THE GRADUATE INSTITUTE GENEVA
CENTRE FOR INTERNATIONAL ENVIRONMENTAL STUDIES

Research Paper 66 | **2021**

# CRIME, INEQUALITY AND SUBSIDIZED HOUSING: EVIDENCE FROM SOUTH AFRICA

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# Crime, Inequality and Subsidized Housing: Evidence from South Africa

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April 2021

**Abstract**

We study the relationship between housing inequality and crime in South Africa. We create a novel panel dataset combining information on crimes at the police station level with census data. We find that housing inequality explains a significant share of the variation in both property and violent crimes, net of spillover effects, time and district fixed effects. An increase of one standard deviation in housing inequality explains between 9 and 13 percent of crime increases. Additionally, we suggest that a prominent post-apartheid housing program for low-income South Africans helped to reduce inequality and violent crimes. Together, these findings suggest the important role that equality in housing conditions can play in the reduction of crime in an emerging economy context.

Keywords: inequality, crime, economic development.
JEL Codes: D630, K140, O100.

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# 1 Introduction

South Africa is the most unequal country in the world. It has the highest Gini coefficient in global cross-country comparisons (World Bank, 2020). Besides high inequality, South Africa also exhibits exceedingly high crime rates. According to the most recent worldwide homicide ranking, South Africa has a homicide rate which is 6 times larger than the world average (Global Burden of Disease Collaborative Network, 2018; South African Police Service, 2020).

Consequently, South Africa provides a unique context to analyze the role of socio-economic inequalities and their relation with crime. To date, the vast majority of studies on inequality and crime have focused on income inequality (Kelly, 2000; Enamorado et al., 2016; Kang, 2016; Metz and Burdina, 2018) while a few of them have also looked into consumption-based or land inequality (Demombynes and Özler, 2005; Buonanno and Vargas, 2019). Yet, an important dimension of inequality - housing inequality - has been neglected in the existing literature examining inequality and crime. Specifically, housing inequality is particularly important for countries where a significant share of the population does not live in formal living arrangements. In post-apartheid South Africa, only 29 percent of households lived in a formal housing unit (Statistics South Africa, 2012). This increased to 74 percent in 2011, and to 81 percent in 2018 (Statistics South Africa, 2019).

In this paper, we aim to provide the first study of the relationship between inequality in housing conditions and various types of violent and property crimes. We also examine the role of a major post-apartheid housing program that was introduced by the South African Government to reduce inequality in living conditions. We investigate whether this large-scale housing program can help explain the variation in inequality and crime across time and space in one large province, the Western Cape. According to our estimates—based on primary data from the Department of Environmental Affairs and Development Planning (2014) and Franklin (2020)—the mean stock of housing projects in the Western Cape Province has evolved from 0 to roughly 2.08 and 4.22 thousand housing units per 100,000 people at the beginning of 1995, 2000 and 2010, respectively. This amounts to approximately 54,250 and 178,500 housing units delivered at the beginning of the years

2000 and 2010, respectively. The scale of this government housing scheme is remarkable—compared to other African countries and emerging economies in general.[1]

We draw upon a unique panel dataset. We merge data on crime at the police station level with socio-economic data from the South African census to form a spatial panel. We collect information from the universe of police stations in the country on both violent offences (aggravated assaults, murders and rapes) and property crimes (thefts out of vehicles and residential burglaries), and we use census data to construct an index describing housing conditions across South Africa's former magisterial districts. In addition, we exploit the spatial nature of the data to identify the magnitude of spillover effects across districts. Finally, we also merge data on the location of housing projects that were approved by the Department of Human Settlements in the Western Cape Province. We use this data to investigate the relationship between improved access to adequate housing and crime.

We find that housing inequality is positively related to the prevalence of all types of crime we investigate, except for murders. For most crimes, an increase of one standard deviation in housing inequality can explain between 9 and 13 percent of increases in criminal offences. The inequality-crime association is stronger for thefts out of vehicles, where a standard deviation increase in housing inequality explains 41 percent of the variation in the number of theft incidents per 100,000 individuals. Spillover effects between districts are significant and stand at approximately 30 percent of a district's own crime levels. Moreover, we show that an increase of 1,000 housing units per 100,000 people (approximately 0.45 standard deviations) reduces housing inequality by roughly 0.04–0.16 standard deviations. When looking at crime, we find that an increase of 1,000 housing units per 100,000 people is associated to a reduction in the rate of violent crimes of about 6 percent. To our knowledge, this is the first study that provides evidence on the role played by inequality in housing conditions in explaining crime. This finding is

[1] According to the Department of Human Settlements, 3 million houses had been delivered by the end of 2017 in South Africa. On the continent, Algeria comes close; however, the context is vastly different as the State provides most of the Algerian housing (Centre for Affordable Housing Finance in Africa, 2019). Another prominent housing intervention is the Integrated Housing Development Program (IHDP) in Ethiopia, but its scale pales compared to South Africa (The Economist, 2017). Morocco has also embarked on a mission to eliminate informal housing arrangements under the Villes Sans Bidonvilles Program, which started in 2004 and delivered 277,583 housing units—according to the Government of Morocco (www.mhpv.gov.ma, accessed September 6, 2020). If anything, the provision of government housing in South Africa is comparable to post-war reconstruction programs in Europe. For instance, Britain built approx. 3 million units of social housing in 1950–70 (The Economist, 2020).

consistent with the predictions of strain theory in criminology. Significant strain can be associated with inequality in housing conditions because of people's failure to achieve the fundamental life goal of decent housing. Agnew (2001) argues that strains that are most likely to cause an offending behavior are usually high in magnitude, i.e., they are intense or lengthy and important to the individual, they are perceived as unjust and happen against the background of low social control.

Our study makes three main contributions to the literature. First, we provide evidence on the role of a neglected dimension of inequality, housing inequality, and its relationship with crime. Second, our analysis relies on a panel dataset whereas much of the previous literature on crime and inequality (particularly in South Africa) has been limited to cross-sectional analyses. This allows us to account for both the spatial autocorrelation in crime and for time-invariant unobservables across districts. More generally, we rely on a high-quality dataset which is very rare in a developing country context. Third, we show that a large-scale housing program, which reduces housing inequality, also demonstrates promise in the mitigation of violent crime. Even at the level of high-income economies with higher-quality data availability, there is insufficient evidence related to housing interventions (Collinson et al., 2015). For developing countries, the evidence is even scarcer.

The rest of the paper proceeds as follows. Section 2 provides an overview of the literature while Section 3 presents background information on the context examined. Section 4 describes the data and presents descriptive statistics. Section 5 describes the empirical strategy and Section 6 presents the results of the empirical analysis. Section 7 provides concluding remarks.

# 2 Literature

## 2.1 Inequality, Property and Violent Crimes

### Theory

Becker (1968) first introduced the concept of crime as a rational individual choice, whereby potential offenders compare costs and benefits of criminal acts to decide whether to undertake illegal activities. Consequently, governments can intervene to either reduce the attractiveness of criminal participation relative to legitimate living or increase the costs of crime by making detection easier or punishment harsher.

Building on this insight, some economists have examined the relationship between inequality and property crimes. For instance, Chiu and Madden (1998) build on Becker (1968) and suggest that an increase in average income, which happens against the background of higher inequality, will increase the potential proceeds from illegal activities as well as the appeal of property-related crimes. This framework also implies that property offences will disproportionately happen in the relatively richer neighborhoods unless the adoption of defense technologies becomes widespread. Similar theoretical insights have been put forward by Freeman (1999), Wu and Wu (2012) and Costantini et al. (2018). Due to its underlying cost-benefit framework, the economics approach is arguably better suited to explaining property crimes rather than violent offences (Kelly, 2000; Wu and Wu, 2012; Draca and Machin, 2015). Property crimes are typically carried out for material gain, which makes them more amenable to a Becker-type cost-benefit analysis (Kelly, 2000; Demombynes and Özler, 2005).

The literature in criminology provides additional insights. While inequality is regarded as a deciding factor in assessing the magnitude of illegal benefits in a cost-benefit framework, the same phenomenon can also be interpreted as a source of strain leading to anger and impulsiveness, which in turn makes violent crimes more likely. Strain theory hypothesizes that criminal behavior may be the result of strain that individuals or societies feel. Such strain is generated by individuals' failure to achieve positively valued goals (Agnew, 1992, 1999, 2001). The strains most likely to cause offending behavior are generally high in magnitude, intense or lengthy and important to individuals, and they are perceived as unjust (Agnew, 2001). Negative emotions, such as anger, frustration and despair, are the hypothesized channels that connect strain to crime (Agnew, 1992, 1999, 2001; Brezina, 2017). Among these, anger is central in the strain theory framework that explains violent crimes (Aseltine et al., 2000; Piquero and Sealock, 2000; Mazerolle et al., 2003).

**Empirics**

The economic theory of crime is supported by evidence relating to the factors that speak to the attractiveness (or lack) of legal earning opportunities. Several studies show that education is a crime-limiting factor (Lochner and Moretti, 2004; Machin et al., 2011; Chalfin and Raphael, 2011; Anderson, 2014; Hjalmarsson et al., 2015; Bell et al., 2016). Other researchers have investigated low wages and unemployment as inducements to a life of crime (Raphael and Winter-Ebmer, 2001; Gould et al., 2002; Machin and Meghir, 2004; Fougère et al., 2009; Bell et al., 2018; Khanna et al., 2019; Hémet, 2020). A number of studies also estimate the effects of inequality on crime incidence. In South Africa, Demombynes and Özler (2005) find a positive and strong correlation between inequality and property crimes using cross-sectional data. The authors show that the incidence of property offences is higher in police precincts that are relatively wealthier than their immediate neighbors. Metz and Burdina (2018) document similar results for a sample of urban centers in the United States. Bourguignon et al. (2003) further argue that the leftmost part of the income distribution disproportionately affects property crimes in Colombia. Thus, a change in income among individuals above a certain threshold would have no significant effect on mitigating crime. The same type of insight is also posited by Machin and Meghir (2004).[2]

The empirical evidence on strain theory comes exclusively from criminology. Using different types of data (e.g. macro-level, individual-level, school or neighborhood-level) these studies find suggestive evidence that strain leads to violence and criminal behavior (Rebellon et al., 2009; Mahler et al., 2017; Brezina et al., 2001; Hoffmann and Ireland, 2004; de Beeck et al., 2012; Warner and Fowler, 2003; Hoffmann, 2003). Although economists have not explicitly tested strain theory, it has been invoked to explain the relationship between inequality and violent offences—e.g. Kelly (2000) for metropolitan areas in the United States; Enamorado et al. (2016) in Mexico, and Buonanno and Vargas (2019) for Colombia—. Kang (2016) further argues that it is a specific type of inequality, i.e., segregation and poverty concentration, that drives violent crimes in the United States.

[2] Researchers have also sought evidence related to the effectiveness of deterrents such as the size and intensity of police activities (Levitt, 2002; Di Tella and Schargrodsky, 2004; Evans and Owens, 2007; Lin, 2009; Draca et al., 2011; DeAngelo and Hansen, 2014; Chalfin and McCrary, 2018) or the magnitude and swiftness of sanctions (Liedka et al., 2006; Drago et al., 2009; Hawken and Kleiman, 2009; Johnson and Raphael, 2012). Overall, improvements in law enforcement systems are systematically linked to reductions in crime; however, sanctions appear to be a relatively weak deterrent.

## 2.2 Crime, Housing Inequality and Related Interventions

The existing literature on the relationship between crime and inequality typically uses data on consumption, expenditure, land ownership or income. To our knowledge, there are no studies that investigate the impacts of housing inequality on crime.

A related but distinct stream of literature has evaluated the impacts of programs targeting housing inequality—e.g. giving ownership titles to informal dwellers, providing infrastructure equitably or introducing housing subsidies—. Field (2004; 2005; 2007) find that an urban titling initiative in Peru significantly increased household labor supply and household investments and renovations, and reduced fertility. Galiani and Schargrodsky (2010) document similar evidence for Buenos Aires, Argentina. In contrast, some studies show no impact or even negative effects of housing subsidies or rent vouchers on individual outcomes such as labor force participation, earnings and health in the United States (Susin, 2005; Newman et al., 2009; Jacob and Ludwig, 2012; Jacob et al., 2015) as well as in India (Barnhardt et al., 2017).

