Crime and Inequality in South Africa:

Non-Linear Outcomes Under Extreme Inequality

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Abstract

How does South Africa's extremely concentrated income inequality affect the incidence of property crime? Studies based on developed countries with much lower inequality levels show that property crime increases monotonically with inequality; but this is not the case for South Africa. We use 2011 South African census data and property crime data locally disaggregated to the police precinct level. The best fitting model is a flexible one including non-linear inequality and income effects as well as an interaction between these two variables. We link this result to extreme inequality signalling both that local elites should invest in security but also relative credit-constraints for potential criminals. Our results are robust to seven different inequality measures, but the precise form of these results varies based on how sensitive measures are to the top or bottom of the income distribution. We conclude that the usual monotonic relationship between property crime and inequality is not robust in high-inequality contexts like South Africa and that measurement of inequality matters in order to correctly specify this relationship.

Keywords

property crime; inequality; GAM; South Africa; non-monotonic

JEL codes

D63; D74; R12

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1. Introduction

Led by the seminal papers of Becker (1968) and Ehrlich (1973), economists have been empirically testing the relationship between crime and income inequality for about 50 years. It has been generally accepted that crime increases with income 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 income 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 income inequality. While there are studies in high income inequality contexts (specifically in Latin America), these focus on violent crime. Our aim is to revisit the topic of property crime and income inequality, specifically in a high crime-high inequality setting, to determine whether a positive relationship still holds at high levels of both variables, through using South Africa as a case study. One reason we may question whether a positive relationship between crime and income inequality would hold in a high-inequality setting is because of how income inequality can impact on the resources available to criminals relative to those available to elites to protect themselves.

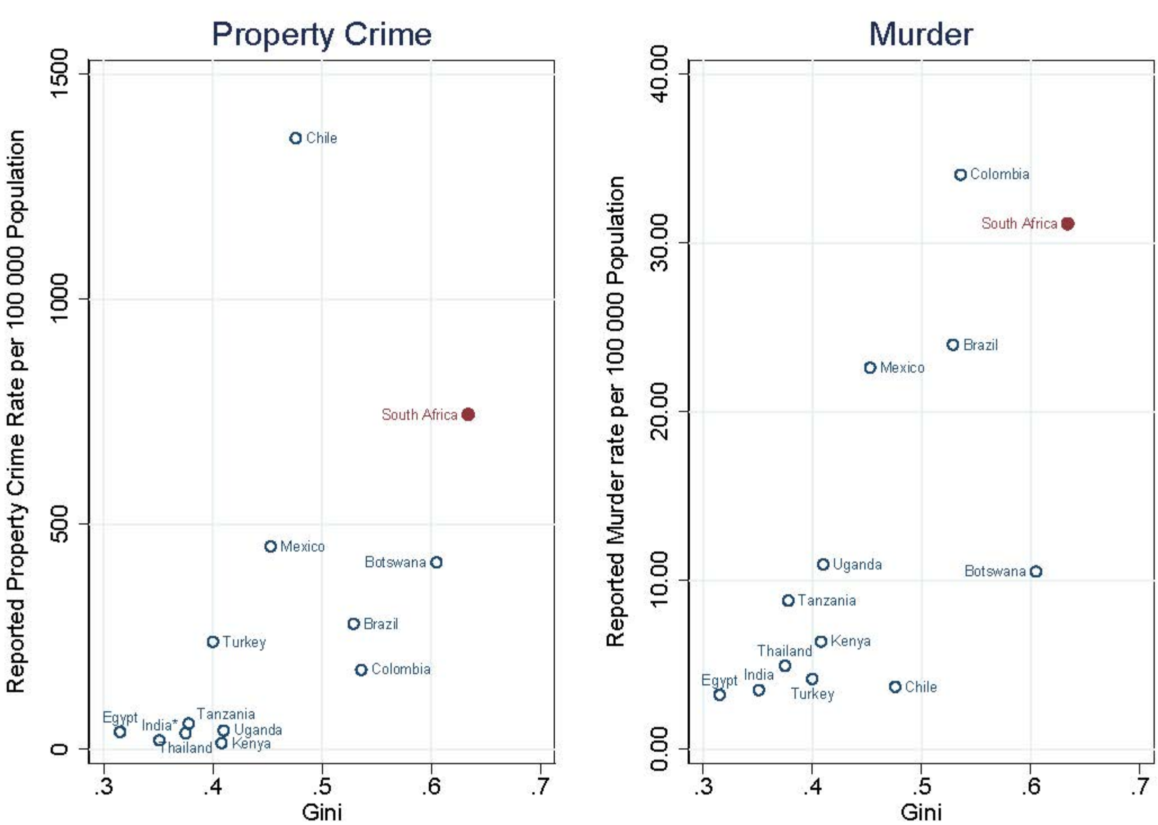
Although there is a perennial difficulty in comparing country-level crime rates due to differences in national reporting rates and recording practices (Soares, 2002), South Africa is considered to have exceptionally high crime rates (Heiskanen, 2010). Figure 1 places South Africa in the international context of crime and income 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 reporting rates in High Income Countries (HICs).

What is immediately apparent from Figure 1 is that South Africa is a global outlier in terms of income 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 income 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 income 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. 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 income 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).

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.

Our initial contribution is testing a well-established relationship at an extreme portion of the income inequality range. It is natural to suppose that South Africa – an outlier certainly in terms of inequality and probably in terms of property crime – would reflect the established consensus especially well. Yet, as our results show, we cannot confirm this in the usual way in which the literature specifies this relationship: significant, positive and monotonic.

Our rationale for why this is the case relates to how we think potential criminals and their victims will be affected by extreme income discrepancies. Local elites interpreting inequality as a reason to invest in private security may introduce non-linearity into the relationship, for example (Bourguignon, 2000). On the other hand, when potential criminals are very poor and inequality is very high, this could represent an insurmountable gulf between the ability of the potential criminals to commit property crime and the ability of elites to protect themselves from such action. In other words, the effect of inequality on crime is modulated by income and this interaction could further destabilize the usual positive monotonic relationship between crime and income inequality. In short, while income signals information about resources available to either steal or protect, inequality signals information about *relative* resources with a potentially similar outcome.

We test both of these hypotheses using seven common measures of income inequality and find evidence for both an interaction and non-linearity, although the shape of the non-linearity is not always consistent with theory. A general additive model (GAM) allowing for non-linearity in the functional form of this interaction is ultimately the most preferred model and is additionally informative about how variation in income inequality measurement affects the shape of this relationship.

The implications of our findings, therefore, are threefold: Firstly, income modulates the rate at which crime increases as inequality increases, and vice versa. Most unexpectedly and of particular interest, at low income ranges, increasing inequality has a flat to negative effect on the predicted probability of crime. Secondly, inequality and income can have a non-linear effect with crime. We attribute this to protective behaviour by potential victims of crime. Thirdly, how income inequality is measured matters for describing its relationship with crime: A negative effect on crime, for example, is found to be more persistent amongst those inequality measures more sensitive to changes in income in the middle of the distribution, than the top or bottom. This paper then is about more carefully specifying how the level and variation in local income affects property crime rates in an extreme inequality setting.

We begin with a discussion of the theory of the relationship between property crime and income inequality, highlighting the probable form that the theory assumes the relationship will take in the high-inequality case. We also set up and motivate our hypotheses about a non-linear and interaction effect between income and inequality. In Section 3 we provide an overview of the data used and methodology followed. Thereafter, we test the relationship in South Africa between property crime and income inequality at the relatively detailed geographical unit of police precinct, 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 comparatively less well-off. 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 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:

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

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.

Chiu and Madden (1998) provide a neighbourhood-level micro-theoretical framework for why we would expect property crime to increase with income inequality, based on Becker's original formulation and empirically supported by studies like Choe (2008) and Demombynes and 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 income inequality in the area. When inequality increases, crime becomes more attractive to lower income residents because the returns from the alternative to crime go down and secondly, the gains from crime go up. Our overall research question is about better understanding the relationship between income inequality and property crime in an extreme case. The theory and evidence discussed here, sets up our first hypothesis that property crime and income inequality should reflect the established relationship that is positive and monotonic.

Our second hypothesis is that property crime could be concave in income inequality if elites invest in private security (Bourguignon, 2000). The idea of elite private security spending can be found in empirical and theoretical literature. 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. In Israel, the deviation of the wealthiest towns from the upward trend between crime and income has been linked to purchases of security measures (Portnov and Rattner, 2003). In an environment where social groups are highly polarized, individuals become increasingly preoccupied with protecting their own interests (Lemanski, 2004). In South Africa then, we may expect some concavity in the relationship between property crime and income if elites take steps to protect themselves.[1]

This idea could be easily extended to income inequality (Bourguignon, 2000). Inequality could similarly signal to local elites that they are potential victims of crime and also stimulate security spending (Bourguignon, 2000). D'Alessio et al. (2005) used American data to show that the size of private police was a concave function of income inequality; in other words, more was spent on private security in more unequal areas. Following Chiu and Madden (1998) where crime occurs within neighbourhoods, the level of inequality as well as a resident's location in the local income distribution can be discerned through housing quality or other conspicuous consumption. Investment in private security could induce concavity in crime rates if either private security is effective at preventing crime or if it displaces crime from elites to the less well-off (Bourguignon, 2000).

Our third hypothesis is that income and inequality interact. Here it is helpful to consider both actors in a neighbourhood, potential criminals and potential victims. In theory, criminals and victims are usually at opposite ends of the local income distribution (Chiu & Madden, 1998), but both can observe signals like housing quality or other consumptive activity that could convey information about relative income. We suggest that income modulates the resources available to both actors to act on the information conveyed to them by these signals. Specifically, income modulates the resources available to potential criminals to commit crime, as well as, the resources available to local elites to purchase security to protect themselves from property crime.

