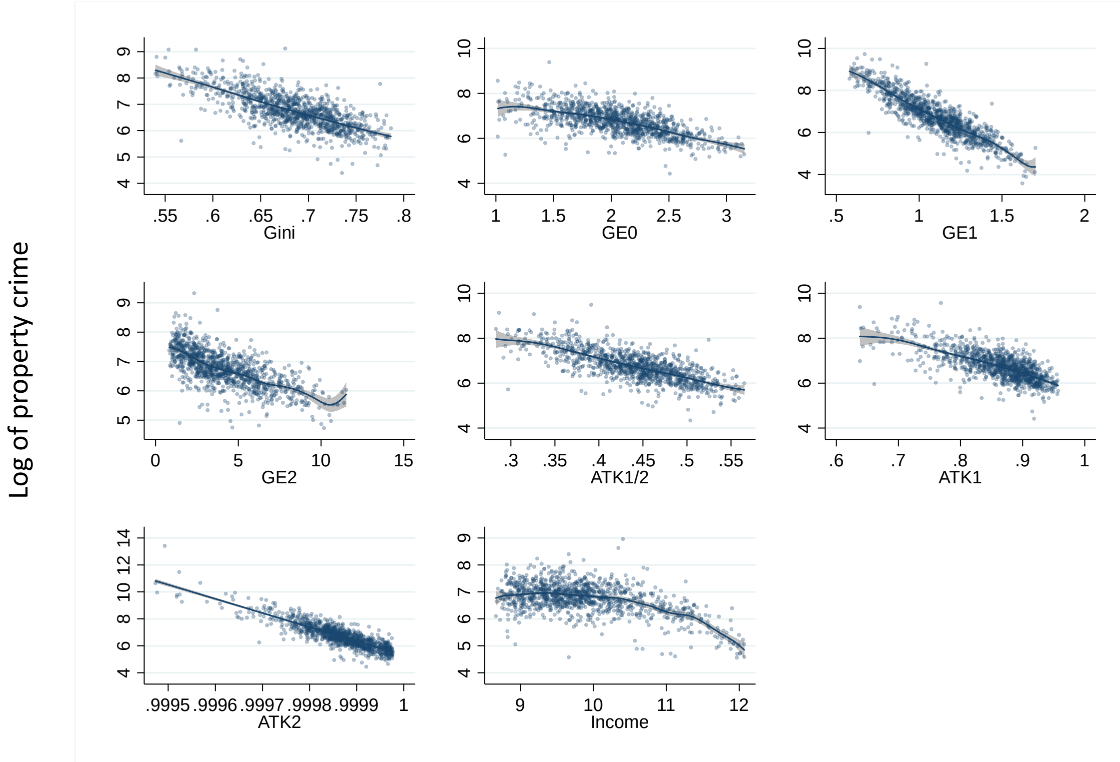
Given the relationship between inequality and income, and the potential for mediation and moderation between them in terms of their relationship with crime, we present the same analysis below but here we include an interaction term between income and the different inequality measures in the set of control variables in the semi-parametric calculation. The results are striking. Figure 5 displays these.

Figure 4. Semi-Parametric Relationship between Precinct Inequality and Property Crime



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the range of inequality.