A smaller number of studies (largely on industrialized countries) investigate the effects of housing programs on crime. For example, Santiago et al. (2003) study public housing in Denver, Colorado, and argue that the program did not impact neither property or violent offences. In contrast, Freedman and Owens (2011) and Woo and Joh (2015) find that the Low-Income Housing Tax Credit program reduced crime in the United States, and in Austin, Texas, respectively. Freedman and Owens (2011) further argue that the program has mitigated violent crimes, but it has had no effects on property crimes. Finally, Disney et al. (2020) show that both violent and property offences have decreased as a result of the Right to Buy scheme in the United Kingdom, which enabled the tenants of public housing to buy their dwellings at subsidized prices.

## 2.3 Crime, Inequality and Housing Policies in South Africa

Although no study has examined the effects of government housing on crime in South Africa, several papers investigated various determinants of crime. Demombynes and Özler (2005) study consumption-based inequality and crime using the 1996 census cross-sectional data. The authors find that inequality is associated with increases in both property and violent crimes, although the evidence is stronger for property offences. Similarly, Bhorat et al. (2017) study income-based inequality using a cross-sectional dataset (2011 census) and find a positive link between inequality and property crimes. Other studies have examined correlates of crime, such as education (Jonck et al., 2015), changes in ethnic composition around the time of democratization (Amodio and Chiovelli, 2018), the weather (Bruederle et al., 2017) and social capital in the former apartheid-time resettlement camps (Abel, 2019a).

No study has examined the impact of subsidized housing on crime in South Africa. Existing research has been limited to examining the effect of subsidized housing on labor market outcomes in specific areas. Franklin (2020) relies on government housing data for metropolitan Cape Town to show that low-cost housing developments had a significant and positive effect on household earnings, particularly those of women. Using data on a subset of metropolitan areas, Picarelli (2019) and Lall et al. (2012) find no impact of housing programs on labor force participation, but document an improvement in children's education.

# 3 Background

## 3.1 Inequality and Crime

Inequality and crime are pressing issues in South Africa. The country has the highest Gini index in the world (World Bank, 2020)[3] and an estimated 65 percent of the pre-tax national income was captured by the top 10 percent of its earners during the past decade (World Inequality Database, 2020). Moreover, the income share of the top 1 percent has increased from 10 to 21 percent between 1993 and 2014 (Alvaredo et al., 2018). In terms of crime, the homicide rate in South Africa is significantly above the global average with 36 cases per 100,000 individuals (South African Police Service, 2018) compared to a global average is of 6.1 homicides per 100,000 people (United Nations Office on Drugs and Crime, 2019). Murder rates have remained extremely high, a reflection of the extraordinary level of violence that exists in the country.

[3]Consumption data from 2014–15 is used to compute the Gini index of South Africa in this cross-country classification. The data can be retrieved from https://databank.worldbank.org. Accessed December 20, 2020.

Property crimes are also high. In 2018, 1 in every 24 households on a suburban block was burgled (Statistics South Africa, 2018).[4] Given these magnitudes, it is not surprising that crime threats are reflected in the way South Africans go about their daily lives. About 32 percent of individuals reported avoiding open spaces due to fear of crime, 17 percent were keeping their children from playing in their neighborhoods and 14 percent were fearful of walking in their own town or using public transportation (Statistics South Africa, 2018). In addition, about 52 percent of South African households took significant measures to protect their homes (Statistics South Africa, 2018). Given the high levels of poverty in the country, this also implies that a large percentage of households allocate part of their limited resources to home protection.

In terms of housing inequality, the World Bank (2018) shows that in 2015 about 98 percent of the richest decile in South Africa was connected to the electricity grid and had access to an improved water source. In contrast, about 78 and 54 percent of the poorest decile enjoyed these same amenities. Similarly, roughly 65 percent of the poor had access to improved sanitation, while the richest decile was nearing universal access (World Bank, 2018). Lastly, only 2–3 percent of the richest decile were living in overcrowded housing, while the rate among the poorest decile was 68 percentage points higher (World Bank, 2018).

## 3.2 Housing Policy

Housing policy in apartheid South Africa had the intent to segregate citizens based on race (Wilkinson, 1998). With the advent of democracy in 1994, the provision of adequate housing became a prominent tool to rebuild the country. In fact, housing policies became a key component of the overarching Reconstruction and Development Program (RDP). The RDP was the master framework of that time, an integrated and coherent program of socio-economic transformation that was designed to spearhead the transition to a racially inclusive democracy. Housing for all was reflective of the vision of the African National Congress. To operationalize this vision, the RDP's medium-term ambition was to build 1 million houses in the first 5 years (African National Congress, 1994; Ministry in the

[4] There are some differences across countries with respect to definitions and propensities to report such incidents; this makes cross-country comparisons more difficult.

Office of the President, 1995). According to the Department of Human Settlements, by the beginning of the year 2000 roughly 87 percent of the target was attained. Although the target was missed and demand outstripped the number of housing units supplied, the achievement was nevertheless significant in the eyes of South Africans and internationally.[5]

The Reconstruction and Development Program was followed by the Growth, Employment and Redistribution Strategy in 1996, the Accelerated and Shared Growth Initiative for South Africa in 2005, the New Growth Path in 2010 and the National Development Plan in 2013 (Adelzadeh, 1996; Gelb, 2006; Naidoo and Maré, 2015). In parallel, the housing dimension of the original RDP also evolved over time, along with the institutions it created and the legislation it inspired. References to RDP have been relatively more persistent in the context of housing policy. Nevertheless, housing schemes, too, have often changed name, along with their strategy or implementation design. Further details on these changes are discussed in Section 6.

In 1994, there were 2.6 million formal housing units in South Africa, 1.7 million shacks on un-serviced sites and 0.6 million shacks on serviced sites. 1.5 million households were roofless (Goodlad, 1996). A quarter of the population did not have access to piped water, and over 40 percent did not have electricity or proper sanitation (Goodlad, 1996). According to the most recent census data, which were collected in 2011, South Africa had 14.4 million households. Of these, 10.6 million lived in adequate housing (74 percent) and 2.5 million lived in an informal dwelling. The remainder lived in traditional structures. To put these numbers into context and facilitate comparisons, note that there were 9 million households in South Africa in 1996. In 2018 the estimated proportion of households living in a formal dwelling stood at 81 percent (Statistics South Africa, 2019).

Although substantial progress has been registered since 1994, average improvements may hide some unaddressed legacies of apartheid. Spatial segregation is still a dominant feature of the south African housing landscape (Wilkinson, 1998) which, in turn, may contribute to breed crime (Kang, 2016). In a more recent iteration of the housing policy, the government states its committed to "*combating crime, promoting social cohesion and improving*

[5] On December 24, 1999, the New York Times ran an article titled "*Small Houses a Big Step for South African Pride*". It underlined the fact that these "*[...] houses are the most tangible symbol of the post-apartheid government's commitment to redressing this country's stark inequalities*". https:/www.nytimes.com/1999/12/24/world/small-houses-a-big-step-for-south-african-pride.html

*quality of life for the poor*" within its broader vision of achieving "*sustainable human settlements and quality housing*" (Department of Human Settlements, 2004).

# 4 Data and Summary Statistics

## 4.1 Data

We use three sources of data. First, we rely on census data released by Statistics South Africa. This includes all the currently existing waves, namely 1996, 2001 and 2011. Second, we obtained crime data for the financial years of 1996–97, 2001–02 and 2011–12 from the Crime Statistics and Research Unit of the South African Police Service (SAPS). The police data includes the universe of crimes that were either reported by the community or recorded as a result of police action. The dataset includes information about the type of crime, including numerous types of violent and property crimes. The SAPS dataset has three dimensions: year, police station and type of crime.[6] Our third source of data includes the GPS coordinates of government housing projects in the Western Cape Province, their date of registration and their planned or approved size. The data was obtained from the Department of Environmental Affairs and Development Planning in the Western Cape, and it was initially published in a technical report (Department of Environmental Affairs and Development Planning, 2014).

We created a unique panel based on the police station-level crime statistics, the census community profiles and the 10-percent census data. To the best of our knowledge, this is the first time that the police data is used for this type of research.[7] We constructed the dataset as follows. We start with the 2011 census which was compiled at the lowest possible level of aggregation, roughly 85,000 small area layers that contain the universe of households and individuals with aggregated characteristics. Since we have the coordinates of the centroids of these small area layers, we assign them to the polygons of South Africa's 354 former Magisterial Districts (MDs). These are the administrative units that stand as the common denominator between the 1996 and 2001 census waves. Using MD-level

[6] In this study, we use references to police districts and police stations interchangeably to define the lowest level at which SAPS aggregates crime indicators.

[7] The SAPS data has been used in the literature for cross-sectional analyses, e.g., Demombynes and Özler (2005) and Bhorat et al. (2017).

aggregation, we can thus append the 1996, 2001 and 2011 census years into a panel of MD-year observations.

We then merge the census panel with the SAPS panel. There are roughly 1,130 police stations, with their number changing only slightly over time. Some police districts have an irregular shape whose centroid can easily fall outside district boundaries. We generate a random point within the boundaries of police districts instead of using the centroid for the merger. In about on-third of cases, a police station shares substantial surface with more than one magisterial district. To address this, we generate multiple random points per police station to better distribute the incidence of crime between the magisterial districts feeding the crime statistics of the police station in question. For stations that cross the borders of multiple MDs, we count the points that fall in each district and assign crimes proportionally to each concerned MD.[8] Lastly, we merge the public housing information point-to-polygon with the MD-year spatial panel, where the points are the project GPS coordinates and the polygons are the MDs.

The result is a panel of 354 MDs observed 3 times (1996, 2001 and 2011) for a total of 1,062 observations. Census data is representative at the level of MDs, and we use this unit to compute inequality indices and average socio-economic characteristics. Each MD is populated with crime data, which is sourced from the universe of crime incidents reported to police stations across the country. Regarding the government housing data, the sample is limited to the universe of housing projects in the Western Cape Province. The Western Cape sample has 42 MDs observed 3 times, which amount to 126 observations.

By allowing the analysis of South African census and police information in a panel setup, the dataset we created is the first of its kind. It is also the first dataset to include project information on government housing for the entire Western Cape Province. Finally, this is a spatial panel, which enables us to grasp the magnitude of spillover crimes between administrative units and model the spatial interdependence of MD-level unobservables.

[8]This assumes that crimes are homogeneously distributed within the boundaries of any police station. We believe this assumption is unlikely to have significant consequences as the size of police districts is proportional to the size of their population. Most importantly, cities have several police districts. If cities were part of larger police districts, crimes would be concentrated in and around the city, while the outside territory would be less afflicted. Police stations with large territories are usually sparsely populated. See Online Appendix A.4 for a presentation of the merger between MDs and stations.

## 4.2 Measurement of Crime and Inequality

The data we use consists of crimes reported to the police. As noted in the literature, objective measures of crime have several advantages with respect to the self-reported ones. On the other hand, failing to include incidents that are not reported to the police is considered less consequential (Pudney et al., 2000; Rufrancos et al., 2013). We measure crime as the natural logarithm of crime incidence per 100,000 people to normalize its distribution.

In order to construct the housing inequality index, we rely on six variables that are indicative of the quality of the housing infrastructure: type of dwelling (permanent, traditional, or informal), access to water (tap water inside the building, in the yard, on a community stand, or no access to piped water), type of toilet facilities (flush/chemical toilet, pit latrine, bucket latrine, or no toilet facilities), type of fuel for cooking and heating (electricity/solar/gas, paraffin/coal, or wood/animal dung), and type of fuel for lighting (electricity/solar, paraffin/gas, or candles). These are the core aspects of housing quality examined, consistent with the existing literature. These are also the housing dimensions that the intervention we evaluate, the subsidized housing program, has targeted in terms of outcomes—whether directly (dwelling type, access to water, type of toilet facilities and electricity) or indirectly (type fuel for cooking and heating via the availability of electricity and the ability to safely store and accumulate assets).

We start by computing inequality in terms of each of these six variables. Then, based on the standardized values of these inequality measures, we use factor analysis to summarize the information into one index (i.e. the latent variable that describes inequality in terms of housing conditions). The online appendix A.1 shows the factor analysis. To check the robustness of our results, we show in the online appendix that our findings hold for different combinations of variables in computing the inequality index.

To accommodate the fact that the variables describing housing conditions are sets of ordered categories, we rely on Cowell and Flachaire (2017) and use Equation 1 to compute inequality:

$$Inequality = -\sum_{i=1}^{K} \left[p_i \times ln\Big(\sum_{j=1}^{i} p_j\Big)\right] \tag{1}$$

where $K$ stands for the number of ordered categories (ordered from best to worst) and $p_i$ is the probability of an individual belonging to category $j = i$.