Whilst this modulation should be present in any setting, including those not in the tails of the global inequality distribution, we argue that this modulation is more pertinent at extreme levels of income inequality. When income is very low, this could reflect that criminals themselves are poorly-resourced (Ackerman & Rossmo, 2014). An increase in already exceedingly high inequality in a neighbourhood with low average income can represent the widening of an almost insurmountable gulf between the ability of criminals to commit crime and of elites to protect themselves. This is pertinent in South Africa where 53.2% of the population were below the poverty line in 2011 (Statistics South Africa, 2017). When income

[1] Demombynes and Ozler (2005) do not find this relationship for South Africa using 1996 data.

is low but inequality is high, we may not necessarily expect to see the usual positive monotonic relationship found in the literature.

On the other hand, when both income and inequality are (relatively) high, we do not expect the protective behaviour of elites to dominate criminal activity for two reasons. Criminals may be more highly motivated by the higher payoff that comes from targeting elites in higher income areas. Further, there could be diminishing marginal returns to security spending. As mentioned above, the relationship between the size of both private (D'Alessio et al., 2005) and public (Jacobs & Helms, 1997) police forces and local inequality was concave in the USA, suggesting diminishing marginal returns to these forms of security. When both income and inequality are high then, we still predict a positive relationship between crime and inequality.

3. Data and Method

Our empirical work has three components. Firstly, we demonstrate that the usual specification of the crime-inequality relationship commonly found in the literature is not robust in South Africa. Secondly, we use standard OLS techniques to explore whether there is evidence for using nonlinear and interaction terms in our modelling. Finally, evidence being found, we move to more flexible models that impose fewer functional assumptions and test the joint hypothesis of non-linearity and an interaction.

Common practice is for an inequality measure, usually the Gini, to appear in a level format on the right-hand side of a regression with some crime measure as the dependent variable (Rufrancos et al., 2013). We therefore begin by running bivariate and multiple OLS regressions with property crime as the dependent variable and a level measure of income inequality. For robustness, we compare the results for seven popular measures of income inequality to ensure it is not choice of indicator that is driving our result. We find that there is little agreement amongst our inequality measures about the sign or significance of the crime-inequality relationship.

We then turn to our alternative hypotheses about non-linearity and an interaction term. We test each separately in a parametric OLS model. We find mixed results for the non-linearity and whilst the interaction term is jointly significant in almost all cases, the results may not be strong enough to be convincing that this is the correct functional form. Although our results are mixed, there is sufficient evidence to explore the hypotheses further.

Rather than including both nonlinear and interaction terms in a parametric model and risk imposing very strict functional form assumptions on a complex relationship, we move to more flexible models that impose fewer functional assumptions and also test the joint hypotheses of non-linearity and an interaction. We set up semi-parametric regressions, or, generalized additive models (GAM), where we allow both income and inequality to enter the model in a non-linear way. We test the GAM with and without an interaction and compare these models to the OLS to test linear additivity. We report test statistics for the significance of the non-linear terms and interpret plots of the effects of income and inequality on crime.

We detail our choice of inequality measures and different regression specifications below. In our descriptive section we also motivate for excluding the top and bottom tails of the inequality and income variables in the remainder of the analysis due to the impact of influential outliers.

3.1 Data

The dataset used to test our hypotheses combine the South African Police Service's (SAPS) official Crime Statistics (SAPS, 2011) and the 2011 South African Census Community Profiles (Statistics South Africa, 2011). The SAPS Crime Statistics provide 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 provide 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 datasets, 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[2]. 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[3].

Property Crime Measures

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

[2] 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 potential error.

[3] 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. Another note is that we drop the precinct of O.R. Tambo International Airport from all of our analysis because it stands out as an outlier in terms of crime rates and numerous descriptive statistics.

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.

Inequality Measures

When testing the relationship between inequality and some dependent variable it is important to ensure that the results are not driven by the choice of inequality measure used (De Maio, 2007). The most common measure of income inequality in the crime literature is the Gini coefficient (Rufrancos et al., 2013). The Gini coefficient ranges from zero (perfect equality) to one (perfect inequality), and 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. The main weakness of the Gini is that it cannot differentiate between different types of inequality; such as, when intersecting Lorenz curves yield the same summary Gini coefficient. Another important characteristic for our purposes is that because the Gini equally weights all changes across the income distribution, it is relatively more sensitive to changes in inequality in the middle of the distribution compared to other measures that weight the tails (World Bank, 2014; De Maio, 2007).

Other popular measures of inequality include the Generalised Entropy measures (GE), parametised by θ (Shorrocks, 1980). The values of GE(θ) measures vary between 0 and ∞, with zero representing an equal distribution and higher values representing a higher level of inequality. The parameter, θ, in the GE class describes how distances between incomes at different parts of the income distribution are weighted. The parameter can take on any real value with θ close to zero increasing sensitivity to changes at the bottom end of the distribution, and values of θ higher than one more sensitive to changes in the top of the distribution (World Bank, 2014). The most common values of θ used are 0, 1 and 2 (referred to hereafter as GE(0), GE(1) and GE(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 (World Bank, 2014).

Atkinson (1975) has proposed another class of inequality measures out of concern that the Gini could not assign weights to different parts of the income spectrum. Atkinson (1975) stressed the importance of the researcher being able to control the weights and therefore incorporate social value judgements into measurement, pointing out that a measure like the Gini implicitly does so and is therefore not 'judgement-free'. The ATK(ε) measures vary between zero and one with lower values indicating a more equal distribution. Like GE, this class, ATK, also has a weighting parameter, ε, which measures aversion to inequality by varying between 0 and ∞. When there is no aversion to inequality, then ε = 0 and the measures rank distributions based only on income; the higher ε grow, the more sensitive ATK(ε) becomes to changes at the lower end of the distribution. Atkinson (1975) suggests that the Gini ranks distributions similarly to an ATK(ε) measure with a relatively low level of inequality aversion of ε = 1 or less. Usually, Atkinson's measures are applied with ε =½, 1, 2 (referred to as ATK(½), ATK(1) and ATK(2) in this paper).

Although the formulae for the indicators are different, we should assume that they are measuring the same underlying concept albeit with slightly different points of emphasis. We can group the indicators according to this emphasis: the Gini, ATK(½) and GE(1) are the measures in each class that disturb the rankings least via weighting and come closest to being 'equally-weighted'. GE(0) and ATK(1) are more sensitive to changes at the lower end of the distribution, with ATK(2) being even more so. Finally, GE(2) stands alone in being the only measure that is sensitive to change at the top end of the distribution (World Bank, 2014).

The analyses that follow use all seven measures of inequality – Gini, GE(0), GE(1), GE(2), ATK(½), ATK(1) and ATK(2) – and assess the level of agreement or disagreement among them. The inequality measures were constructed 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, and could be expected to lead to under- rather than overestimates of inequality (Alvaredo, 2011). We use the midpoint of each bracket and apply this to all households in the same bracket; we multiply the top bracket by 1.5 to reach a value for those households. Households with zero annual income were all assigned an annual household income of 1 – a sufficiently small number – so that these households would remain in sample for calculation of inequality measures. [4] As will be seen below, despite the use of brackets in the income measure, when the Gini is calculated for this dataset we reach a very similar estimate as has been reported in other research for South Africa over the same time period.

Confirmatory OLS Model Specification

Our aim with this model is to confirm the result commonly found in the literature which is a significant positive monotonic relationship between property crime and a level income inequality measure. We specify the following two OLS regressions:

Bivariate Confirmatory OLS Model:

$$\ell n(C_i)=\boldsymbol{B}_0+\boldsymbol{\gamma} I_i+\varepsilon_i \qquad \text{(Model 1)}$$

Multiple Confirmatory OLS Model:

$$\ell n(C_i)=\boldsymbol{B}_0+\boldsymbol{\gamma} I_i+\boldsymbol{B}_1\ell n(INC_i)+\boldsymbol{B}_2\ell n(INC_i)^2+\boldsymbol{B}_3\mathbf{X}_i+\varepsilon_i \qquad \text{(Model 2)}$$

In the equation, C_i represents the property crime rate (number of crimes per 100 000 residents) in precinct *i* (i=1, 2,…,1 124) 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 with zero reported property crime, this does not affect our analysis.

I_i represents our inequality measure. The variable INC_i represents average per capita annual household income for the precinct *i*, constructed from mid-points of the same 12 income

[4] We use the Stata package *ineqdeco.ado* (Jenkins, 1999) to calculate all of our seven inequality measures. In order to calculate within-precinct inequality with *ineqdeco* we manipulate the data into a household-level (as opposed to a precinct-level) file for each precinct to calculate a household-level inequality measure for each precinct.

bands used to make the *I* variable. 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.

Non-Linear and Interactive OLS Model Specification

We run an OLS specification to test our hypothesis that there is nonlinearity in inequality and that there is an interaction between income and inequality. This takes the following form with the same variable specifications as given above:

Non-linear OLS Model:

$$\ell n(C_i)=\boldsymbol{B}_0 + \boldsymbol{\gamma}_1 I_i + \boldsymbol{\gamma}_2 I_i^2 + \boldsymbol{B}_1 \ell n(INC_i) + \boldsymbol{B}_2 \ell n(INC_i)^2 + \boldsymbol{B}_5 \mathbf{X}_i + \varepsilon_i \qquad \text{(Model 3)}$$

Interactive OLS Model:

$$\ell n(C_i)=\boldsymbol{B}_0 + \boldsymbol{\gamma} I_i + \boldsymbol{B}_1 \ell n(INC_i) + \boldsymbol{B}_2 \ell n(INC_i)^2 + \mathbf{B_3} I * \ell n(INC_i) + \mathbf{B_4} I * \ell n(INC_i)^2 + \boldsymbol{B}_5 \mathbf{X}_i + \varepsilon_i \qquad \text{(Model 4)}$$

Model 3 tests the nonlinearity in inequality while Model 4 tests the interaction term. We run a likelihood ratio test to determine whether the specifications yield better model fits than the OLS Model 2 above.