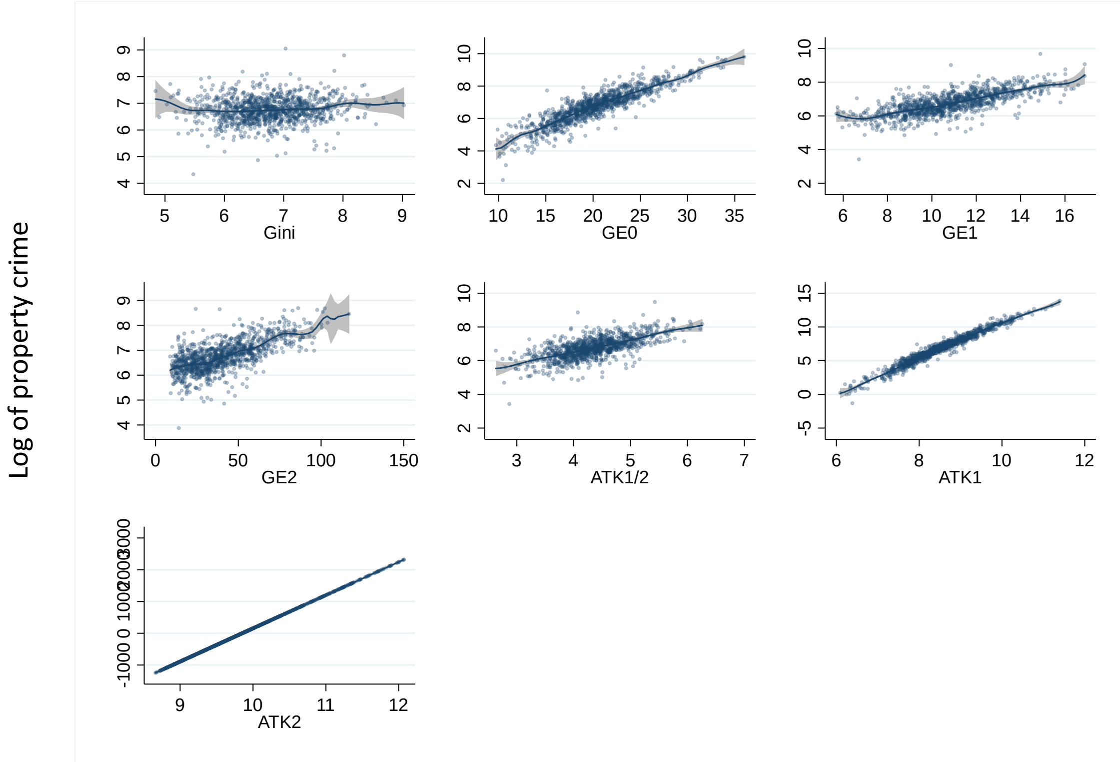
Figure 5. Semi-Parametric Relationship between Precinct Inequality and Property Crime with Inequality-Income Interaction



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the range of the inequality.

There is no longer any disagreement between the different inequality measures. All display a strongly downward sloping curve. Figure 6 displays the same semi-parametric analysis but this time the interaction term is allowed to vary non-parametrically. The interaction term is upward sloping in all cases, except for the Gini which appears flat.

Figure 6. Semi-Parametric Relationship between a Precinct Income-Inequality Interaction and Property Crime



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the range of the income-inequality interaction term.

These results are striking and offer strong evidence that crime can be modelled as a decreasing function of inequality, with the vital condition that an inequality-income interaction is included as well as a quadratic form of income. The next section will test the statistical significance of these results before the interpretation is provided in Section 5, Discussion.

4.4 4.4 Regression Results

The OLS regressions presented in this section will confirm whether and to what extent the relationships seen above are statistically significant. In Table 2 below two sets of regression specifications are presented for each inequality measure. On the left, the tails of the distribution are included, while on the right they are excluded. All regressions include the controls already mentioned in Section 3.2, Methodology, as well as a level and squared form of income.

In the first specification, which includes the tails of the inequality distributions, the results vary somewhat. This is unsurprising given the results seen above in the non-parametric analyses. Three of the seven measures display significant correlations, the Gini, GE1, and ATK½. In these cases, the direction of the relationships between crime and inequality and the income-inequality interaction are as expected from the analyses above: The level inequality term varies negatively with crime and the income-inequality interaction varies positively with crime. ATK1, although not significant in this specification, also displays these relationships. In contrast, the GE0 suggests that both variables are negatively decreasing with crime and the ATK2 suggests that inequality is increasing with crime and the interaction term is decreasing with crime. None of these latter relationships are significant however.