### 4.3 Summary Statistics

Table 1 reports the summary statistics that describe the 1,062 MD-year observations in the analytical sample.[9] Table 1 shows that crime incidence has increased slightly between 1996 and 2001, and it has thereafter decreased sharply. Murders have been the exception. They have decreased across all waves. The inequality index points to a gentle decrease between 1996 and 2001, and a sharp decrease between 2001 and 2011. Moreover, average education has improved significantly between 1996 and 2011, and so have most variables proxying for household socio-economic status.

[Table 1: Descriptive Statistics. Insert here.]

Figures 1a and 1b present the raw categories that are reported by the South African Police Service for violent and property crimes, respectively. These figures include the analytical sample years (1996, 2001 and 2011), as well as the out-of-sample year of 2019 to give an indication of the current situation. Figures 1a and 1b confirm the insights of Table 1—i.e. crime incidence first increased between 1996 and 2001 and then decreased.

[Figure 1a: Violent Crimes. Insert here.]

[Figure 1b: Property Crimes. Insert here.]

Following on from the existing literature, we focus on the core crime categories. Specifically, the empirical analysis includes: aggravated assaults, murders, rapes, residential burglaries, and thefts out of vehicles. Figure 1a shows that aggravated assaults are the most commonly reported type of violent crime. As documented in the existing literature, murders are the least likely type of crime to suffer from misreporting. We also explore the evolution of rapes. South Africa has one of the highest incidences of rape in the world, and crimes against women have been at the forefront of recent public debates. Finally, we focus on the two most reported types of property offences (Figure 1b)—i.e. burglar-

[9] In computing these summary statistics, MDs are assigned the same weight regardless of their population or surface.

ies at residential places and thefts out of vehicles. These are also the crime categories that are most often analyzed in the literature (Kelly, 2000; Lochner and Moretti, 2004; Demombynes and Özler, 2005; Kang, 2016).

Figure A.5 in the online appendix shows the spatial distribution of crime and housing inequality across South Africa's MDs (averaged over the three census waves). Violent crimes appear to cluster in the Western, Northern and Eastern Cape Provinces, while property crimes are predominant in and around metropolitan areas. Housing inequality shows a spatial pattern whereby higher disparities are evident in the the Eastern side of the country, particularly in and around areas which were designated by the apartheid regime as 'homelands'.

The summary statistics presented in this section suggest a positive correlation between crime and housing inequality. Inequality has only slightly declined between 1996 and 2001, while it has registered a substantial decrease between 2001 and 2011. Crime has followed a similar path. These trends are consistent with our hypothesis that lower housing inequality may help reduce crime. We explore this link in the following sections by conducting a spatial fixed effects analysis and by examining the role of a large-scale subsidized housing program.

# 5 Empirical Analysis

## 5.1 Housing Inequality and Crime

We estimate the relationship between housing inequality and crime by taking advantage of variation over time and space across magisterial districts. We begin our estimations with a simple fixed effects specification:

$$C_{nt} = \alpha_n + \lambda_t \iota_n + \beta H_{nt} + X_{nt}\gamma + \epsilon_{nt} \tag{2}$$

$C_{nt} = (C_{1t}, C_{2t}, \ldots, C_{Nt})^T$ is the natural log of crime incidence per 100,000 people, where $n$ represents the magisterial district and $t$ represents the time period. As discussed above, we have $N = 354$ magisterial districts and $T = 3$ waves of data. $H_{nt}$ is the housing inequality index. Equation 2 includes both the district fixed effects $\alpha$ and the time fixed effect $\lambda$ ($\iota_n$ is a vector of 1s). $X_{nt}$ includes covariates such as time-varying individual and household characteristics (averaged at the MD level) as well as population density.

[Table 2: Fixed Effects Estimates. Insert here.]

Table 2 shows the coefficient estimates from Equation 2. We estimate the model separately for different types of violent and property crimes. The results show a positive association between housing inequality and crime rates. This is true for all types of crimes, with the exception of murders and residential burglaries, where we do not find a statistically significant coefficient. Controlling for a large set of confounding factors, Table 2 shows that a standard deviation increase in the housing inequality index is associated with an approximate increase of 0.11 and 0.09 log points in overall violent and property crimes, respectively. When looking at specific types of crimes, we notice that thefts out of vehicles appear to be particularly sensitive to housing inequality, as the coefficient reaches 0.45 log points. Table 2 also reports the coefficient estimates for some of the control variables included in the model. Of particular note is the generally negative correlation between average education and crime.

As a robustness check, we also use a non-linear specification to account for the fact that the distribution of the untransformed crime variables resembles a Poisson. The estimated coefficients are reported in Appendix A.3. The coefficients on housing inequality are very similar in the two specifications.

## 5.2 Accounting for Spillover Effects

The estimation above does not take into account the potential spillover effects across magisterial districts. We can use a spatial model to measure spillovers, which amounts to including a spatial lag on the dependent variable as follows:

$$C_{nt} = \alpha_n + \lambda_t \iota_n + \rho W_n C_{nt} + \beta H_{nt} + X_{nt}\gamma + \eta_{nt} \quad (3)$$

where $\eta_{nt} = \phi M_n \eta_{nt} + \varepsilon_{nt}$, and $W$ and $M$ are square matrices that describe the spatial dependency between magisterial districts. $W$ applies the same positive weight for contiguous spatial units and a zero weight for all other units, while $M$ is the inverse distance weighting matrix. $\rho$ and $\phi$ are scalars.[10]

The specification above implies that any change to a variable that increases crime in a given magisterial district can affect the dependent variable in that district's neighbors, which spills into other districts provided that $\rho$ is different from zero. This allows us to estimate a spatial autoregressive combined (SAC) model with individual and time fixed effects, as presented in Equation 4 (LeSage and Pace, 2009; Lee and Yu, 2010).

$$C_{nt} = (I_n - \rho W_n)^{-1}(\alpha_n + \lambda_t \iota_n + \beta H_{nt} + X_{nt}\gamma) + (I_n - \rho W_n)^{-1}(I_n - \phi M_n)^{-1}\varepsilon_{nt} \tag{4}$$

The defining characteristics of a SAC model are the inclusion of a spatial lag on the dependent variable and the spatial interdependence of the disturbance terms. The SAC specification controls not only for time-invariant omitted variables, but also for time-varying omitted variables or unobserved latent influences that explain the spatial clustering of the dependent variable (LeSage and Pace, 2009). It is well established that crime incidence exhibits spatial dependency (Chainey et al., 2008; Ratcliffe, 2010). In fact, the use of spatial models is relatively common in studies of crime precisely because they help mitigate the omitted variables bias.

It is important to note that the spatial dependency of the district observations makes the estimated coefficients of interest not easily interpretable, as the derivative of the dependent variable with respect to the explanatory variables is no longer simply $\beta$ or $\gamma$.[11] Instead, average direct and total effects can be computed (LeSage and Pace, 2009).

For a given magisterial district $n$, the average direct impact measures the effect of a change in $X_n$ on crime in district $n$ inclusive of feedback loops, whereby observation $n$ affects its neighbor, and these neighbor will in return loop back and affect $n$. The average total impact for district $n$ will include the own derivative (direct impact) as well as all of the cross derivatives (i.e. spillover effects) (LeSage and Pace, 2009).

[10] Individuals are less likely to travel across multiple districts to perpetrate crimes, hence the $W$ matrix. We are less restrictive about the spatially correlated unobservables, which can go beyond first-order neighbors, hence the $M$ matrix. When the two scalars are not statistically different from zero, the use of spatial lags is considered not necessary for neither the dependent variable or the error term.

[11] This is because the derivative of $C_{nt}$ with respect to $X^k_{mt}$, where $m$ can be different from $n$, is potentially non-zero. $k$ denotes the $k$th variable in the $X$ matrix.

While spillover effects motivate the inclusion of spatial lags in the dependent variable, the spatial lags on the error term are motivated by the assumption of spatial heterogeneity (LeSage and Pace, 2009). Thus, in addition to the individual heterogeneity modelled by the fixed effects framework, we are now allowing some of the unobserved characteristics of any given district to be similar to those of its neighbors. The intensity of this similarity is decreasing the further away districts are from each other.[12]

[Table 3: Spatial Autoregressive Combined, Fixed Effects Estimates. Insert here.]

Table 3 shows the results from estimating Equation 4. Spillover effects, as estimated by $\rho$, appear to be present in most cases. Spillover effects from neighboring districts are roughly one third of a district's own crime incidence. $\phi$ is also generally significant, which points to the existence of spatial heterogeneity in the error terms. If the SAC model identifies the data generating process correctly, then the estimates in Table 3 will suffer less from omitted variables compared to the simple fixed effects model. This allows us to get as close as possible (given the available data) to a causal interpretation of the effects of housing inequality on crime rates.

For violent crimes, the estimated direct effect of housing inequality is 0.085 log points (8.9 percent), while the total effect is about 0.109 log points. The direct impact of housing inequality on aggravated assaults and rape is 0.094 and 0.124, respectively, while the total impacts are 0.124 and 0.135 log points. Note also that the coefficient on education is negative across the board—i.e. districts that are more educated have less crime—. The direct impact of a one-year increase in average education varies between a reduction of 0.130 log points in the case of rapes and 0.204 for murders.

Moving to property crimes, we note that spillover effects are slightly smaller than for violent crimes, although there is one notable exception: thefts out of vehicles. The impact of housing inequality on residential burglaries is positive and significant. The direct and total effects are 0.086 and 0.105 log points, respectively. Similarly, the direct impact of an increase of one standard deviation in housing inequality is associated to a 0.099 log points increase in all property crimes—the equivalent of 10.4 percent. In the case of thefts out

[12] We also assume that spillover effects at the borders between South Africa and its neighbouring countries are negligible. Since these are national borders with strict controls, it seems a plausible assumption.

of vehicles, the direct impact is 0.345 log points, i.e. 41 percent. The total impacts are 0.124 and 0.522 log points, respectively.[13] Education is also negatively related to property crimes across the board. Online appendix Table A.3 shows that the results in Table 3 are robust to the choice of variables that are used to build the housing inequality index and to the use of a PCA instead of factor analysis.

In summary, the empirical results in this section show that higher housing inequality can lead to higher crime, whether violent or property related. While we cannot identify the causal effect of housing inequality on crime, our estimates do account for time and magisterial district fixed effects, as well as for spatial heterogeneity in the error terms. Our novel empirical finding contributes to the growing literature on the relationship between inequality and crime by providing first evidence of this unexplored dimension of inequality, i.e. housing conditions. This is of high relevance for contexts where, like South Africa, access to adequate housing is limited and very unequally distributed.

# 6 Subsidized Housing, Inequality and Crime

This section examines the implications of a large, subsidized housing program for both inequality and crime. In democratic South Africa, the purpose of government housing has been to supply low-income citizens with fully serviced housing units. In the White Paper on Reconstruction and Development (Parliament of the Republic of South Africa, 1994), the government confirmed its commitment to addressing the inequalities inherited from the previous regime. The same document defines the Reconstruction and Development Program (RDP) as an overarching policy framework to promote long-term socio-economic progress, which includes meeting the housing needs of all citizens. In this context, the government introduced several housing subsidies schemes, which changed nature and name since 1994. We collected detailed information and data on the universe of these housing projects and our empirical analysis examines them.

At the outset, there were four schemes: project-linked, individual, consolidation and institutional subsidies (Department of Housing, 1997). Among these, the project-linked

[13] The relatively higher responsiveness of thefts out of vehicles to housing inequality may be explained by this crime's more opportunistic nature and ease of perpetration.

subsidy scheme has been the most prevalent. As of 2010, according to the database provided by the Western Cape Department of Environmental Affairs and Development Planning (2014), 72 percent of all government subsidies were project-linked. As the purpose of different schemes can be diverse, our empirical analysis focuses on project-linked subsidies. This is because we know with certainty that these subsidies were aimed to provide fully serviced housing units to people who had not benefited from any previous housing subsidies.[14]

Initially, project-linked subsidies only consisted of projects implemented by external developers whose proposals were approved by the government. Developers were required to meet specific milestones to draw down on the contract value. This procedure explains why these projects were called "*Progress Payment Housing Projects*". Housing beneficiaries were granted subsidies as one-off grants based on their level of income. For the poorest, the subsidy would cover the cost of the house entirely, with the fully subsidized houses colloquially referred to as "*RDP houses*" (Tomlinson, 1999).