Semi-parametric Model Specification

The semi-parametric analysis plots Generalised Additive Models (GAMs) where we apply a smoother to income and inequality, whilst still controlling for the same set of linear covariates in $\boldsymbol{X_i}$ described above. The following specifications are run where Model 5 puts smoothers on inequality and income and Model 6 additionally includes and smooths the interaction term. These models allow for testing the hypotheses that both non-linearity and an interaction are relevant.

GAM:

$$\ell n(C_i)=\boldsymbol{B}_0 + f(I_i) + f(\ell n(INC_i)) + \boldsymbol{B}_3 \mathbf{X}_i + \varepsilon_i \qquad \text{(Model 5)}$$

GAM Interaction:

[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.

$$\ell n(C_i)=\boldsymbol{B}_0 + f(I_i) + f(\ell n(INC_i)) + f(I_i, \ell n(INC_i)) + \boldsymbol{B}_3\mathbf{X}_i + \varepsilon_i \qquad \text{(Model 6)}$$

Given the initial evidence for nonlinearity and the interaction that Models 3 and 4 provide (as will be shown below), we now expect Model 6 to be the best fitting model. To test our hypotheses more specifically, however, we run the following three likelihood ratio tests: Firstly, we compare Model 2 (Confirmatory OLS) to Model 5 (GAM). This tests whether allowing inequality to enter the model non-parametrically in the GAM provides a better model fit than the usual model in the rest of the literature, which is Model 2. We then compare Model 5 to 6; that is, whether a GAM outperforms a GAM with an interaction. As we will show, this test establishes that an interaction embedded in a flexible functional form (Model 6) yields the best model fit. Together these two tests show that both non-linearity and an interaction are pertinent which is a main result of this paper. A final test is then between Model 6 and Model 4 – the GAM with an interaction compared to an OLS with an interaction - in order to be certain that non-linear additivity fits the data better than linear additivity.

4. Results

4.1 Descriptive Statistics

Our sample consists of 1 124 police precincts[7], and all of the summary statistics presented in

Table *1* are at this level. In the Census Community Profiles data, there are roughly 51 million individuals and 14 million households who have been allocated into these 1 124 police precincts (own calculations; Statistics South Africa, 2011). 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 (own calculations; Statistics South Africa, 2011).

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 (

Table *1*). 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

[7] Influential outliers have an outsized effect on our results to the extent of altering the sign on regression coefficients. We exclude the top and bottom percentile of each inequality distribution to avoid this problem. This restricts the sample size from 1 124 precincts per inequality indicator in the following way for simple regression (i.e. Model 1): Gini (1100 precincts); GE(1) (1101 precincts); ATK(½) (1100 precincts); GE(0) (1100 precincts); ATK(1) (1100 precincts); ATK(2) (1100 precincts); GE(2) (1101 precincts). The sample size changes in the following way when all the variables for the multiple regression are included (i.e. Models 2 – 6): Gini (1079 precincts); GE(1) (1079 precincts); ATK(½) (1078 precincts); GE(0) (1078 precincts); ATK(2) (1081 precincts); GE(2) (1080 precincts). These sample sizes apply throughout the paper where simple or multiple regression are employed.

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[8] 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 0.69, 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 (for this sample) were a mixed collection of entirely urban areas and entirely rural areas, as well as a mixture of different provinces.

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 (USD$)	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

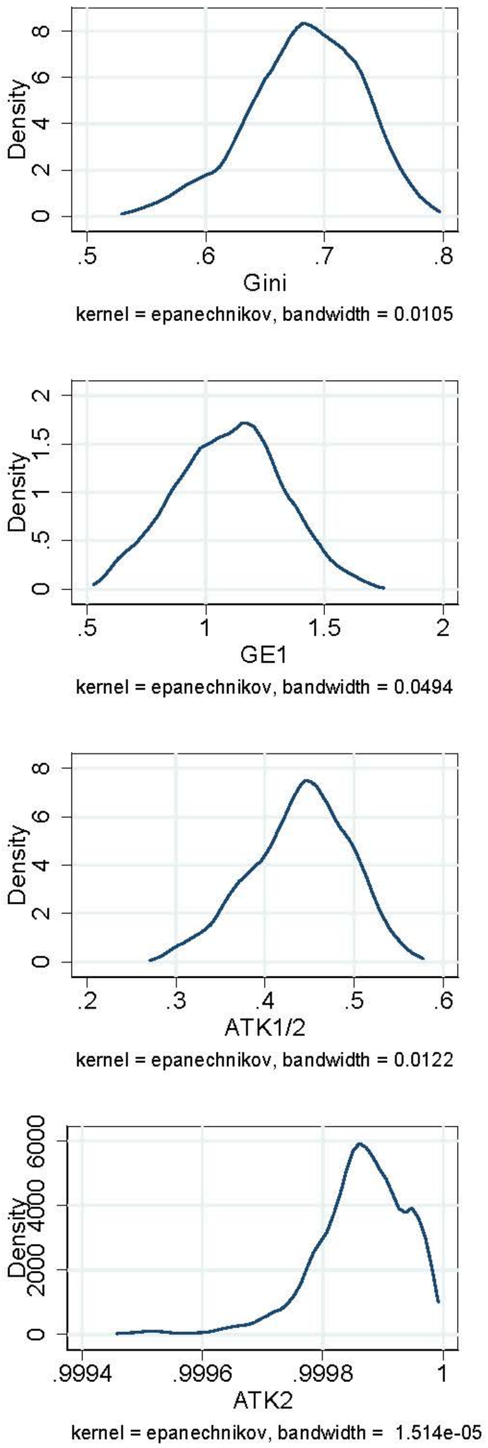
Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). N = 1124. Dollar-Rand exchange rate of $1=R8.13 from 30 November 2011 used.

Figure 2 below plots the density of each of our inequality indicators. Previously we described how different measures were more of less sensitive to variation at different parts of the income distribution and this is to some degree evident in Figure 2. The measures that are most sensitive to changes in the middle of the distribution are the Gini, GE(1) and ATK(half),

[8] Using a Dollar-Rand exchange rate of 8.13, which corresponds to the exchange rate on 30 November 2011.

all of which are close to being normally distributed. GE(0), ATK(1) and ATK(2) are more sensitive to changes at the bottom of the distribution. ATK(1) and ATK(2) are both left-skewed, although the GE(0) also appears more normally-distributed. ATK(2) is very sensitive to the bottom of the distribution compared to ATK(1) and GE(0) and is more extremely left-skewed than the others. GE(2), which is sensitive to changes at the top end of the distribution, is the clear deviant here being right-skewed.

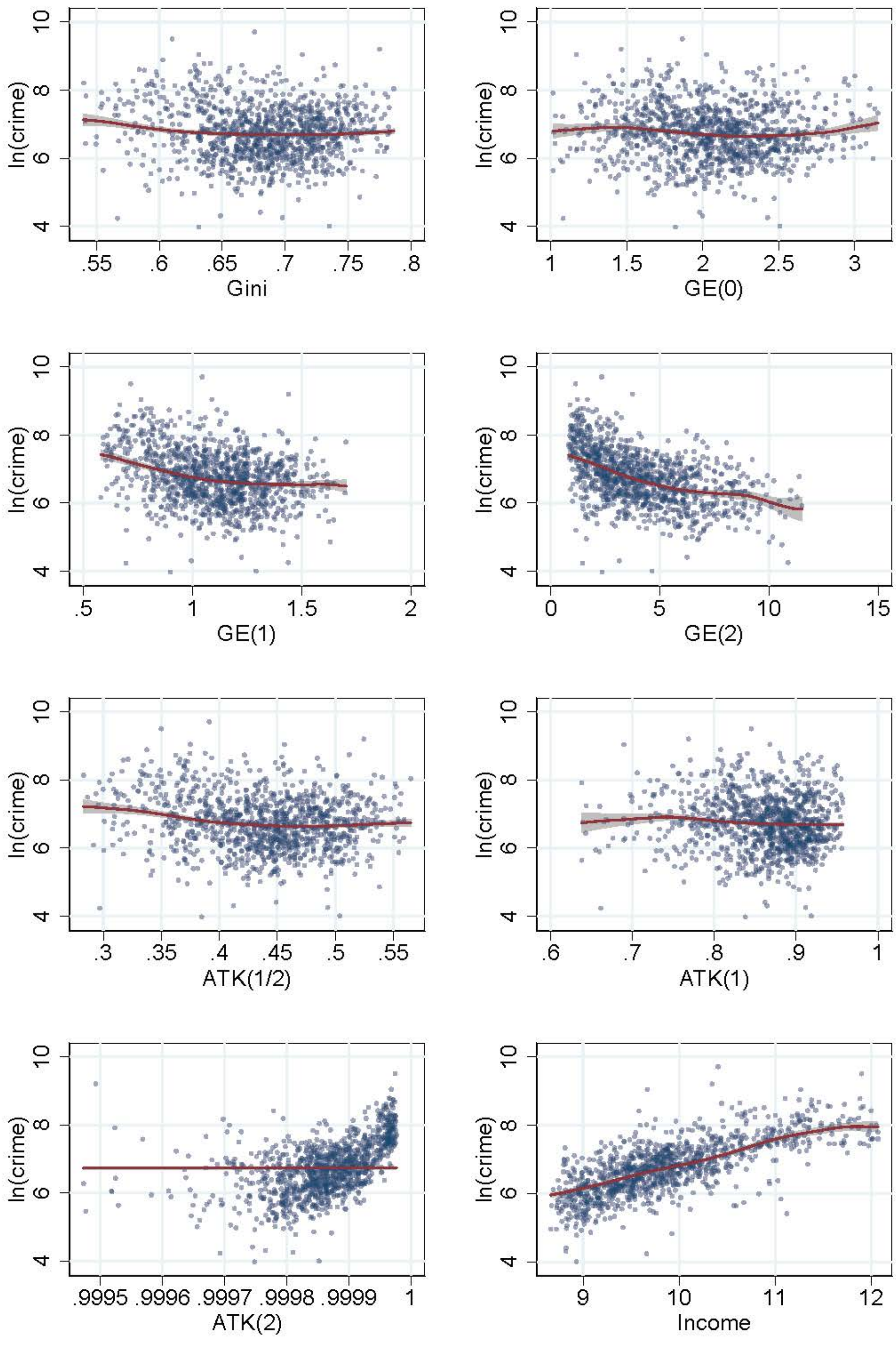
Figure 2. Kernel Densities of Police Precinct-level Inequality Measures



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); inequality measures plotted from the 1st to the 99th percentile.