In the second specification on the right, which excludes the tails of the inequality distributions, all measures agree on the direction of the relationships with crime for both inequality and the inequality-income interaction term. All measures suggest a negative relationship between crime and inequality and a positive relationship between crime and the interaction term. This is congruent with the semi-parametric results seen above. Moreover, all relationships are statistically significant in this specification, although only at the 5 percent level.

Table 2. Precinct Property Crime Rate on Precinct Income and Inequality: OLS Regression

		Specification (1): Tails		Specification (2): No Tails	
		Sign	Significance	Sign	Significance
Gini	**Level**	-	*	-	*
	Interaction	+	*	+	*
GE(0)	**Level**	-		-	
	Interaction	-		+	*
GE(1)	**Level**	-	*	-	*
	Interaction	+	*	+	*
GE(2)	**Level**	+		-	
	Interaction	-		+	
ATK(½)	**Level**	-	*	-	*
	Interaction	+	*	+	*
ATK(1)	**Level**	-		-	
	Interaction	+		+	*
ATK(2)	**Level**	+		-	*
	Interaction	-		+	*

Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Significance starts denote: * significant at p<0.05, ** significant at p<0.01 and *** significant at p<0.001

The results presented here are a strong case for an argument that, at least in the case of South Africa in 2011, crime and inequality varied negatively with one another, taking into account a positive relationship between crime and an interaction between inequality and income and a quadratic form of income. The discussion presented below presents an interpretation of these novel results.

5. Discussion

Our results show that property crime increases and then decreases with income at the police precinct level, and at the same time increases with an interaction term of income with inequality, and crucially that property crime decreases with inequality on its own. This result is robust to the measure of inequality used. This result is relevant in country settings with high inequality, but the result is also important in and of itself as a novel, value-addition to our understanding of the linkage between inequality and the incidence of crime. To our knowledge, the nature of the relationship between property crime and inequality has not been empirically tested at such an extreme range of inequality.

It is certainly surprising to find such strong evidence of a decreasing relationship between crime and inequality, when all literature, theory, and intuition would suggest otherwise. However, the inclusion and effect of the interaction term is crucial to an understanding of what is happening here. Beginning with income, these results tell us that property crime increases with income, until a certain point at which it levels off and begins to decrease. This is in line with Chu and Madden (1998) who explicitly allow for a decrease in property crime at high levels of income due to the ability of the rich to defend themselves against crime by purchasing private security. This was discussed in Section 2, Theories of Crime and Inequality.

The positively varying interaction term between income and inequality suggests that at low levels of both income and inequality, property crime is also low, while at high levels property crime is high. The finding that crime varies positively with the interaction between income and inequality is not surprising and fits neatly into the literature. As income and inequality increase, so too does crime.

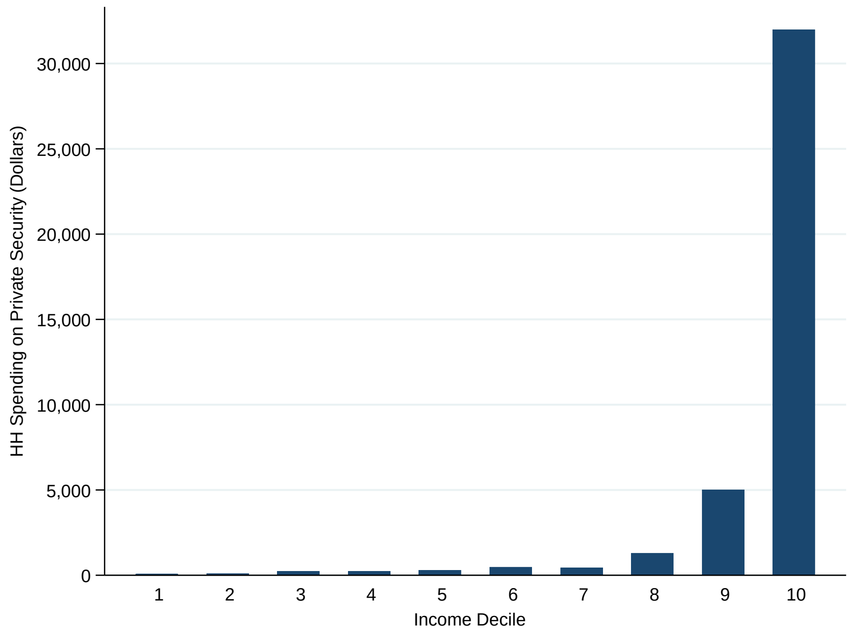
The negative relationship between crime and inequality, when interpreted in light of the above, is no longer as surprising. What this is telling us is that, at a given level of income, crime is a decreasing function of inequality, but as income increases, crime increases with inequality. As an illustration, if there exist two neighbourhoods with the same average level of income, then the results indicate that the neighbourhood with the lower inequality will have a higher crime rate. We can interpret this along the lines of the Chu and Madden (1998) model, and assume that it is private protection of the local elites in the more unequal neighbourhood (who have higher than the average income for the neighbourhood) that results in lower crime rates for that neighbourhood. However, if there is an increase in average income in one neighbourhood, then we expect crime to increase regardless of the level of inequality. Similarly, if both inequality and income increase, then we expect an unambiguous increase in crime.