In 1998, a new subsidy scheme was introduced: the People's Housing Process (PHP). Under this scheme, beneficiaries would build or manage the construction of their own houses (Public Service Commission, 2003). In parallel, the scheme of the Progress Payment Housing Projects underwent important changes from 2001, with the provincial and municipal governments progressively taking over the role of developers (Department of Human Settlements, 2016). In 2007, the existing schemes were abolished (Gordon et al., 2011) and further reforms followed. From 2009, the provision of government housing was done under the new Integrated Residential Development Program (IRDP).

To simplify the discussion, we will group the IRDP and its predecessor (the Progress Payment Housing Projects) under the same label "*IRDP*", while the PHP projects will remain a separate category. When we refer to government housing, we mean projects under both the IRDP and PHP labels. Regardless of their name, the objective of these schemes has been the same: to provide low-income South Africans with fully serviced housing units. Against a backdrop of large informal settlements, government houses are

[14]Beneficiaries were assigned to housing units based on a waiting list. A serviced site is defined by the following minimum requirements: (i) a piped water supply with at least one stand pipe per 25 households; (ii) a properly functioning sanitation system for each household; and (iii) suitable access to each property and a storm water drainage system (Department of Human Settlements, 2009).

permanent houses constructed with solid materials, endowed with access to tap water, flush toilet facilities and electricity (Tissington, 2011).

## 6.1 Government Housing and Inequality

We first investigate whether the introduction and expansion of government projects affected housing inequality. Due to data availability, this part of the empirical analysis is limited to one province: the Western Cape.[15] We rely on the list of housing projects provided by the provincial Department of Environmental Affairs and Development Planning. This covers projects that were registered between 1994 and 2009. The list is comprised of the geo-referenced location of housing projects, the year in which they were registered by the provincial Housing (Development) Board and their approved size.[16] We compute a yearly average rate of housing execution per project between 1995 and 2008, which gives us an estimated distribution of housing units across the provincial territory over the period of interest.[17]

In order to link the housing data to the census years (1996, 2001 and 2011), our analysis relies on the stock of housing units at the beginning of 1995, 2000 and 2010. The average stock of housing projects has increased from 0 to 2.08 thousand units per 100,000 people between 1995 and 2000, and to an average of 4.22 thousand units per 100,000 people at the beginning of 2010. Stock numbers include the units delivered by IRDP and PHP. Figure 2 shows the estimated distribution of housing units across the magisterial districts of the Western Cape over the period of interest.

[Figure 2: Stock of Government Housing in the Western Cape Province. Insert here.]

Our dataset, while the first of its kind in the literature, entails three main caveats for studying the housing subsidy program. First, the smaller provincial sample (42 magisterial districts observed in three years) considerably reduces the precision of our estimates. Second, the imputation of government housing stocks introduces measurement error in

[15] This province includes one of the largest metropolitan areas in the country (Cape Town) and represents 11 and 12 percent of the country's surface and population, respectively.

[16] For 78 of 558 projects, we must rely on the planned as opposed to approved size due missing information.

[17] We use data from Franklin (2020) to obtain the execution rate in Cape Town over this period and apply the same execution rates to the entire Province.

the key independent variable and a consequent risk of attenuation bias under classical assumptions. Third, since we cannot assume the absence of crime spillover effects between districts at either side of provincial borders, we can no longer use the spatial model in our regression analysis and thus revert to the simple fixed effects estimation.

[Table 4: Government Housing and Inequality. Insert here.]

Table 4 reports the coefficient estimates from different models regressing the housing inequality index on the lagged stock ($t = 1, 2, 3$ years) of subsidized units. We use lags as the benefits of housing projects may take time to materialize. The results in Table 4 show that an increase of 1,000 units per 100,000 people (roughly 0.45 of a standard deviation) is associated with a decrease in the housing inequality index between 0.11 and 0.15 standard deviations (columns 1, 3, and 5). When we include controls for each separate component of the inequality index (as we did in the previous section), the estimated coefficients fall between -0.04 and -0.05. We suggest that the magnitude of the true effect of the projects on housing inequality lies between the estimates from these two specifications. This is because not all variation in the variables defining the index may be linked to the government subsidies.

## 6.2 Government Housing and Crime

This section provides the first estimates of the effect of housing projects on crime rates in South Africa. While falling short of providing causally identified impact estimates, the coefficients presented here are net of district and time fixed effects, and account for a variety of potential confounding factors that are related to the development of government housing (e.g. prevalence of informal housing, access to public amenities, etc.).[18] Table 5a and 5b report the estimated coefficients on crime rates. To increase power, we pool incidents into two macro-categories: violent and property crimes. Table 5a shows that government housing is negatively related to violent crimes. An increase of 1,000 housing units per 100,000 people is associated to a decrease in the crime rate between 5 and 6 percent (columns 2, 4, and 6). The coefficients are large in magnitude and are greater for

[18] To the extent that we are vulnerable to time-varying unobservables that are endogenous to project development and crime, we note that housing projects may be more likely to be developed in areas of increasing crime over time. This would lead to our specification possibly understating the impact of government housing on crime.

higher lags of the housing stock. This provides suggestive evidence that it may take time for the benefits of the housing subsidies to materialize. Column 3, 5, and 7 include in the estimation both the index of housing inequality and the stock of government housing. The coefficients on the housing projects decrease in magnitude and lose significance in these specifications (in part because of the small sample size in a single province). This is consistent with our hypothesis that improvements in the housing stock may affect crime partially through changes in housing inequality. This is also visible when comparing the effect of housing inequality on crime with and without controls for subsidized housing, as shown by the estimates in the top row of Table 5a—column 1 versus columns 3, 5 and 7.[19]

[Table 5a: Government Housing and Violent Crimes. Insert here.]

[Table 5b: Government Housing and Property Crimes. Insert here.]

Table 5b shows no significant effects of the IRDP-PHP projects on property crimes. Moreover, the coefficients on housing inequality do not exhibit the same variation across columns (top row of Table 5b) that we see in Table 5a for violent crimes.

## 6.3 Falsification Test

To probe the plausibility of the empirical mechanism we suggest above, we explore here a different policy intervention whose timing overlapped with that of the housing subsidies. This provides us with a simple falsification test. The policy intervention is the old-age pension, which was introduced by the Social Assistance Act of 1992. Both the housing and pension schemes have been implemented in post-apartheid South Africa with an explicit attempt to mend the inequalities created by the racialized policies of the previous regime.

Pension eligibility is based on age and income. In 1996 and 2001, women aged 60 or above and men aged 65 or above were eligible to receive the pension if they were below a specified income threshold. The law was later amended to equalize age eligibility across genders and in 2011 both women and men were eligible to receive pensions as of their 60th birthday, conditional on meeting the income criterion. The South African old-age

[19]We can reject the null of coefficient equality between column 1 and columns 3 and 5 at the 10 percent level, while the p-value of the null for specification in column 7 is 0.11.

pension scheme has been studied extensively. The literature has shown that the program had a variety of effects on the most disadvantaged groups in the population.[20] Black and Colored populations have been the main beneficiaries of the policy, along with few Whites earning below the income threshold (Case and Deaton, 1998). That is, similar to subsidized housing, the old-age pension has reached a large number of low-income beneficiaries against the background of apartheid-inherited socio-economic inequalities.

We obtain variation in the intensity of the old age pension policy across magisterial districts by using the percentage of age-eligible individuals of different population groups. In particular, we use the district-level percentage of age-eligible African Blacks and Colored.[21] Table 6 shows that the proportion of people eligible for the pension does not have a significant effect on the housing inequality index. In addition, we show in Table 7 that our proxy for pension eligibility does not show any evidence of a negative effect on crime either. If anything, the point estimate suggests a positive correlation between the prevalence of pension-eligible individuals and crime (whether violent or property-related). Overall, this simple falsification test supports our interpretation of the main results in this section. That is, the negative relationship between housing projects and crime is not spurious and is suggestive of an inequality-mediated effect of subsidized housing, which has been so far understudied in the literature.

[Table 6: Old-Age Pension Eligibility and Housing Inequality. Insert here.]

[Table 7: Old-Age Pension Eligibility and Crime. Insert here.]

## 6.4 Discussion

As discussed in Section 1, previous studies suggest that social protection interventions can help limit strain, either directly through the achievement of positively valued goals or indirectly via reduced inequality. This literature also suggests that reduced inequality and strain are associated with lower levels of crime, particularly violent crimes (Agnew, 1992,

[20]Duflo (2000) and Duflo (2003) show a positive effect on anthropometric indicators for girls. Other studies have estimated the impact on the labor supply of both the elderly and their working-age household co-residents (Ranchhod, 2006; Ardington et al., 2009; Abel, 2019b). Finally, there is also evidence that the pension scheme had an effect on decision-making processes within households and household composition (Hamoudi and Thomas, 2014; Ambler, 2016).

[21]We run sensitivity regressions using several combinations of different population groups and the implications of the analysis are unchanged.

1999, 2001; Shaw and McKay, 1942). The empirical results presented in this section are consistent with this body of work. In particular, we add first evidence on an understudied policy intervention: housing subsidies. We show that the development of government housing projects is associated with lower housing inequality (Table 4) and, consistent with strain theory, we show that that this lower inequality can help mitigate violent crime (Table 5a).

Meth and Charlton (2017) report that male beneficiaries of government housing in South Africa were enabled to achieve their aspirations, which are not limited to tangible assets, but extend to other dimensions, such as masculinity, social status, self-esteem and respect. These positive valued goals are correlated with the individual transition from the state of informal dweller to that of homeowner. Men are the main perpetrators of violent crimes in South Africa (Centre for the Study of Violence and Reconciliation, 2007). Men's capacity to achieve standard goals or socially constructed aspirations may mitigate collective strain, which can reduce frustrations and limit impulsive, anger-led outbursts of violence. This may help explain the observed differential effects of subsidized housing on violent crimes versus property crimes (Table 5a–5b). Reductions in anger are less likely to play a primary role in the mitigation of financially motivated crimes. On the other hand, anger is central in strain theory's explanation of crime (Agnew, 2001), and evidence from criminology suggests that anger chiefly impacts violent crimes (Aseltine et al., 2000; Mazerolle et al., 2003; Piquero and Sealock, 2000).

# 7 Conclusion

Our paper provides a contribution to the literature examining the link between inequality and crime. While most existing studies focus on inequality in income or consumption, we explore disparities in terms of housing conditions. We show that variations in housing quality in a highly unequal emerging economy explain a significant share of the variation in most types of crime. An increase of one standard deviation in an index of housing inequality explains around 12 percent of crime increases.

Different dimensions of inequality may matter in distinct ways in developing countries as compared to high-income economies (Demombynes and Özler, 2005; Enamorado et al., 2016). Our findings expand the very limited evidence on the Global South. We collect and merge data from different South African sources, which we exploit to account for key confounding factors, as well as to quantify the magnitude of spillover effects.

Crime is a prominent issue in societies characterized by high levels of inequality. Governments have tried different policy measures (both direct and indirect) to reduce it. We show that a housing program aimed at fast-tracking socio-economic development in South Africa may have had the indirect effect of mitigating violent crimes by partially reducing inequality. As argued by Kelly (2000), different economic and sociological theories may explain different types of crime. In particular, property crimes may be best explained by cost-benefit analyses, while violent crimes may be better understood from a strain or social disorganization perspective. We argue that strain theory can help interpret our results on the relationship between subsidized housing, inequality and the incidence of violent crimes. We suggest that housing subsidies may reduce violent crimes by alleviating the levels of strain that have been conducive to violence.

Finally, our study contributes to the broader literature investigating the relationship between social protection policies (e.g. education policy, labor market interventions) and crime. Most of these programs are meant to lift people out of poverty and ensure a more equal distribution of the socio-economic means and opportunities, which can help reduce crime. It may be superfluous to note that these types of policies are not incompatible with actions aimed at improving the criminal justice and law enforcement systems. In fact, it is reasonable to assume that a larger set of complementary policies may be necessary to obtain long-lasting reductions in crime rates.

# References


Abel, M. (2019a). Long-Run Effects of Forced Resettlement: Evidence from Apartheid South Africa. *Journal of Economic History*, 79(4):915–953.

Abel, M. (2019b). Unintended Labor Supply Effects of Cash Transfer Programs: New Evidence from South Africa's Pension. *Journal of African Economies*, 28(5):558–581.