Our last descriptive exercise is to run local polynomial regressions of crime on inequality, income, and an interaction of crime and inequality. Figure 3 displays local polynomial regressions between property crime and inequality. None of the figures display a clear upward sloping relationship, as we have come to expect from the literature. Most measures appear either flat or slightly downward sloping. The suggestion of a downward slope is unexpected and contrary to conventional wisdom on the topic.

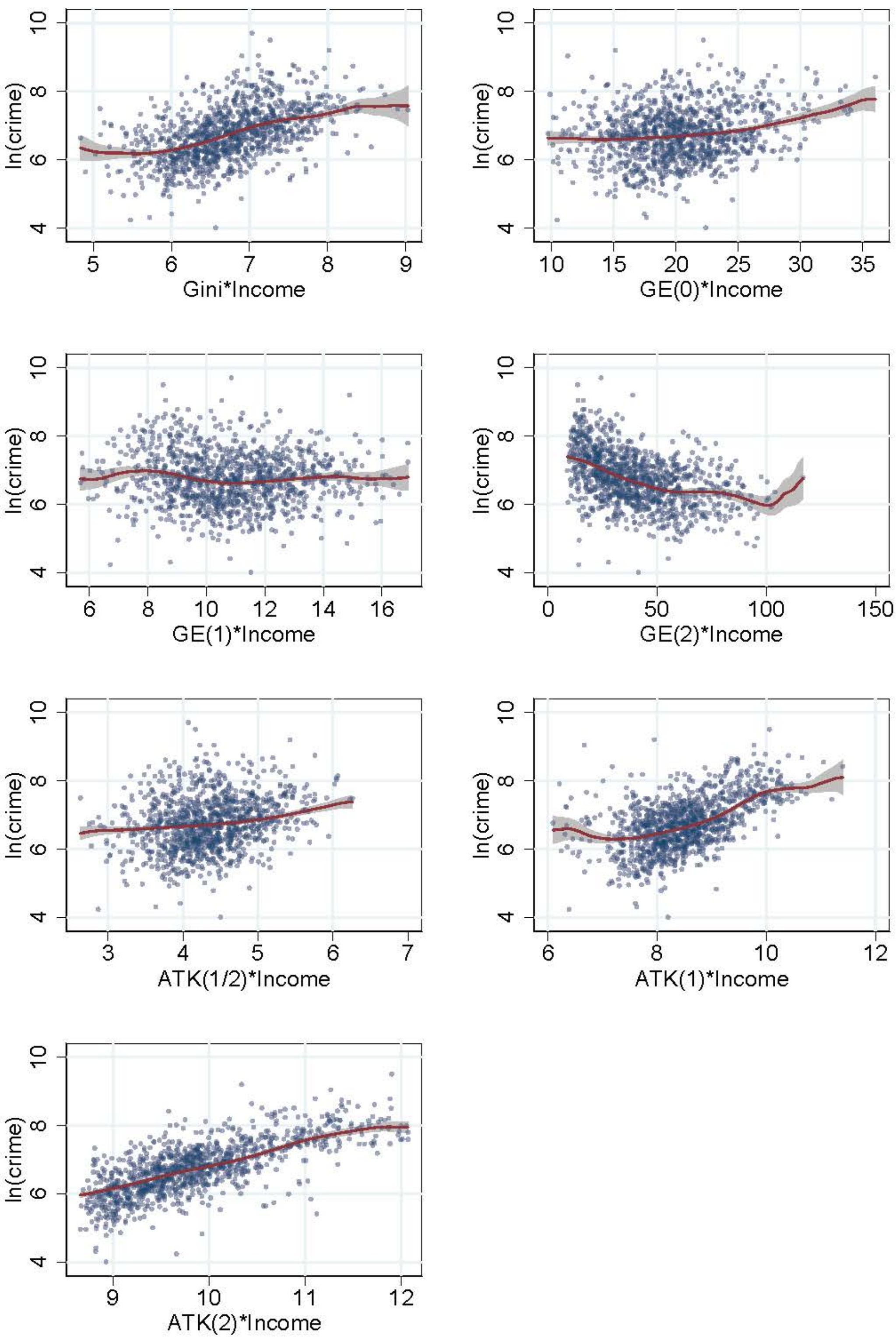
Figure 3. Local Polynomial Regression of Property Crime on Inequality



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the 2nd – 98th percentile of inequality.

Continuing with our non-parametric exploration of the data, we also compare property crime to an interaction of logged average per capita household income and inequality in Figure 4 below. With the exception of GE(2) and GE(1), this provides some indication that there may be a positive interaction between income and inequality in explaining property crime. This is some initial evidence that an interaction could be relevant for the parametric analysis that follows.

Figure 4. Local Polynomial Regression of Property Crime on an Interaction of Income and Inequality



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011); property crime rate graphed across the 2nd – 98th percentile of inequality; interaction defined as logged average per capita household income multiplied by inequality all at the precinct level.

4.2 Confirmatory OLS Analysis of Crime and Inequality

Table 2 presents the results for specifications in Models 1 (bivariate) and 2 (multiple) as described in the methodology above. More detailed output including the results for the income variable are in appendix Table 6. All of the coefficients are negative and significant in the bivariate case, with the exception of ATK(2), which yields a positive and significant coefficient. The standard relationship found in the literature is only confirmed in three cases of a significant positive coefficients on inequality in the multiple regression for (GE(0), ATK(1), and ATK(2)). There are two cases of significant negative coefficients (GE(1) and GE(2)) and two cases of insignificant coefficients (Gini and ATK(½)) in the multiple regression.

If we think about common groups of measurement emphasis, then there is slightly more consistency. Specifically, there is evidence that there is a positive monotonic relationship between inequality measures that emphasise changes in the lower part of the income distribution and property crime. GE(0), ATK(1) and ATK(2) are all in agreement that there is a positive monotonic relationship between inequality and property crime in the multiple regression. Amongst the indicators that are more sensitive to the middle, however, there is disagreement in terms of both sign and significance. Overall, if we think these indicators are all capturing the same latent concept, then these results are mixed and are not robust evidence of a significant positive monotonic relationship between property crime and inequality.

Table 2. Regression Results for the Bivariate and Confirmatory OLS Models: Model 1 and 2

	Bivariate Confirmatory OLS Model 1		Multiple Confirmatory OLS Model 2	
Measure	**Sign**	**Significance**	**Sign**	**Significance**
		Equally-weighted indicators		
Gini	-	**	-	
GE(1)	-	***	-	*
ATK(½)	-	***	+	
		Bottom-weighted indicators		
GE(0)	-	*	+	**
ATK(1)	-	*	+	***
ATK(2)	+	***	+	***
		Top-weighted indicators		
GE(2)	-	***	-	***

Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Significance stars denote: * significant at p<0.05, ** significant at p<0.01 and *** significant at p<0.001. Top and bottom percentile excluded from the inequality and income variable.

4.3 OLS Model with a Non-Linear and Interaction Term

Having noted the discord in the level OLS regression, we present the results of Model 3 below, which includes a nonlinear inequality term (and still excludes the interaction term). The full results are reported in the appendix Table 7, but the key points are summarized by Table 3. Results vary by how indicators are weighted. Equally weighted indicators and, GE(2) which is sensitive to the top of the distribution, yield a convex shape, although all of these models are statistically insignificant except GE(2). Indicators more sensitive to the bottom of the income distribution significantly yield the predicted concave shape, with the exception of ATK (2), which is more extremely bottom-weighted than ATK(1). Recall that income enters non-linearly in all of the models in Table 3 and is significant and concave in all models (see Table 7 in appendix for the results for income). This means that in the case of GE(0) and ATK(1), we have found a statistically significant concave relationship between crime and income and crime and inequality at the same time.

Table 3. Regression Results for the Non-Linear OLS Model: Model 4

	Level Term		Square Term	
	Sign	**Significance**	**Sign**	**Significance**
Equally-weighted indicators				
Gini	-		+	
GE(1)	-		+	
ATK(½)	-		+	
Bottom-weighted indicators				
GE(0)	+	***	-	***
ATK(1)	+	**	-	*
ATK(2)	-		+	
Top-weighted indicators				
GE(2)	-	***	+	*

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. Sample excludes the top and bottom percentiles of the inequality and income variables.