Following Chu and Madden (1998), we explain this result by linking inequality to the purchase of private security. Local elites interpret rising local inequality as indicative of a higher threat of falling victim to crime. Consequently, they invest in private security measures of some kind (e.g. a lock, a dog, a high wall), which reduces the level of crime in the area. This may be because security acts as a deterrent or otherwise thwarts criminals in the act.

Our explanation for the negative relationship found—protective behaviours—is an important linkage but one that we are unable to test empirically due to a lack of reliable data. The data on private security expenditure that is available is sparsely populated and is not highly geographically disaggregated, resulting in power concerns. However, there is a growing literature on inequality and private security from elsewhere in the world that shows that the size of private security increases with inequality in an area. Specifically, two papers using American data find a quadratic shape between inequality and the size of private security in an area: there are decreasing marginal returns to investing in private security (Jacobs & Helms, 1997; D'Alessio et al., 2005).

In an effort to link inequality to protective behavior through an indirect angle, though, we use the South African 2010/11 Income and Expenditure Survey (IES; Statistics South Africa, 2012) to compare income and security spending. Figure 7 shows a clear positive relationship between income and private protection spending – consistent with D'Alessio et al. (2005). This data is based on household income and not geographical area. Therefore, if we assume that many wealthy individuals live close to poorer individuals (i.e. local area inequality is high) then we also know that it is the wealthy in an area of high inequality that are purchasing private protection. This is not a rigorous testing of how private security spending varies with inequality, but rather a crude point of entry given the data limitations.

Figure 7. Total Household Spending on Private Security by Income Decile in South Africa, 2011



Notes: Source IES 2010/11 (Statistics South Africa, 2012). Amount annualised to March 2011 (in Dollars). Security spending includes: padlocks, security systems for cars, firearms and ammunition, security structures (including fences, electronic gates), security services (including reaction services and neighbourhood watch), security systems (including alarms, panic buttons) and purchases of watchdogs.

6. Conclusion

Our results stand in contrast to the bulk of literature on crime and inequality. We uncover a robust negative linear relationship between property crime and inequality instead of a positive linear one. The fact that this relationship has not been uncovered in data from other countries could be because inequality is not serious enough to trigger this response (e.g. in the developed world), that research has not focused on property crime (e.g. in Latin American literature), or that the models used do not include an interaction term between income and inequality. Our theory for why property crime can decrease with inequality is that local elites purchase private security. However, this link remains speculative in our research because of the dearth of data on private security. Our conclusions therefore suggest two interlinked streams for a future research agenda: investigating whether the crime-inequality relationship observed in South Africa can be detected in other countries; and, a closer examination of the impact of protective behaviours on crime, and vice versa, led by more data collection in this area.

7. References

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