Adelzadeh, A. (1996). From the RDP to GEAR: The Gradual Embracing of Neo-Liberalism in Economic Policy. *Transformation: Critical Perspectives on Southern Africa*, (31).

African National Congress (1994). A Basic Guide to the Reconstruction and Development Programme.

Agnew, R. (1992). Foundation for a General Strain Theory of Crime and Delinquency. *Criminology*, 30(1):47–88.

Agnew, R. (1999). A General Strain Theory of Community Differences in Crime Rates. *Journal of Research in Crime and Delinquency*, 36(2):123–155.

Agnew, R. (2001). Building on the Foundation of General Strain Theory: Specifying the Types of Strain Most Likely to Lead to Crime and Delinquency. *Journal of Research in Crime and Delinquency*, 38(4):319–361.

Alvaredo, F., Chancel, L., Piketty, T., Saez, E., and Zucman, G. (2018). *World Inequality Report*. Belknap Press.

Ambler, K. (2016). Bargaining with Grandma: The Impact of the South African Pension on Household Decision-making. *Journal of Human Resources*, 51(4):900–932.

Amodio, F. and Chiovelli, G. (2018). Ethnicity and Violence During Democratic Transitions: Evidence from South Africa. *Journal of the European Economic Association*, 16(4):1234–1280.

Anderson, D. M. (2014). In School and Out of Trouble? The Minimum Dropout Age and Juvenile Crime. *Review of Economics and Statistics*, 96(2):318–331.

Ardington, C., Case, A., and Hosegood, V. (2009). Labor Supply Responses to Large Social Transfers: Longitudinal Evidence from South Africa. *American Economic Journal: Applied Economics*, 1(1):22–48.

Aseltine, R. H., Gore, S., and Gordon, J. (2000). Life Stress, Anger and Anxiety, and Delinquency: An Empirical Test of General Strain Theory. *Journal of Health and Social Behavior*, pages 256–275.

Barnhardt, S., Field, E., and Pande, R. (2017). Moving to Opportunity or Isolation? Network Effects of a Randomized Housing Lottery in Urban India. *American Economic Journal: Applied Economics*, 9(1):1–32.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. In *The Economic Dimensions of Crime*, pages 13–68. Springer.

Bell, B., Bindler, A., and Machin, S. (2018). Crime Scars: Recessions and the Making of Career Criminals. *Review of Economics and Statistics*, 100(3):392–404.

Bell, B., Costa, R., and Machin, S. (2016). Crime, Compulsory Schooling Laws and Education. *Economics of Education Review*, 54:214–226.

Bhorat, H., Lilenstein, A., Monnakgotla, J., Thornton, A., and Van der Zee, K. (2017). Socio-Economic Determinants of Crime in South Africa: An Empirical Assessment. Working Paper 201704.

Bourguignon, F., Nuñez, J., and Sanchez, F. (2003). A Structural Model of Crime and Inequality in Colombia. *Journal of the European Economic Association*, 1(2-3):440–449.

Brezina, T. (2017). General Strain Theory. In *Oxford Research Encyclopedia of Criminology and Criminal Justice*.

Brezina, T., Piquero, A. R., and Mazerolle, P. (2001). Student Anger and Aggressive Behavior in School: An Initial Test of Agnew's Macro-Level Strain Theory. *Journal of Research in Crime and Delinquency*, 38(4):362–386.

Bruederle, A., Peters, J., and Roberts, G. (2017). Weather and Crime in South Africa.

Buonanno, P. and Vargas, J. F. (2019). Inequality, Crime, and the Long Run Legacy of Slavery. *Journal of Economic Behavior & Organization*, 159:539–552.

Case, A. and Deaton, A. (1998). Large Cash Transfers to the Elderly in South Africa. *The Economic Journal*, 108(450):1330–1361.

Centre for Affordable Housing Finance in Africa (2019). Housing Finance in Africa. A Review of Africa's Housing Finance Markets. Technical report, Johannesburg, South Africa.

Centre for the Study of Violence and Reconciliation (2007). The Violent Nature of Crime in South Africa. Technical report, Department of Safety and Security, Government of South Africa. A concept paper for the Justice, Crime Prevention and Security Cluster.

Chainey, S., Tompson, L., and Uhlig, S. (2008). The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime. *Security Journal*, 21(1-2):4–28.

Chalfin, A. and McCrary, J. (2018). Are US Cities Underpoliced? Theory and Evidence. *Review of Economics and Statistics*, 100(1):167–186.

Chalfin, A. and Raphael, S. (2011). Work and Crime. In *The Oxford Handbook of Crime and Criminal Justice*, page 444.

Chiu, W. H. and Madden, P. (1998). Burglary and Income Inequality. *Journal of Public Economics*, 69(1):123–141.

Collinson, R., Ellen, I. G., and Ludwig, J. (2015). Low-Income Housing Policy. In *Economics of Means-Tested Transfer Programs in the United States, Volume 2*, pages 59–126. University of Chicago Press.

Costantini, M., Meco, I., and Paradiso, A. (2018). Do Inequality, Unemployment and Deterrence Affect Crime over the Long Run? *Regional Studies*, 52(4):558–571.

Cowell, F. A. and Flachaire, E. (2017). Inequality with Ordinal Data. *Economica*, 84(334):290–321.

de Beeck, H. O., Pauwels, L. J., and Put, J. (2012). Schools, Strain and Offending: Testing a School Contextual Version of General Strain Theory. *European Journal of Criminology*, 9(1):52–72.

DeAngelo, G. and Hansen, B. (2014). Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities. *American Economic Journal: Economic Policy*, 6(2):231–257.

Demombynes, G. and Özler, B. (2005). Crime and Local Inequalities in South Africa. *Journal of Development Economics*, 769(2):265–292.

Department of Environmental Affairs and Development Planning (2014). Western Cape Provincial Spatial Development Framework. Technical report, Western Cape Government, Cape Town. Chapter 3.3.6, Informality, Housing Delivery, Inclusion and Urban Land Markets.

Department of Housing (1997). Urban Development Framework. Technical report, Government of South Africa.

Department of Human Settlements (2004). Breaking New Ground. Technical report, Government of South Africa.

Department of Human Settlements (2009). The National Housing Code. Technical and General Guidelines, Part 3, Volume 2.

Department of Human Settlements (2016). Design and Implementation Evaluation of the Integrated Residential Development Programme - Evaluation Report. Technical report, Government of South Africa.

Di Tella, R. and Schargrodsky, E. (2004). Do Police Reduce Crime? Estimates Using the Allocation of Police Forces After a Terrorist Attack. *American Economic Review*, 94(1):115–133.

Disney, R., Gathergood, J., Machin, S., Sandi, M., et al. (2020). Does Homeownership Reduce Crime? A Radical Housing Reform in Britain. Technical report, Centre for Economic Performance, LSE.

Draca, M. and Machin, S. (2015). Crime and Economic Incentives. *Annual Review of Economics*, 7(1):389–408.

Draca, M., Machin, S., and Witt, R. (2011). Panic on the Streets of London: Police, Crime, and the July 2005 Terror Attacks. *American Economic Review*, 101(5):2157–81.

Drago, F., Galbiati, R., and Vertova, P. (2009). The Deterrent Effects of Prison: Evidence from a Natural Experiment. *Journal of Political Economy*, 117(2):257–280.

Duflo, E. (2000). Child Health and Household Resources in South Africa: Evidence from the Old Age Pension Program. *American Economic Review*, 90(2):393–398.

Duflo, E. (2003). Grandmothers and Granddaughters: Old-Age Pensions and Intrahousehold Allocation in South Africa. *The World Bank Economic Review*, 17(1):1–25.

Enamorado, T., López-Calva, L. F., Rodríguez-Castelán, C., and Winkler, H. (2016). Income Inequality and Violent Crime: Evidence from Mexico's Drug War. *Journal of Development Economics*, 120:128–143.

Evans, W. N. and Owens, E. G. (2007). COPS and Crime. *Journal of Public Economics*, 91(1-2):181–201.

Field, E. (2004). Property Rights, Community Public Goods, and Household Time Allocation in Urban Squatter Communities: Evidence from Peru. *Wiliam & Mary Law Review*, 45(3):837–888.

Field, E. (2005). Property Rights and Investment in Urban Slums. *Journal of the European Economic Association*, 3(2-3):279–290.

Field, E. (2007). Entitled to Work: Urban Property Rights and Labor Supply in Peru. *The Quarterly Journal of Economics*, 122(4):1561–1602.

Fougère, D., Kramarz, F., and Pouget, J. (2009). Youth Unemployment and Crime in France. *Journal of the European Economic Association*, 7(5):909–938.

Franklin, S. (2020). Enabled to Work: The Impact of Government Housing on Slum Dwellers in South Africa. *Journal of Urban Economics*, 118.

Freedman, M. and Owens, E. G. (2011). Low-income Housing Development and Crime. *Journal of Urban Economics*, 70(2-3):115–131.

Freeman, R. B. (1999). The Economics of Crime. *Handbook of Labor Economics*, 3:3529–3571.

Galiani, S. and Schargrodsky, E. (2010). Property Rights for the Poor: Effects of Land Titling. *Journal of Public Economics*, 94(9-10):700–729.

Gelb, S. (2006). The RDP, GEAR and All That: Reflections Ten Years Later. *Transformation: Critical Perspectives on Southern Africa*, 62(1):1–8.

Global Burden of Disease Collaborative Network (2018). Global Burden of Disease Study, Results. Technical report, Institute for Health Metrics and Evaluation, Seattle, United States.

Goodlad, R. (1996). The Housing Challenge in South Africa. *Urban Studies*, 33(9):1629–1646.

Gordon, R., Nell, M., and di Lollo, A. (2011). Investigation into the Delays in Issuing Title Deeds to Beneficiaries of Housing Projects Funded by the Capital Subsidy. Technical report. Report commissioned by Urban LandMark and undertaken by Shisaka Development Management Services.

Gould, E. D., Weinberg, B. A., and Mustard, D. B. (2002). Crime Rates and Local Labor Market Opportunities in the United States: 1979–1997. *Review of Economics and Statistics*, 84(1):45–61.

Hamoudi, A. and Thomas, D. (2014). Endogenous Coresidence and Program Incidence: South Africa's Old Age Pension. *Journal of Development Economics*, 109:30–37.

Hawken, A. and Kleiman, M. (2009). Managing Drug Involved Probationers with Swift and Certain Sanctions: Evaluating Hawaii's HOPE. *Washington, DC: National Criminal Justice Reference Services.*

Hémet, C. (2020). Unemployment and Crime Victimization: A Local Approach.

Hjalmarsson, R., Holmlund, H., and Lindquist, M. J. (2015). The Effect of Education on Criminal Convictions and Incarceration: Causal Evidence from Micro-Data. *The Economic Journal*, 125(587):1290–1326.

Hoffmann, J. P. (2003). A Contextual Analysis of Differential Association, Social Control, and Strain Theories of Delinquency. *Social Forces*, 81(3):753–785.

Hoffmann, J. P. and Ireland, T. O. (2004). Strain and Opportunity Structures. *Journal of Quantitative Criminology*, 20(3):263–292.

Jacob, B. A., Kapustin, M., and Ludwig, J. (2015). The Impact of Housing Assistance on Child Outcomes: Evidence from a Randomized Housing Lottery. *The Quarterly Journal of Economics*, 130(1):465–506.

Jacob, B. A. and Ludwig, J. (2012). The Effects of Housing Assistance on Labor Supply: Evidence from a Voucher Lottery. *American Economic Review*, 102(1):272–304.

Johnson, R. and Raphael, S. (2012). How Much Crime Reduction Does the Marginal Prisoner Buy? *Journal of Law and Economics*, 55(2):275–310.

Jonck, P., Goujon, A., Testa, M. R., and Kandala, J. (2015). Education and Crime Engagement in South Africa: A National and Provincial Perspective. *International Journal of Educational Development*, 45:141–151.

Kang, S. (2016). Inequality and Crime Revisited: Effects of Local Inequality and Economic Segregation on Crime. *Journal of Population Economics*, 29(2):593–626.

Kelly, M. (2000). Inequality and Crime. *Review of Economics and Statistics*, 82(4):530–539.

Khanna, G., Medina, C., Nyshadham, A., and Tamayo, J. A. (2019). Formal Employment and Organized Crime: Regression Discontinuity Evidence from Colombia.

Lall, S. V., van den Brink, R., Dasgupta, B., and Leresche, K. M. (2012). Shelter from the Storm but Disconnected from Jobs. *World Bank Policy Research Working Paper*, 6173.