Next, we present the results of Model 4 below, which includes a level inequality term and an interaction between inequality and income. Again, the full results are reported in the appendix

Table 8, and we report sign and significance of the coefficients along with a Chi-squared statistic from an LR test comparing this model to Model 2, in Table 4. The first thing to note, is the lack of significance for any of the individual terms. The supporting evidence for the interaction model comes from the joint significance of the two interaction terms in all the indicators in Model 4, save that using GE(2). There is consistency within types of indicators, but not between. In fact, there are four different shapes in Table 4. The equally weighted indicators, The Gini, GE(1), and ATK(½), agree on positive terms for the inequality term and the interaction of inequality and income squared, with a negative sign on the interaction of inequality and income. The inverse of this shape is yielded by GE(0) and ATK(2), and still two other formulations are provided by GE(2) and ATK(1). Whilst the model fit is improved by the inclusion of the interaction, we do not necessarily have more clarity on the shape of the relationship between income, inequality and property crime. Something else to note are the very large standard errors on many of the coefficients in this model which are reported in the appendix. Despite the mixed results, there is sufficient evidence from the tests of joint significance to warrant further exploration into whether an interaction term between inequality and income is relevant.

Table 4. Regression Results for Interactive OLS Model: Model 5

	Level Term		Interaction Term		Interaction Sq.		Chi-Sq (2)
	Sign	Signif.	Sign	Signif.	Sign	Signif.	
Equally-weighted indicators							
Gini	-		+		-		7.01*
GE(1)	-		+		-		6.30*
ATK(½)	-		+		-		6.62*
Bottom-weighted indicators							
GE(0)	+		-		+		6.96*
ATK(1)	-		-		+		7.34*
ATK(2)	+		-		+		8.58*
Top-weighted indicators							
GE(2)	-		+		+		0.00

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. Sample excludes the top and bottom percentiles of the inequality and income variables. The Chi-sq. statistic is from a likelihood ratio test using the confirmatory specification in of Model 2 as the restricted model and the interaction specification in this table as the unrestricted model – the difference being the two interaction terms of inequality*income and inequality*income squared.

4.4 Generalised Additive Models of Crime and Inequality

The results of Models 3 and 4 suggest there is mixed evidence for non-linearity and stronger evidence for an interaction, but the inconsistency in the direction of the coefficients motivates us to explore more flexible functional forms for specifying this relationship. We employ a GAM because the complexity of both non-linearity and interaction may be difficult for a parametric model to handle. We set up a GAM with and without the interaction term as detailed above in Models 5 and 6, respectively. We use model fit statistics in

Table 5 to assess which model is the best specification and plots to interpret what our results mean substantively.

In Table 5 below, we report the results of the GAM models on the left hand side of the table, and the results of the likelihood ratio tests on the right hand side. In the prior case, we report the F statistic for the inclusion of each variable with effective degrees of freedom in parentheses. For the latter, we report the Chi-squared statistic, also with effective degrees of freedom in parentheses. The first LR test tests the hypothesis that non-linearity in inequality as captured by a more flexible functional form provides a better model fit than only including a level inequality term. To do this we compare GAM Model 5 to the Confirmatory OLS Model 2 with a level inequality term. The second LR test compares the GAM without the interaction (GAM Model 5) to the GAM with an interaction (GAM Model 6) to test the relevance of an interaction in the presence of non-linearity. The third test compares the GAM with an interaction (GAM Model 6) to the OLS with an interaction (Model 4) to test the relevance of non-linear as opposed to linear additivity.

The first LR test finds that GAM Model 5 produces a better model fit in all cases besides that of ATK(½). Adding an interaction to the GAM Model further improves model fit in the second LR test: GAM Model 6 with an interaction outperforms a GAM without an interaction in Model 5. Model 6, a flexible functional form including an interaction therefore yields the best model fit for property crime and inequality in our data.[9] A final test confirms that the more complex model form is a statistically significantly better model fit for the interaction. With significance at least at the 1 percent level in all cases non-linear additivity improves the model fit between the GAM with an interaction (Model 6) and an OLS with an interaction (Model 4). We can also see that there is much more significance for individual variables in the GAM interaction model compared to the OLS interaction model.

We conclude that the GAM Model 6 is the best fit for our data meaning that both nonlinearity in inequality and income and the interaction of these two variables are supported. The question of what this model looks like – and whether there is more consistency than in the OLS case - needs to interpreted graphically.

[9] Further, Table 9 in the appendix shows that the GAM with the interaction out-performs both the OLS with non-linear inequality (model 4) and OLS with level inequality (model 3), the latter of which is important because it is the standard model in the literature.

Table 5. Model Fit Statistics for Two Generalised Additive Model Specifications and Likelihood Ratio Tests: Model 6 and 7

	GAM Model 5		GAM w Interaction Model 6			LR Tests		
	Inequality	**Income**	**Inequality**	**Income**	**Inequality * Income**	**Model 5 vs. Model 2**	**Model 5 vs. Model 6**	**Model 6 vs. Model 4**
	F-stat	*F-stat*	*F-stat*	*F-stat*	*F-stat*	*Chi-sq. stat*	*Chi-sq. stat*	*Chi-sq. stat*
	(edf)	*(edf)*	*(edf)*	*(edf)*	*(edf)*	*(edf)*	*(edf)*	*(edf)*
Equally-weighted indicators								
Gini	0.66	7.39***	0.31	12.69***	2.06*	9.07†	24.49**	9.34**
	(1.72)	(4.85)	(1.00)	(3.86)	(9.48)	(3.57)	(7.77)	(26.55)
GE(1)	1.957	11.77***	2.11†	13.83***	2.44*	8.66†	9.34**	11.70**
	(2.66)	(4.40)	(2.61)	(3.68)	(2.10)	(4.06)	(1.33)	(3.39)
ATK(½)	0.19	8.12***	0.09	12.19***	2.21*	5.85	26.99***	26.22***
	(1.00)	(4.67)	(1.00)	(3.76)	(8.51)	(2.67)	(7.60)	(8.27)
Bottom-weighted indicators								
GE(0)	6.37***	8.49***	5.89**	10.89***	1.78†	19.02***	15.87**	27.94***
	(2.59)	(4.38)	(2.28)	(3.46)	(5.70)	(3.97)	(4.46)	(6.43)
ATK(1)	7.67***	8.28***	6.25***	10.74***	1.94†	10.31*	15.13**	18.10**
	(2.33)	(4.38)	(2.06)	(3.43)	(5.04)	(3.71)	(3.81)	(5.52)
ATK(2)	5.47***	5.48***	18.62***	12.87***	5.09***	20.53**	26.53***	38.48***
	(5.36)	(4.29)	(1.00)	(4.00)	(5.05)	(6.65)	(0.39)	(5.04)
Top-weighted indicators								
GE(2)	4.42***	14.61***	4.38**	14.09***	0.67	14.49*	5.59†	20.08**
	(3.92)	(4.17)	(2.83)	(3.50)	(3.36)	(5.09)	(1.59)	(4.69)

Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Significance stars denote: † significant at p<0.1, * significant at p<0.05, ** significant at p<0.01 and *** significant at p<0.001. Sample excludes the top and bottom percentiles of the inequality and income variables. F-statistics are reported for the GAM models with effective degrees of freedom in parentheses. Chi-squared test statistics reported for the likelihood ratio tests with effective degrees of freedom in parentheses.

Figure 5 uses Model 6 to plot the predicted probability of crime against the joint distribution of income and inequality in a 3D-space. All of these plots clearly illustrate the interaction between income and inequality; that is, the effect of one variable varies across the level of the other. For clarity, Model 6 is also plotted in a 2D-space showing how predicted crime levels vary with inequality at chosen levels of income in Figure 6.[10] In Figure 6, we plot the conditional effect of inequality when average annual per capita income at the precinct level is equal to log of 9, 10, and 11. These values correspond to 2011 USD values of \$ 984 (slightly above the 10th percentile), \$2 706 (between the median and the mean), and \$7 380 (slightly less than the 90th percentile), respectively.[11] The logged variable ranges from 8.6 to 12.05 making these sensible cut-points.

There are three main strands to be drawn out of these results: Interaction; non-linearity; and measurement of inequality. The shape and magnitude of the former two are determined somewhat by the latter. Two broad patterns seem to be emerging in Figure 25 which correspond to common points of emphasis in measuring inequality. The equally-weighted indicators (Gini, GE(1) and ATK(½)) appear to adhere to one pattern; whilst, indicators more sensitive to the bottom (GE(0) and ATK(1)) seem to follow another. The outliers are ATK(2) and GE(2) which are extremely sensitive to the bottom or top of the income distribution, respectively, making it unsurprising that they have shapes all of their own.

Although the groups appear distinctive, there are some important common features of all of these plots that can assist us in understanding how income and inequality explain property crime. A common feature amongst the plots is the presence of an interaction. Not only does the direction in which crime moves with inequality change as income increases, but so too does the presence of non-linearity. Non-linearity appears much more important at mid-to high levels of income.

Another common feature is a non-positive effect of a unit increase in inequality, usually at low levels of the income range. This is plotted more clearly in the conditional effect plots in Figure 6. Predicted Probability of Crime and Conditional Effect of Inequality at Chosen Levels of Income

6. The equally-weighted indicators exhibit a negative effect: in poorer precincts, an increase in inequality reduces the level of crime. The bottom-weighted indicators and GE(2) exhibit a close to flat relationship between crime and inequality at low levels of income. Our rationale for a non-positive effect in low-income precincts is that criminals are so credit-constrained in these locations, that an increase in inequality represents the ability of protective behaviour by elites to dominate criminal activity.