Lee, L.-F. and Yu, J. (2010). Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects. *Journal of Econometrics*, 154(2):165–185.

LeSage, J. and Pace, R. K. (2009). *Introduction to Spatial Econometrics.*

Levitt, S. D. (2002). Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply. *American Economic Review*, 92(4):1244–1250.

Liedka, R. V., Piehl, A. M., and Useem, B. (2006). The Crime-Control Effect of Incarceration: Does Scale Matter? *Criminology & Public Policy*, 5(2):245–276.

Lin, M.-J. (2009). More Police, Less Crime: Evidence from US State Data. *International Review of Law and Economics*, 29(2):73–80.

Lochner, L. and Moretti, E. (2004). The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-reports. *American Economic Review*, 94(1):155–189.

Machin, S., Marie, O., and Vujić, S. (2011). The Crime Reducing Effect of Education. *The Economic Journal*, 121(552):463–484.

Machin, S. and Meghir, C. (2004). Crime and Economic Incentives. *Journal of Human Resources*, 39(4):958–979.

Mahler, A., Simmons, C., Frick, P. J., Steinberg, L., and Cauffman, E. (2017). Aspirations, Expectations and Delinquency: The Moderating Effect of Impulse Control. *Journal of Youth and Adolescence*, 46(7):1503–1514.

Mazerolle, P., Piquero, A. R., and Capowich, G. E. (2003). Examining the Links between Strain, Situational and Dispositional Anger, and Crime: Further Specifying and Testing General Strain Theory. *Youth & Society*, 35(2):131–157.

Meth, P. and Charlton, S. (2017). Men's Experiences of State Sponsored Housing in South Africa: Emerging Issues and Key Questions. *Housing Studies*, 32(4):470–490.

Metz, N. and Burdina, M. (2018). Neighbourhood Income Inequality and Property Crime. *Urban Studies*, 55(1):133–150.

Ministry in the Office of the President (1995). The RDP. April 27 1995. The First Year Reviewed.

Naidoo, V. and Maré, A. (2015). Implementing the National Development Plan? Lessons from Co-ordinating Grand Economic Policies in South Africa. *Politikon*, 42(3):407–427.

Newman, S., Holupka, C. S., and Harkness, J. (2009). The Long-term Effects of Housing Assistance on Work and Welfare. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 28(1):81–101.

Parliament of the Republic of South Africa (1994). White Paper on Reconstruction and Development.

Picarelli, N. (2019). There is No Free House. *Journal of Urban Economics*, 111:35–52.

Piquero, N. L. and Sealock, M. D. (2000). Generalizing General Strain Theory: An Examination of an Offending Population. *Justice Quarterly*, 17(3):449–484.

Public Service Commission (2003). Report on the Evaluation of the National Housing Subsidy Scheme. Technical report, Government of South Africa.

Pudney, S., Deadman, D., and Pyle, D. (2000). The Relationship Between Crime, Punishment and Economic Conditions: Is Reliable Inference Possible When Crimes Are

Under-Recorded? *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 163(1):81–97.

Ranchhod, V. (2006). The Effect of the South African Old Age Pension on Labour Supply of the Elderly. *South African Journal of Economics*, 74(4):725–744.

Raphael, S. and Winter-Ebmer, R. (2001). Identifying the Effect of Unemployment on Crime. *The Journal of Law and Economics*, 44(1):259–283.

Ratcliffe, J. H. (2010). The Spatial Dependency of Crime Increase Dispersion. *Security Journal*, 23(1):18–36.

Rebellon, C. J., Leeper Piquero, N., Piquero, A. R., and Thaxton, S. (2009). Do Frustrated Economic Expectations and Objective Economic Inequity Promote Crime? A Randomized Experiment Testing Agnew's General Strain Theory. *European Journal of Criminology*, 6(1):47–71.

Rufrancos, H., Power, M., Pickett, K. E., and Wilkinson, R. (2013). Income Inequality and Crime: A Review and Explanation of the Time-Series Evidence. *Sociology and Criminology*.

Santiago, A. M., Galster, G. C., and Pettit, K. L. (2003). Neighbourhood Crime and Scattered-Site Public Housing. *Urban Studies*, 40(11):2147–2163.

Shaw, C. R. and McKay, H. D. (1942). Juvenile Delinquency and Urban Areas.

South African Police Service (2018). Annual Report 2017/2018. Technical report, Government of South Africa. Addendum to the SAPS Annual Report.

South African Police Service (2020). 2019–2020 Crime Stats Presentation. Online, www.saps.gov.za.

Statistics South Africa (2012). Census 2011 Statistical Release. Technical report. P0301.4.

Statistics South Africa (2018). Victims of Crime Survey. Technical report, Government of South Africa. Statistical release P0341.

Statistics South Africa (2019). Inequality Trends in South Africa: A Multidimensional Diagnostic of Inequality. Technical report. Report No. 03-10-194.

Susin, S. (2005). Longitudinal Outcomes of Subsidized Housing Recipients in Matched Survey and Administrative Data. *Cityscape*, pages 189–218.

The Economist (2017). Ethiopia is Struggling to Make Housing Affordable. Online.

The Economist (2020). Governments are Rethinking the Provision of Public Housing. Online.

Tissington, K. (2011). A Resource Guide to Housing in South Africa 1994–2010. Technical report, Socio-economic Rights Institute of South Africa.

Tomlinson, M. R. (1999). From Rejection to Resignation: Beneficiaries' Views on the South African Government's New Housing Subsidy System. *Urban Studies*, 36(8):1349–1359.

United Nations Office on Drugs and Crime (2019). Global Study on Homicide. Technical report.

Warner, B. D. and Fowler, S. K. (2003). Strain and Violence: Testing a General Strain Theory Model of Community Violence. *Journal of Criminal Justice*, 31(6):511–521.

Wilkinson, P. (1998). Housing Policy in South Africa. *Habitat International*, 22(3):215–229.

Woo, A. and Joh, K. (2015). Beyond Anecdotal Evidence: Do Subsidized Housing Developments Increase Neighborhood Crime? *Applied Geography*, 64:87–96.

World Bank (2018). Overcoming Poverty and Inequality in South Africa. Technical report.

World Bank (2020). Data Bank. WDI Database Archives. Online. Gini index, World Bank estimate.

World Inequality Database (2020). World View: Top 10 Percent Share. Online, https://wid.world/.

Wu, D. and Wu, Z. (2012). Crime, Inequality and Unemployment in England and Wales. *Applied Economics*, 44(29):3765–3775.

# Tables and Figures

Table 1: Descriptive Statistics

| | Per Year, Across MDs | | | Across Years and MDs | | | |
|---|---|---|---|---|---|---|---|
| | Mean values | | | Mean | $\sigma$ | Min | Max |
| | 1996 | 2001 | 2011 | 1996–2011 | | | |
| **Crimes declared at police stations** | | | | | | | |
| All violent crimes per 100,000 people | 2,528 | 2,816 | 1,700 | 2,348 | 1,882 | 296 | 28,428 |
| Aggravated assaults per 100,000 people | 828 | 896 | 548 | 758 | 640 | 74 | 6,400 |
| Murders per 100,000 people | 71 | 52 | 35 | 53 | 40 | 3 | 395 |
| Rapes per 100,000 people | 140 | 141 | 116 | 132 | 86 | 0 | 1,429 |
| All property crimes per 100,000 people | 1,694 | 1,796 | 1,066 | 1,519 | 1,384 | 117 | 16,812 |
| Thefts out of vehicles per 100,000 people | 321 | 350 | 174 | 282 | 500 | 0 | 5,064 |
| Residential burglaries per 100,000 people | 639 | 748 | 503 | 630 | 573 | 42 | 8,426 |
| **Factor analysis of Cowell-Flachaire measures** | | | | | | | |
| Inequality index housing conditions | 0.35 | 0.25 | -0.60 | 0.00 | 0.96 | -2.49 | 1.76 |
| Inequality index housing conditions, standardized | 0.36 | 0.26 | -0.62 | 0.00 | 1.00 | -2.61 | 1.84 |
| **MD-averaged individual characteristics** | | | | | | | |
| Average years of education | 5.55 | 5.92 | 7.18 | 6.22 | 1.34 | 2.21 | 10.00 |
| Percentage Black | 71.43 | 73.93 | 75.47 | 73.61 | 31.26 | 0.00 | 100.00 |
| Percentage Colored | 16.81 | 16.35 | 15.69 | 16.29 | 26.75 | 0.00 | 91.77 |
| Percentage Asian | 1.06 | 0.97 | 1.06 | 1.03 | 4.95 | 0.00 | 90.75 |
| Percentage unemployed | 17.96 | 22.39 | 14.83 | 18.39 | 6.61 | 2.68 | 44.70 |
| Percentage discouraged | 4.84 | 12.15 | 6.58 | 7.86 | 5.06 | 0.63 | 29.94 |
| Percentage moved in past 10 years | 35.77 | 37.93 | 15.41 | 29.70 | 20.06 | 0.99 | 95.41 |
| **MD-averaged household characteristics** | | | | | | | |
| Average household size | 4.15 | 3.94 | 3.37 | 3.82 | 0.69 | 2.25 | 6.52 |
| Average number rooms per household | 3.75 | 3.83 | 4.09 | 3.89 | 0.50 | 2.11 | 5.54 |
| Percentage living informal dwelling | 13.24 | 11.66 | 8.74 | 11.21 | 11.02 | 0.00 | 67.49 |
| Percentage access to water on premises | 58.55 | 59.78 | 71.65 | 63.33 | 28.67 | 0.77 | 98.79 |
| Percentage access flush or chemical toilet | 39.70 | 44.87 | 57.36 | 47.31 | 30.36 | 0.19 | 98.09 |
| Percentage access to electricity | 53.52 | 66.35 | 83.01 | 67.63 | 23.90 | 1.04 | 99.01 |
| Percentage authority removes rubbish | 47.04 | 49.09 | 54.84 | 50.32 | 30.91 | 0.04 | 99.21 |
| Percentage owns dwelling of residence | 72.62 | 53.71 | 54.47 | 60.27 | 16.55 | 7.68 | 98.53 |
| **MD specific** | | | | | | | |
| Density (1,000 people per $km^2$) | 0.24 | 0.25 | 0.30 | 0.27 | 0.95 | 0.00 | 9.19 |
| **Sample size** | 354 | 354 | 354 | 1,062 | 1,062 | 1,062 | 1,062 |

Average education is for individuals aged 5 or above. The inequality index is based on a factor analysis of 6 variables denoting inequality in terms of housing conditions: type of dwelling, access to piped water, type of toilet facilities and type of fuel for lighting, cooking and heating. Whites are the reference population group. Percentage unemployed counts individuals who do not have a job and are looking for employment. Percentage discouraged includes the unemployed who are not looking for a job and those individuals who choose not to work. The denominator consists of the population aged between 15 and 64 years old, included.

Table 2: Fixed Effects Estimates

| | VIOLENT CRIMES Log of crime per 100,000 people | | | | PROPERTY CRIMES Log of crime per 100,000 people | | |
|---|---|---|---|---|---|---|---|
| | **All Violent Crimes** | **Aggra-vated Assaults** | **Murders** | **Rapes** | **All Property Crimes** | **Thefts out of Vehicles** | **Resi-dential Burglaries** |
| **Explanatory variables** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Housing inequality index | 0.108*** | 0.129*** | -0.064 | 0.131*** | 0.085*** | 0.449*** | 0.059 |
| | (0.030) | (0.033) | (0.050) | (0.045) | (0.032) | (0.076) | (0.037) |
| Avg. education (years) | -0.138 | -0.108 | -0.191* | -0.115 | -0.244** | -0.503*** | -0.235** |
| | (0.098) | (0.092) | (0.104) | (0.095) | (0.102) | (0.123) | (0.105) |
| Perc. unemployed | -0.004 | -0.005 | -0.002 | -0.005 | -0.002 | -0.017*** | -0.001 |
| | (0.003) | (0.003) | (0.005) | (0.005) | (0.003) | (0.006) | (0.004) |
| Perc. discouraged | -0.006 | 0.001 | -0.020*** | -0.004 | -0.009 | -0.009 | -0.008 |
| | (0.005) | (0.006) | (0.008) | (0.006) | (0.005) | (0.010) | (0.006) |
| Within $R^2$ | 0.52 | 0.47 | 0.47 | 0.25 | 0.54 | 0.44 | 0.38 |
| F | 44 | 32 | 34 | 13 | 52 | 39 | 32 |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are reported in parenthesis. The inequality index is based on a factor analysis of inequality in terms of water access, type of dwelling, type of toilet and type of fuel/energy for lighting, heating and cooking. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity, and percentage of dwelling owners.