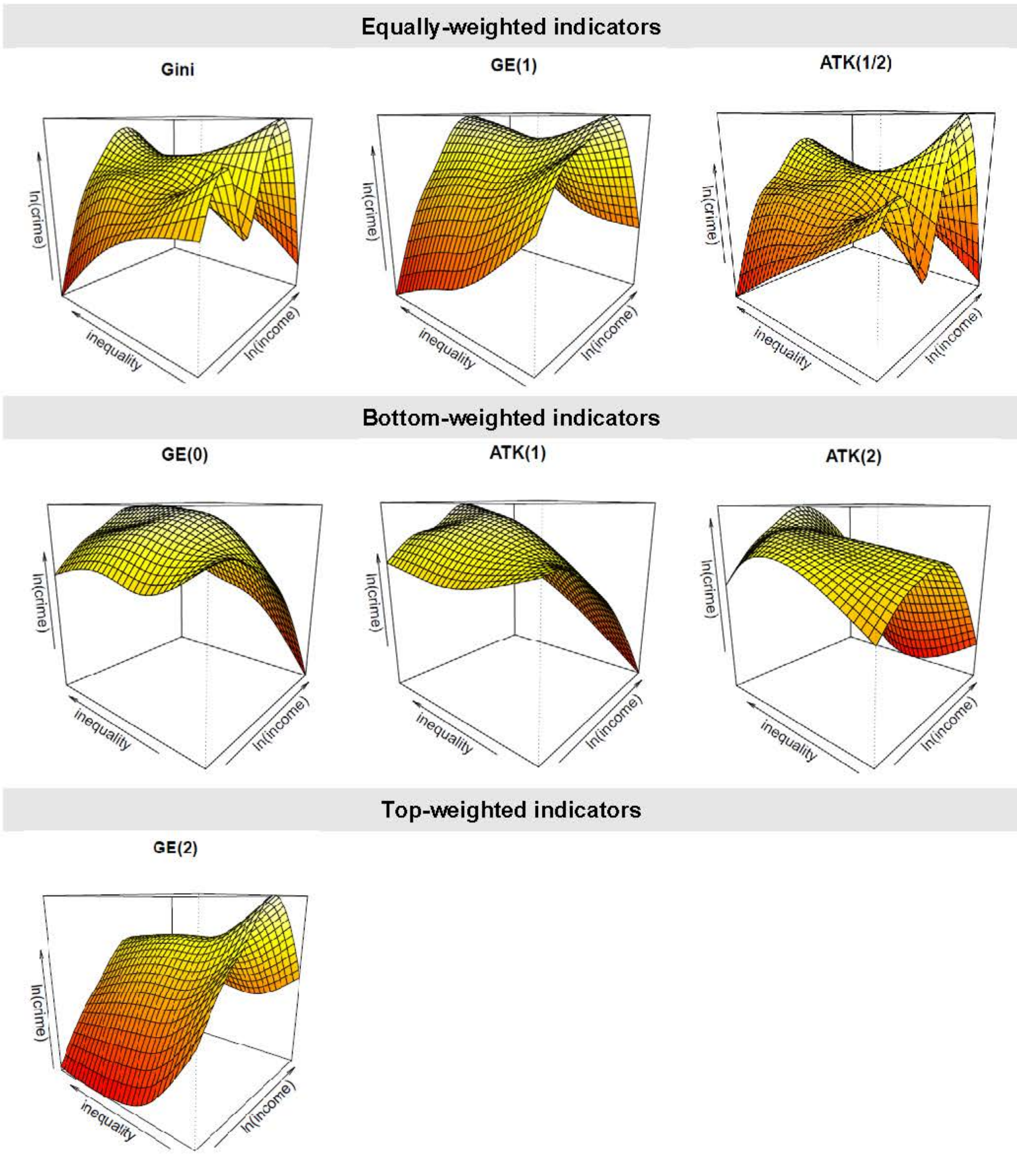
In the middle of the income distribution, all measures with perhaps the exception of GE(2), agree that there is a positive relationship between crime and inequality. At high levels of income, though, the Gini-group reflects convexity whilst the GE(0)-group reflects concavity as inequality increases. The concavity amongst the bottom-weighted indicators is well in line with our theory that inequality can act as a signal to invest in private security. The convexity amongst the equally weighted indicators is harder to rationalize. Further inspection of Figure 5 shows that crime eventually becomes concave in inequality as measured by the Gini, ATK(½) and GE(1) but at much higher levels of income. Divergence between the two groups can

[10] For reasons of space, the plot for GE(2) is provided in the appendix as it is of less interest to the discussion.
[11] In 2011 Rands, these numbers were R8 000, R22 000 and R60 000. These were converted to USD using the Rand-Dollar exchange rate from 31 November 2011 which was R8.13 to \$1.

reflect differences in how the measures capture either the relative increase in the ability of elites to protect themselves versus the ability of criminals to commit crime. This is a reflection of how different emphasis in weighting can change our understanding of how inequality and crime relate.

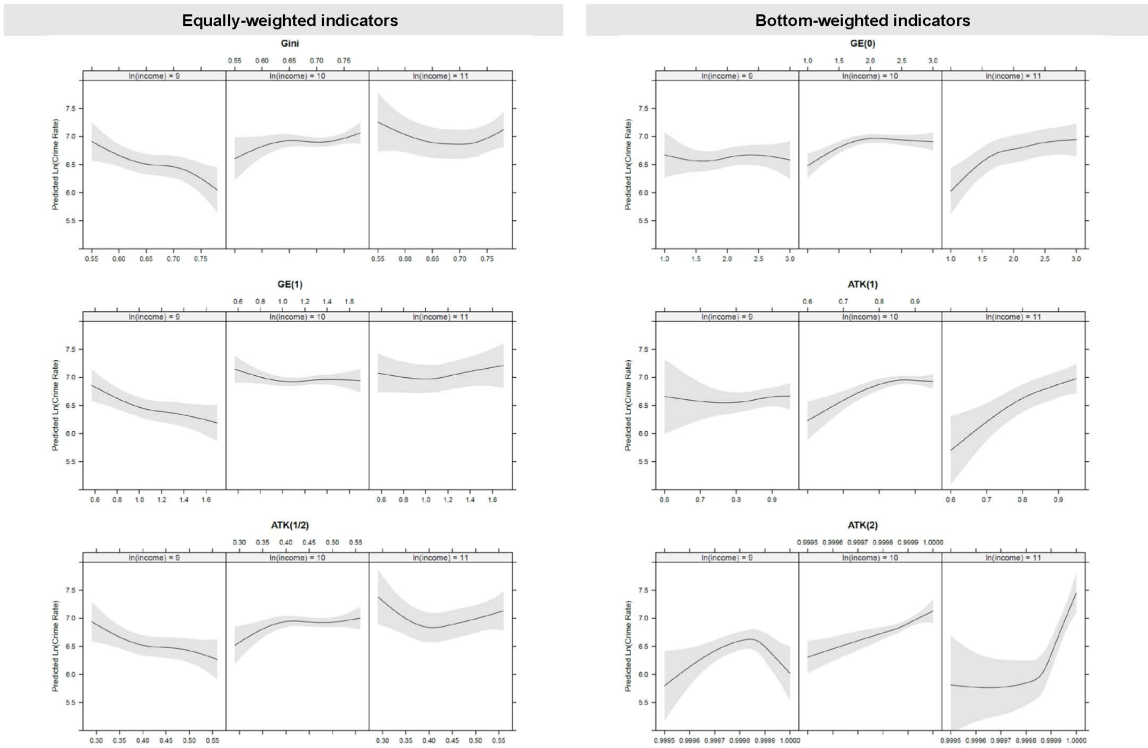
Another common feature amongst all plots is non-linearity in income and crime. For a given value of any indicator of inequality, crime first increases and then decreases as income rises. Again, the difference in emphasis in measurement emerges. Income exhibits an inverse-U shape amongst the equally weighted indicators, but the bottom-weighted indicators yield a shape closer to an inverse-J. All agree, though, that there is a broadly quadratic shape to the marginal effect of income, given some level of inequality. This shape is in line with our thinking about elite purchase of security. Increasing income not only makes households more of a target, but also increases their ability to invest in security.

Figure 5. Predicted Probability of Crime and the Joint Distribution of Inequality and Income



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Predicted probability of crime calculated from model 7 using the *vis.gam* command in the *mgcv* package in R. Sample excludes the top and bottom percentiles of the inequality and income variables.

Figure 6. Predicted Probability of Crime and Conditional Effect of Inequality at Chosen Levels of Income



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Predicted probability of crime calculated from model 7 using the vis.gam *command in the* mgcv *package in R. Sample excludes the top and bottom percentiles of the inequality and income variables. Note that the version of this plot for GE(2) is in the appendix in Figure 8.*

5. Discussion

Uncovering a significant, positive and monotonic relationship between property crime and income inequality in South Africa depends on how you measure inequality. Indicators that are more sensitive to changes in the lower end of the income distribution yield a significant positive monotonic outcome; but, those that are more sensitive to the middle or top yield mixed results in terms of sign and significance. If we think that all of these indicators are measuring the same underlying concept (with slight permutations on emphasis), then this overall disagreement is unconvincing. By contrast, both parametric and semi-parametric analysis in this paper provide evidence that an interaction between income and inequality yields a better model fit for property crime in South Africa, regardless of how you measure inequality. Further, we find evidence that a non-linear interaction between income and inequality in a semi-parametric model provides the best fit compared to a linear parametric model. These results can be explained when we think about how inequality and income are informative about the resources available to elites to protect themselves relative to the resources available to potential criminals to commit crime.

The analysis yielded three main insights: (a) an interaction between income and inequality exists for predicting crime rates and means a flat and even sometimes negative relationship between crime and inequality when income is low; (b) crime is non-linear in both income and inequality at the same time; and, (c) how you measure inequality matters for the shape of its relation to crime. We propose that this non-positive effect at low income levels is related both to how criminal and elite actors in a precinct are affected by the interaction of inequality and income. When income is low, this could convey that criminals themselves are credit-constrained which will limit their ability to carry out property crime. At the same time, elites in the same area will be several times better off because inequality is high and therefore more able to protect themselves with some private security. This gap between the resources of these two actors becomes relevant to the relationship between crime and inequality precisely because South Africa is located in the top tail of inequality worldwide. Even the most 'equal' precinct in South Africa had a Gini coefficient of 0.43 in 2011. To put this in perspective, this figure was about two percentage points more than the US national Gini in 2015 of 0.41 (World Bank, 2019). This means that this interaction may not necessarily be generalisable to more equal contexts.

With regards to the non-linearity in both income and inequality with crime, there was strong concavity in the case of income and in some cases of inequality, depending on measurement. Non-linearity in income is usually linked to elites spending on security to protect themselves (Chiu and Madden, 1998; Portnov and Rattner, 2003) and we think the same logic can be applied to inequality. Visible discrepancy in housing quality or other conspicuous consumption activities could communicate the outlier status of an elite household both to would-be criminals and to themselves, prompting elites to take precautions. It is possible that local inequality is such a salient signal in South Africa precisely because inequality is so extreme, and therefore, observable and readily interpretable (Lemanski, 2004). However, even in the USA, the size of private police increased with local area inequality (D'Alessio et al., 2005).

Something that emerges clearly in this paper is that how inequality is measured matters for its relationship with property crime. Our original confirmatory OLS result shows that indicators which are more sensitive to the existence of low incomes will yield significant positive monotonic coefficients; other indicators do not even though these indicators all measure the same latent concept. The difference between confirming or not confirming the usual result then is simply the weighting assigned to changes at different portions of the income distribution. Can we call the standard monotonic relationship robust if weighting can make such a difference? We think not, at least for the high inequality-high crime case of South Africa. Furthermore, our models allowing for non-linearity and interaction achieved more robust and consistent results, suggesting these specifications more closely describe the relationship between inequality and property crime in South Africa.

Within these flexible models, though, two slightly different characterizations of the income-inequality-crime relationship emerge based on whether indictors emphasize the bottom of the income distribution or not. Is one of these more correctly capturing the relationship in South Africa? Kaplow (2005) puts forward that *a priori* there is no 'best' measure of inequality, arguing that the measure should be chosen based on the purpose of the study at hand and uses crime as an example. The channel theorized to drive crime should motivate the choice of indicators. Kaplow (2005) contrasts two ideas. If crime is driven by a lack of economic opportunities as alternatives to criminal activity, then information about the bottom of the income distribution is most important. However, if crime is driven by "envy of the rich" and very lucrative payoffs, then changes at the top end of the distribution matter the most (Kaplow, 2005:72).

In South Africa, there is strong reason to believe that either could be the case. On the one hand, lack of economic opportunities is undoubtedly a particularly substantial issue in the country, given the extreme unemployment, poverty, and lack of informal economic sector (Banerjee et al., 2008). On the other hand, the crime rate in South Africa is particularly high, even when compared to other economically constrained economies – as seen in the introduction to this paper. One explanation for this is the violent oppressive *apartheid* regime which ended only 25 years ago and created the vast inequality we see in the country today. The injustice of South Africa's inequality is foremost in the minds of citizens and an increase in inequality driven by the top end of the spectrum could therefore drive further feelings of injustice and hence criminal activity. It is not immediately clear which pathway would dominate. The former channel would lead us to favour the bottom weighted indicators such as GE(0) and ATK(1), while the latter channel would lead us to favour the top weighted indicator, GE(2). Either way, the equally weighted indicators, GE(1), ATK(½), and the Gini, are unlikely to be the best indicators for crime and income inequality in South Africa. Similar arguments could be made for any research hoping to include inequality in a model of crime. This paper is an illustration of why Kaplow (2005) is right: Different measures can yield different results, and this happens because they capture different ideas. It is up to the researcher to decide which is most relevant theoretically, and assuming equally weighted indicators are neutral is problematic.

The studies we have seen usually only employ one measure of inequality[12], and different studies use different measures, although the Gini is by far the most common (Rufrancos et al., 2013).[13] This practice assumes that measurement of inequality will not make a substantive difference to the overall relationship researchers are trying to capture. To reiterate, this assumption could be true in more equal contexts, but we have not seen this explicitly tested. One question that comes out of this research then is that researchers should

[12] An exception is Fajnzylber et al. (2002) in the violent crime and inequality literature. These authors compared the Gini to the ratio of the income of the richest to the poorest quintile in the population; an index of income polarisation; and, the standard deviation of the educational attainment of the adult population. These authors found their results were robust to these alternative measures for a cross-country sample.

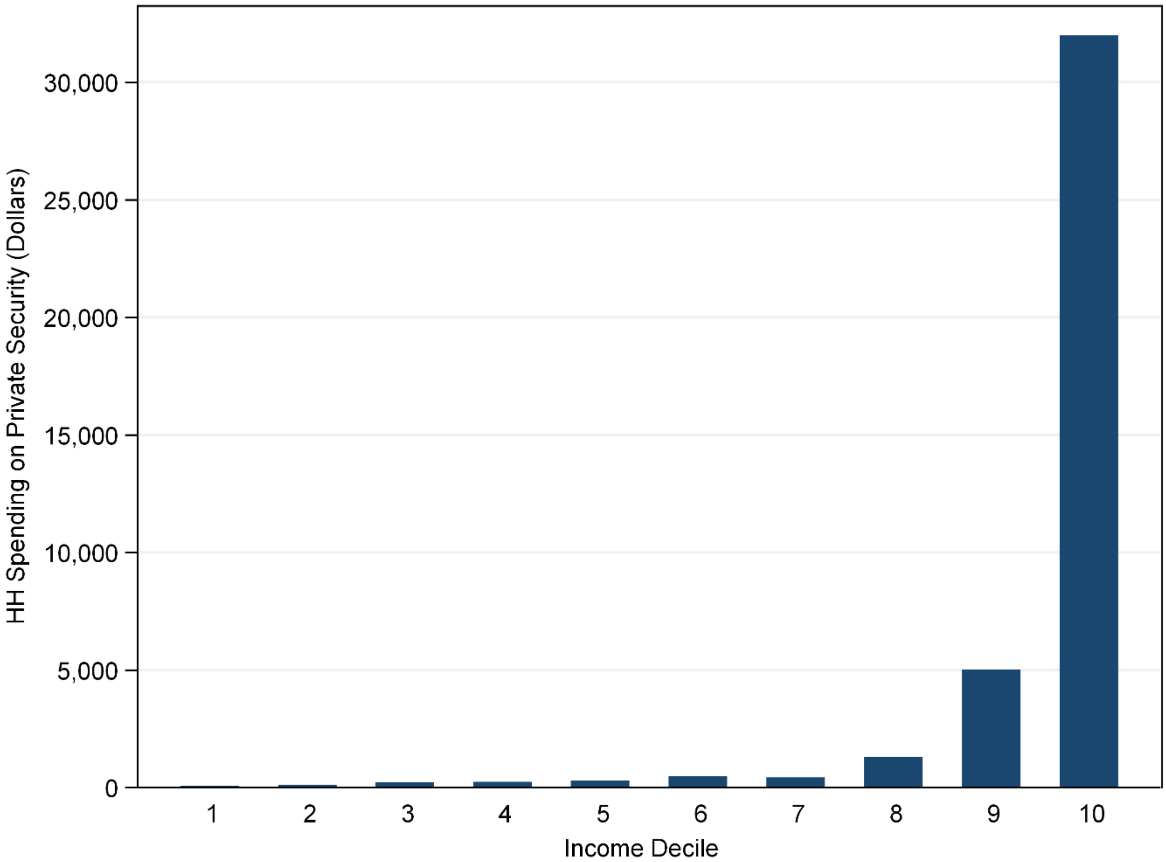
[13] Aside from the Gini there were seven different measures of inequality in the 17 studies reviewed by Rufrancos et al. (2013) and which the authors describe as "atypical", often chosen due to data limitations. Of the eight studies analysing property crime, three used the Gini. The alternative indicators were: permanent income inequality; relative poverty; an index of relative income inequality; and, the 90-10 wage ratio.

think more carefully about the assumption that indicator choice is neutral. Specifically: when we assert that property crime increases with inequality, what exactly do we mean by inequality? Do we think any increase in income is important, or do we think changes at the bottom end should have more gravity? In line with Kaplow (2005), how does inequality channel crime? Tackling this question could help us get marginally closer to answering the question posed by Rufrancos et al (2013): In their meta-analysis, these authors point out that whilst the relationship between property crime and inequality is well-established, the mechanism is a lot less well-understood.

One of the mechanisms discussed in this paper – protective behaviours – is an important linkage but one that we are unable to test empirically due to a lack of reliable data. Many papers testing the link between property crime and inequality also usually omit this variable but still find a significant positive and monotonic relationship with European and American data (Choe, 2008; Dahlberg and Gustavsson, 2008; Portnov and Rattner, 2003; Nilsson, 2004). The data on private security expenditure that is available for South Africa is sparsely populated and is not highly geographically disaggregated, resulting in power concerns. In an effort to link inequality to protective behavior through an indirect angle, we use the South African 2010/11 Income and Expenditure Survey (IES; Statistics South Africa, 2012) to compare income and security spending.

7 shows a clear positive relationship between income and private protection spending. 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.