Table 3: Spatial Autoregressive Combined, Fixed Effects Estimates

| | **VIOLENT CRIMES Log of crime per 100,000 people** | | | | | | | | **PROPERTY CRIMES Log of crime per 100,000 people** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **All Violent Crimes** | | **Aggravated Assaults** | | **Murders** | | **Rapes** | | **All Property Crimes** | | **Thefts out of Vehicles** | | **Residential Burglaries** | |
| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | | (7) | |
| **Explanatory variables** | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total |
| Housing inequality index | 0.085*** | 0.109*** | 0.094*** | 0.124*** | -0.030 | -0.038 | 0.124*** | 0.135*** | 0.099*** | 0.124*** | 0.345*** | 0.522*** | 0.086** | 0.105** |
| | (0.029) | (0.037) | (0.031) | (0.041) | (0.044) | (0.055) | (0.037) | (0.040) | (0.030) | (0.038) | (0.058) | (0.093) | (0.035) | (0.043) |
| Avg. education (years) | -0.181*** | -0.233*** | -0.153*** | -0.201*** | -0.204*** | -0.256*** | -0.130** | -0.142** | -0.250*** | -0.311*** | -0.448*** | -0.677*** | -0.231*** | -0.281*** |
| | (0.047) | (0.062) | (0.050) | (0.067) | (0.071) | (0.090) | (0.060) | (0.066) | (0.049) | (0.063) | (0.095) | (0.155) | (0.056) | (0.070) |
| Perc. unemployed | 0.002 | 0.003 | 0.003 | 0.004 | 0.005 | 0.006 | -0.002 | -0.002 | 0.001 | 0.001 | -0.014** | -0.020** | 0.003 | 0.004 |
| | (0.003) | (0.004) | (0.004) | (0.005) | (0.005) | (0.006) | (0.004) | (0.005) | (0.003) | (0.004) | (0.007) | (0.010) | (0.004) | (0.005) |
| Perc. discouraged | -0.002 | -0.003 | 0.005 | 0.007 | -0.010 | -0.012 | -0.004 | -0.004 | -0.006 | -0.007 | -0.009 | -0.013 | -0.005 | -0.006 |
| | (0.005) | (0.006) | (0.005) | (0.006) | (0.007) | (0.009) | (0.006) | (0.006) | (0.005) | (0.006) | (0.009) | (0.014) | (0.005) | (0.007) |
| $\rho$ | 0.314*** | | 0.340*** | | 0.291*** | | 0.121 | | 0.280*** | | 0.479*** | | 0.257*** | |
| | (0.000) | | (0.000) | | (0.000) | | (0.148) | | (0.000) | | (0.000) | | (0.000) | |
| $\phi$ | 0.932*** | | 0.938*** | | 0.904*** | | 0.753*** | | 0.906*** | | 0.500 | | 0.893*** | |
| | (0.000) | | (0.000) | | (0.000) | | (0.001) | | (0.000) | | (0.204) | | (0.000) | |
| Pseudo $R^2$ | 0.14 | | 0.22 | | 0.09 | | 0.06 | | 0.14 | | 0.01 | | 0.12 | |
| $\chi^2$ | 294 | | 270 | | 142 | | 145 | | 307 | | 386 | | 203 | |
| Other controls | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | | Yes | |
| N | 1,062 | | 1,062 | | 1,062 | | 1,062 | | 1,062 | | 1,062 | | 1,062 | |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Errors are reported in parenthesis. Crime is assumed to be spatially correlated with the level of crime in a district's first-order neighbor. Errors are assumed to be correlated with those of all other neighbors inversely proportional to the distance between districts. The inequality index is based on a factor analysis of inequality in terms of water access, type of dwelling, type of toilet and type of fuel/energy for lighting, heating and cooking. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity and finally, percentage of households who own their dwelling.

Table 4: Government Housing and Inequality

| | HOUSING INEQUALITY INDEX $\mu = 0$ and $\sigma = 1$ | | | | | |
|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | (2) | (3) | (4) | (5) | (6) |
| Lag 1 RDP and PHP | -0.114*** | -0.040** | | | | |
| | (0.037) | (0.018) | | | | |
| Lag 2 RDP and PHP | | | -0.127*** | -0.043** | | |
| | | | (0.037) | (0.018) | | |
| Lag 3 RDP and PHP | | | | | -0.151*** | -0.050** |
| | | | | | (0.035) | (0.020) |
| Within $R^2$ | 0.85 | 0.97 | 0.85 | 0.97 | 0.86 | 0.97 |
| F | 47 | 129 | 45 | 129 | 58 | 132 |
| Other controls | I | II | I | II | I | II |
| N | 126 | 126 | 126 | 126 | 126 | 126 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects. Robust standard errors in parenthesis. The reported explanatory variables are measured as 1,000 units per 100,000 people. The dependent variable is standardized. The inequality index is based on a factor analysis of MD-level inequality in terms of: water access, type of dwelling and toilet, type of fuel for cooking, heating and lighting. Group I includes the following set of covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group, average education, percentage unemployed, percentage discouraged and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage who have their rubbish removed by authorities and percentage of households who own their dwelling of residence. In addition to Group-I variables, Group II further includes: percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet and percentage with access to electricity.

Table 5a: Government Housing and Violent Crimes

| | ALL VIOLENT CRIMES Log of crime per 100,000 people | | | | | | |
|---|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Housing inequality index | 0.323* | | 0.236 | | 0.228 | | 0.207 |
| | (0.192) | | (0.200) | | (0.204) | | (0.218) |
| Lag 1 RDP and PHP | | -0.053** | -0.044 | | | | |
| | | (0.026) | (0.028) | | | | |
| Lag 2 RDP and PHP | | | | -0.056* | -0.046 | | |
| | | | | (0.029) | (0.031) | | |
| Lag 3 RDP and PHP | | | | | | -0.062** | -0.051 |
| | | | | | | (0.029) | (0.033) |
| Avg. education (years) | -0.685** | -0.686** | -0.667** | -0.680** | -0.663** | -0.659** | -0.647** |
| | (0.277) | (0.284) | (0.274) | (0.282) | (0.273) | (0.281) | (0.274) |
| Perc. unemployed | -0.001 | 0.002 | -0.000 | 0.002 | 0.001 | 0.002 | 0.001 |
| | (0.009) | (0.008) | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| Perc. discouraged | -0.008 | 0.000 | 0.007 | -0.006 | 0.001 | -0.017 | -0.008 |
| | (0.026) | (0.027) | (0.028) | (0.026) | (0.027) | (0.026) | (0.027) |
| Within $R^2$ | 0.72 | 0.72 | 0.72 | 0.72 | 0.73 | 0.72 | 0.73 |
| F | 54 | 53 | 46 | 52 | 47 | 56 | 54 |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 126 | 126 | 126 | 126 | 126 | 126 | 126 |
| *Inequality index* | | | *(3) - (1)* | | *(5) - (1)* | | *(7) - (1)* |
| Wald test† $\chi^2$ | | | 2.68 | | 2.65 | | 2.51 |
| P-value | | | 0.10 | | 0.10 | | 0.11 |
| *IRDP-PHP* | | | *(3) - (2)* | | *(5) - (4)* | | *(7) - (6)* |
| Wald test‡ $\chi^2$ | | | 1.21 | | 1.19 | | 0.99 |
| P-value | | | 0.27 | | 0.27 | | 0.32 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects estimates. Robust standard errors in parenthesis. The inequality index is based on a factor analysis of MD-level inequality in terms of: water access, type of dwelling and toilet, type of fuel for cooking, heating and lighting. The housing stock is measured as 1,000 units per 100,000 people. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity and finally, percentage of households who own their dwelling.

†This test checks whether the coefficient on housing inequality is statistically indistinguishable with or without controlling for IRDP-PHP stocks. Coefficients in (3), (5) and (7) are tested against (1).

‡This test checks whether the impact of the IRDP-PHP stocks is statistically indistinguishable with or without the inclusion of the inequality index. Coefficients in (3), (5) and (7) are tested against (2), (4) and (6). The tests are done using seemingly unrelated regressions with errors clustered at the MD level.

Table 5b: Government Housing and Property Crimes

| | **ALL PROPERTY CRIMES** **Log of crime per 100,000 people** | | | | | | |
|---|---|---|---|---|---|---|---|
| **Explanatory variables** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Housing inequality index | 0.228 | | 0.224 | | 0.217 | | 0.196 |
| | (0.169) | | (0.174) | | (0.174) | | (0.186) |
| Lag 1 IRDP and PHP | | -0.011 | -0.002 | | | | |
| | | (0.027) | (0.028) | | | | |
| Lag 2 IRDP and PHP | | | | -0.015 | -0.006 | | |
| | | | | (0.028) | (0.029) | | |
| Lag 3 IRDP and PHP | | | | | | -0.024 | -0.014 |
| | | | | | | (0.027) | (0.030) |
| Avg. education (years) | -0.574** | -0.590** | -0.573** | -0.586** | -0.571** | -0.574** | -0.563** |
| | (0.271) | (0.282) | (0.272) | (0.281) | (0.272) | (0.280) | (0.274) |
| Perc. unemployed | -0.003 | -0.002 | -0.003 | -0.002 | -0.003 | -0.001 | -0.003 |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Perc. discouraged | -0.005 | -0.011 | -0.005 | -0.012 | -0.004 | -0.014 | -0.005 |
| | (0.028) | (0.025) | (0.026) | (0.025) | (0.027) | (0.027) | (0.028) |
| Within $R^2$ | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.70 | 0.71 |
| F | 26 | 26 | 24 | 25 | 24 | 26 | 25 |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 126 | 126 | 126 | 126 | 126 | 126 | 126 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects estimates. Robust standard errors in parenthesis. The inequality index is based on a factor analysis of MD-level inequality in terms of: water access, type of dwelling and toilet, type of fuel for cooking, heating and lighting. The housing stock is measured as 1,000 units per 100,000 people. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity and finally, percentage of households who own their dwelling.

Table 6: Old-Age Pension Eligibility and Housing Inequality

| | **HOUSING INEQUALITY INDEX** | |
|---|---|---|
| | $\mu = 0$ and $\sigma = 1$ | |
| **Explanatory variable** | (1) | (2) |
| Perc. eligible pension | -0.042 | -0.035 |
| | (0.060) | (0.036) |
| Within $R^2$ | 0.82 | 0.97 |
| F | 31 | 122 |
| Other controls | I | II |
| N | 126 | 126 |

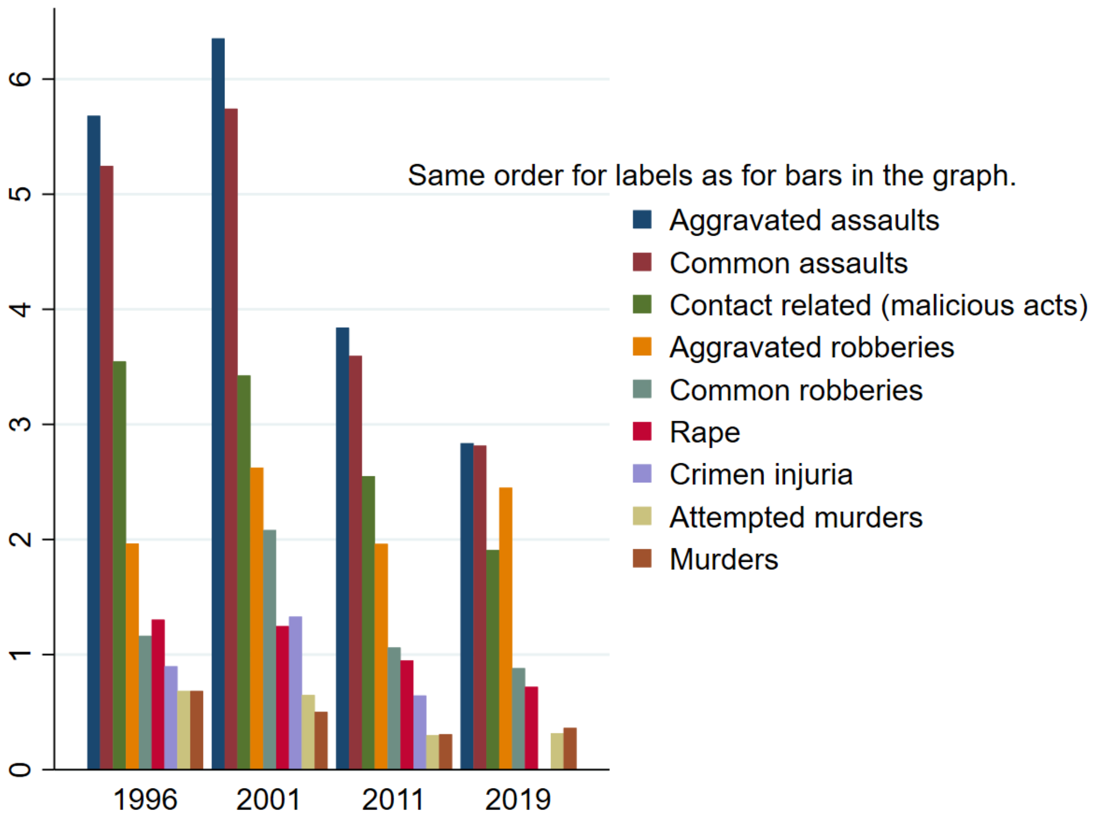
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effect estimates. Robust standard errors in parenthesis. The dependent variable is standardized. The inequality index is based on a factor analysis of MD-level inequality in terms of: water access, type of dwelling and toilet, type of fuel for cooking, heating and lighting. The percentage eligible for old-age pensions is computed considering the Black and Colored populations that meet the age criterion. Group I includes the following set of covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group average education, percentage unemployed, percentage discouraged and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage who have their rubbish removed by authorities and percentage of households who own their dwelling of residence. In addition to Group-I variables, Group II further includes: percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet and percentage with access to electricity.