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

A positive monotonic relationship between property crime and inequality is well-established in both the theoretical and empirical literature. We present evidence that this relationship is not robust for the extreme top tail of the inequality range, using South Africa as a high crime-high inequality case study. In our preferred specification, crime does not increase with inequality at low levels of income, and then increases at a decreasing rate at middle to high levels of income. We were motivated to test for this non-linearity and interaction based on our idea that inequality is informative about the resources available to potential criminals to commit crime relative to the resources available to local elites to protect themselves. Elites could be most successful at protecting themselves both when there is a wide divergence in resources and especially when criminals themselves are very poor. Whether this interaction is a product of extreme inequality or whether it can be generalisable to other more equal contexts therefore remains to be understood. However, it could be generalisable to other unequal contexts and to our knowledge this has not been scrutinized in this way so far. We employed seven different measures of inequality for robustness. All seven inequality measures agreed that an interaction was significant and almost all agreed that at low levels of income, increasing inequality had a negative or flat association with crime; whilst at medium to high levels of income, increasing inequality usually meant an increase in crime.

Most analyses of crime and inequality employ a single measure of inequality, often across different countries. This highlights a second insight from our work which is that how inequality is measured and choice of indicator matter for how the relationship is characterised. Inequality indicators vary by how sensitive they are to changes at different portions of the income distribution and generally the shape of the distributions of marginal effects corresponds to this sensitivity. Although GE(0) has long been favoured in inequality research, the Gini is very popular in research on crime and inequality. We've shown that the Gini is not a neutral measure, and as such measure choice should be carefully considered in this field.

One important part of our hypothesis was purchase of private security – something we cannot observe in our data. This link represents a crucial mechanism but 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 criminal activity.

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8. Appendix Tables

Table 6: Detailed Output for Regression Results for the Bivariate and Confirmatory OLS Models: Model 1 and 2

	Bivariate Confirmatory OLS Model 1	Multiple Confirmatory OLS Model 2		
	Inequality	Inequality	Income	Income sq.
Equally-weighted indicators				
Gini	-1.34**	-0.05	5.11***	-0.24***
	(0.51)	(0.44)	(0.97)	(0.05)
GE(1)	-1.10***	-0.20*	5.61***	-0.26***
	(0.1)	(0.09)	(0.93)	(0.05)
ATK(1/2)	-2.35***	0.10	5.02***	-0.24***
	(0.43)	(0.36)	(0.94)	(0.05)
Bottom-weighted indicators				
GE(0)	-0.12*	0.16**	5.17***	-0.25***
	(0.06)	(0.05)	(0.9)	(0.05)
ATK(1)	-1.00*	1.54***	5.15***	-0.25***
	(0.41)	(0.36)	(0.9)	(0.05)
ATK(2)	5130.72***	1634.88***	4.45***	-0.22***
	(265.14)	(340.98)	(0.95)	(0.05)
Top-weighted indicators				
GE(2)	-0.18***	-0.03***	5.17***	-0.24***
	(0.01)	(0.01)	(0.91)	(0.05)

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. Sample excludes the top and bottom percentiles of the inequality and income variables.

Table 7. Detailed Output for Regression Results for the Non-Linear OLS Model: Model 3

	Inequality	Inequality Sq.	Income	Income sq.
	Equally-weighted indicators			
Gini	-10.88	8.00	5.19***	-0.25***
	(07.28)	(05.37)	(0.97)	(0.05)
GE(1)	-0.91	0.31	5.74***	-0.27***
	(0.62)	(0.27)	(0.94)	(0.05)
ATK(1/2)	-1.07	1.33	5.04***	-0.24***
	(03.67)	(04.17)	(0.94)	(0.05)
	Bottom-weighted indicators			
GE(0)	1.27***	-0.27***	5.24***	-0.26***
	(0.3)	(0.07)	(0.9)	(0.05)
ATK(1)	14.41**	-7.81*	5.30***	-0.26***
	(05.12)	(03.1)	(0.9)	(0.05)
ATK(2)	-11838.36	6738.51	4.45***	-0.22***
	(1859800.3)	(930161.38)	(0.95)	(0.05)
	Top-weighted indicators			
GE(2)	-0.11***	0.01*	5.61***	-0.26***
	(0.03)	(0.00)	(0.93)	(0.05)

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. Sample excludes the top and bottom percentiles of the inequality and income variables.

Table 8. Detailed Output for Regression Results for the Interactive OLS Model: Model 4

	Inequality	Income	Income sq.	Inequality* Income	Inequality* Income sq.
			Equally-weighted indicators		
Gini	-53.39	-0.90	0.01	9.44	-0.41
	(47.03)	(6.23)	(0.3)	(9.2)	(.45)
GE(1)	-11.00	3.37	-0.17	1.88	-0.08
	(11.63)	(2.53)	(.13)	(2.31)	(0.11)
ATK(1/2)	-45.45	1.65	-0.09	8.05	-0.35
	(42.36)	(3.67)	(0.18)	(8.28)	(0.4)
			Bottom-weighted indicators		
GE(0)	2.93	6.51*	-0.33**	-0.67	0.04
	(5.89)	(2.55)	(0.13)	(1.15)	(0.06)
ATK(1)	-2.31	5.22	-0.30	-0.24	0.06
	(41.41)	(7.03)	(0.34)	(8.06)	(0.39)
ATK(2)	30913.94	7410.18	-449.99	-7404.80	449.74
	(44077.66)	(9012.81)	(461.11)	(9013.74)	(461.15)
			Top-weighted indicators		
GE(2)	-0.11	5.12***	-0.24***	0.01	0.00
	(1.62)	(1.28)	(0.07)	(0.34)	(0.02)

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. Sample excludes the top and bottom percentiles of the inequality and income variables.

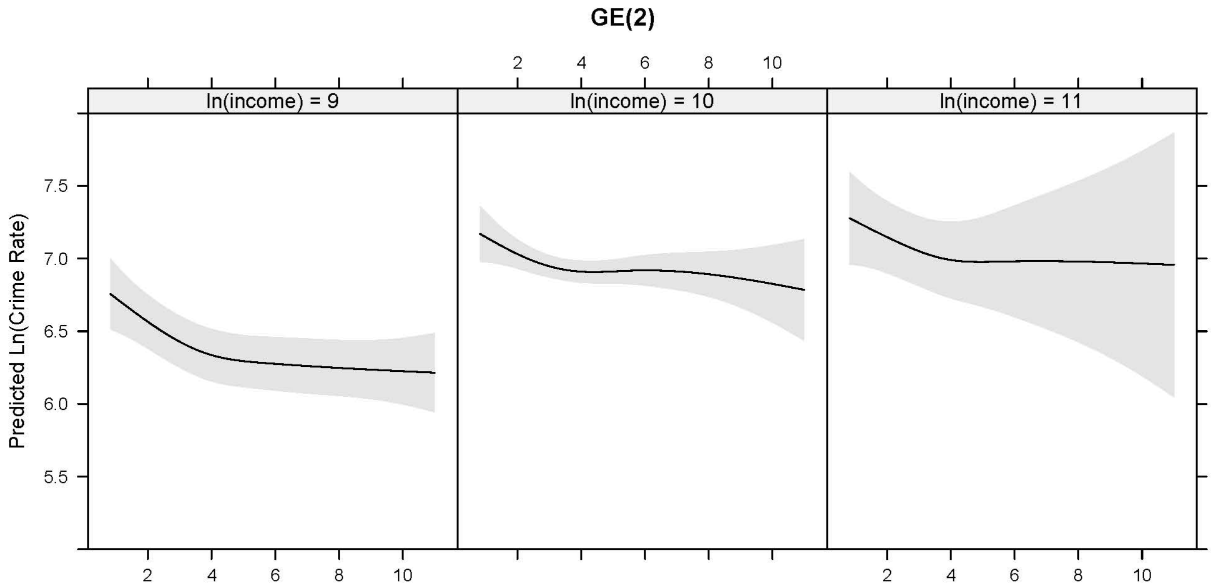
Table 9. Additional LR Tests for GAM Model 6 and 7

	GAM Interaction vs. Non-Linear OLS (Model 6 vs. Model 3)	GAM Interaction vs. Confirmatory OLS (Model 6 vs. Model 2)	GAM vs. Non-Linear OLS (Model 5 vs. Model 3)
	Equally-weighted indicators		
Gini	31.27*** (10.34)	33.56*** (11.34)	6.77† (2.57)
GE(1)	16.62** (4.39)	17.99** (5.39)	7.28† (3.06)
ATK(1/2)	32.73*** (9.26)	32.84*** (10.27)	5.75† (1.67)
	Bottom-weighted indicators		
GE(0)	20.42** (7.43)	34.89*** (8.43)	4.45 (2.96)
ATK(1)	18.92** (6.52)	25.44** (7.52)	3.78 (2.71)
ATK(2)	47.06*** (7.04)	47.06*** (7.04)	20.53** (6.65)
	Top-weighted indicators		
GE(2)	14.37* (5.69)	20.08** (6.69)	8.77† (4.09)

Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Significance starts denote: † significant at p<0.1, * significant at p<0.05, ** significant at p<0.01 and *** significant at p<0.001. Effective degrees of freedom in parentheses. Sample excludes the top and bottom percentiles of the inequality and income variables.

9. Appendix Figures

Figure 8. Predicted Probability of Crime and Conditional Effect of GE(2) at Chosen Levels of Income



Notes: Authors' calculations using SAPS (2011) and Statistics South Africa (2011). Predicted probability of crime calculated from model 7 using the *vis.gam* command in the *mgcv* package in R. Sample excludes the top and bottom percentiles of the inequality and income variables.

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