Table 7: Old-Age Pension Eligibility and Crime

| | ALL VIOLENT CRIMES Log of crime per 100,000 people | | ALL PROPERTY CRIMES Log of crime per 100,000 people | |
|---|---|---|---|---|
| **Explanatory variables** | (1) | (2) | (3) | (4) |
| Housing inequality index | | 0.378* | | 0.259 |
| | | (0.201) | | (0.198) |
| Perc. eligible pension | 0.075 | 0.088 | 0.040 | 0.049 |
| | (0.066) | (0.065) | (0.061) | (0.063) |
| Avg. education (years) | -0.697** | -0.655** | -0.586** | -0.557** |
| | (0.277) | (0.256) | (0.269) | (0.254) |
| Perc. unemployed | -0.001 | -0.003 | -0.003 | -0.005 |
| | (0.009) | (0.009) | (0.010) | (0.010) |
| Perc. discouraged | -0.005 | 0.016 | -0.006 | 0.008 |
| | (0.027) | (0.033) | (0.029) | (0.034) |
| Within $R^2$ | 0.72 | 0.73 | 0.70 | 0.71 |
| F | 74 | 69 | 29 | 25 |
| Other controls | Yes | Yes | Yes | Yes |
| N | 126 | 126 | 126 | 126 |

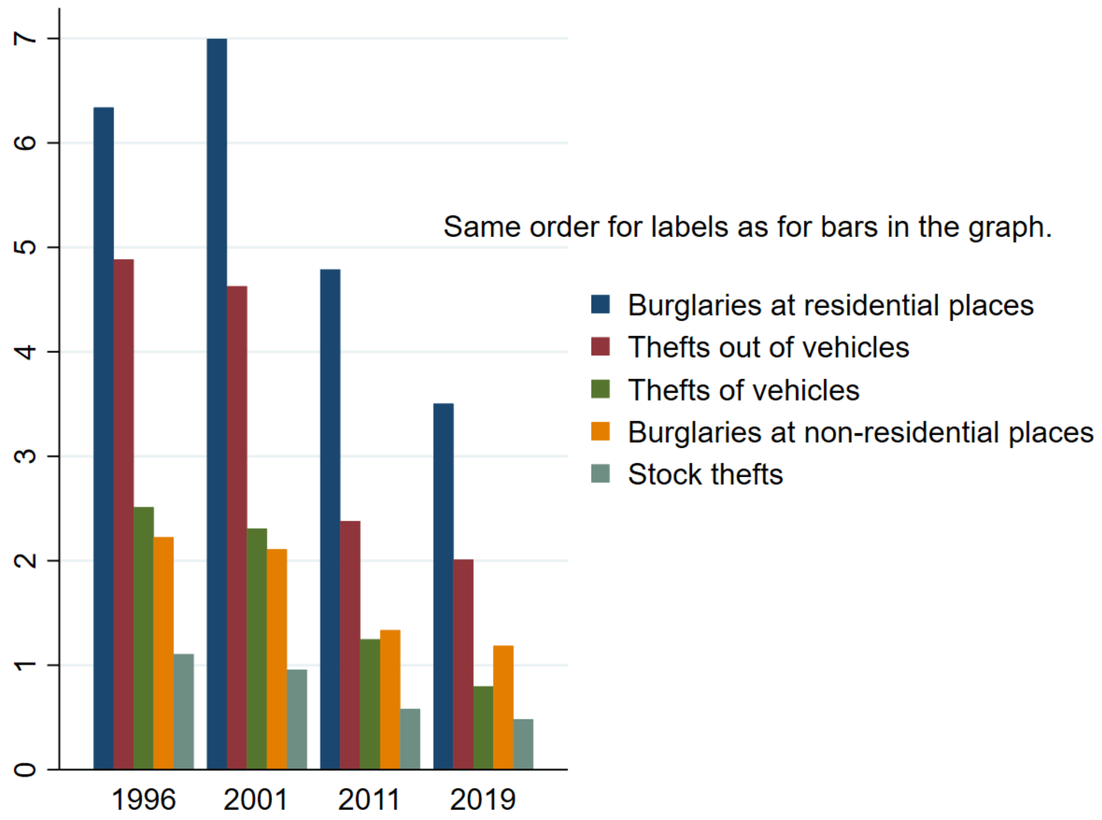
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effect estimates. Robust errors are reported in parenthesis. The inequality index is based on a factor analysis of inequality in terms of: water access, type of dwelling and toilet, type of fuel for cooking, heating and lighting. The percentage eligible for old-age pensions is computed considering the Black and Colored populations that meet the age criterion. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity and finally, percentage of households who own their dwelling.

Figure 1a: Violent Crimes (Incidence per 1,000 People Nation-Wide)



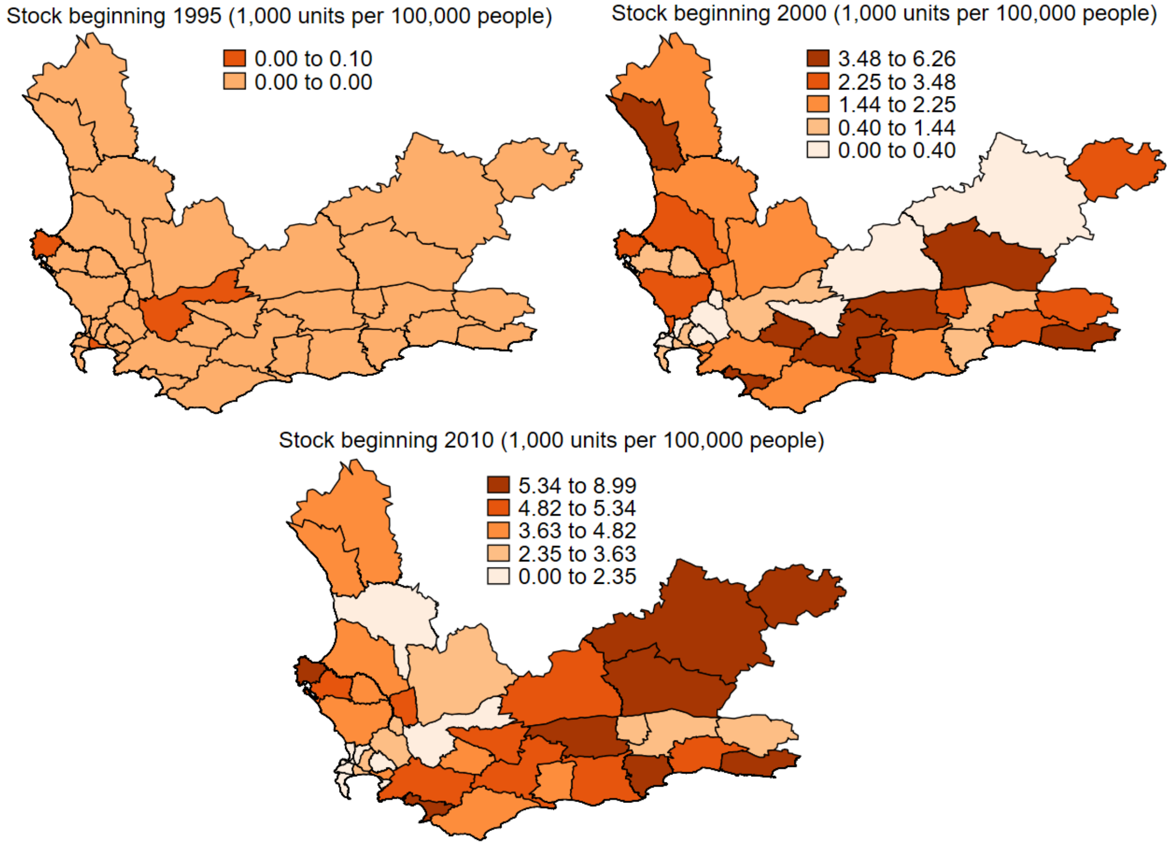

Violent crimes include contact and contact-related crimes. These would have been the universe of violent crimes, but due to the imperfect overlap between crime categories across the years, we had to drop some sexual offences. Nevertheless, due to their relatively small magnitude (as far as reporting to the police is regarded), this omission does not impact the picture that this graph is meant to give.

Figure 1b: Property Crimes (Incidence per 1,000 People Nation-Wide)




This is the universe of property crimes in South Africa.

Figure 2: Stock of Government Housing in the Western Cape Province




Stock numbers include the units delivered by the following subsidy schemes: the Integrated Reconstruction and Development Program (IRDP, which includes its predecessor project-linked subsidies) and the People's Housing Process (PHP). There are 42 magisterial districts in the Western Cape Province.

# Online Appendix

## A.1 Housing Conditions Inequality, Factor Analysis

| **Inequality in terms of:** | **Factor Loadings** | **Uniqueness** |
|---|---|---|
| Type of dwelling | 0.65 | 0.46 |
| Access to water | 0.72 | 0.44 |
| Type of toilet | 0.78 | 0.39 |
| Type of energy for lighting | 0.75 | 0.31 |
| Type of fuel for cooking | 0.91 | 0.15 |
| Type of fuel for heating | 0.76 | 0.30 |

The analysis is based on the full sample of 1,062 observations and standardized inequality measures. Vector 1 is the only factor with an eigenvalue greater than 1, namely 3.52. The Kaiser-Meyer-Olkin measure of sampling adequacy is 0.83.

## A.2 Negative Binomial Estimates

| | VIOLENT CRIMES Log of crime per 100,000 people | | | | PROPERTY CRIMES Log of crime per 100,000 people | | |
|---|---|---|---|---|---|---|---|
| | All Violent Crimes | Aggra- vated Assaults | Murders | Rapes | All Property Crimes | Thefts out of Vehicles | Resi- dential Burglaries |
| **Explanatory variables** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Housing inequality index | 0.107*** | 0.125*** | -0.035 | 0.145*** | 0.091*** | 0.324*** | 0.054* |
| | (0.026) | (0.029) | (0.040) | (0.030) | (0.028) | (0.049) | (0.031) |
| Avg. education (years) | -0.034 | -0.013 | -0.010 | 0.016 | -0.128*** | -0.089 | -0.090** |
| | (0.038) | (0.040) | (0.053) | (0.043) | (0.038) | (0.058) | (0.042) |
| Perc. unemployed | -0.005* | -0.005 | -0.003 | -0.004 | -0.004 | -0.017*** | -0.002 |
| | (0.003) | (0.003) | (0.005) | (0.003) | (0.003) | (0.006) | (0.004) |
| Perc. discouraged | -0.002 | 0.004 | -0.014** | 0.000 | -0.004 | -0.006 | -0.003 |
| | (0.004) | (0.005) | (0.007) | (0.005) | (0.004) | (0.007) | (0.005) |
| $\chi^2$ | 778 | 565 | 651 | 304 | 910 | 686 | 469 |
| Other controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 | 1,062 |

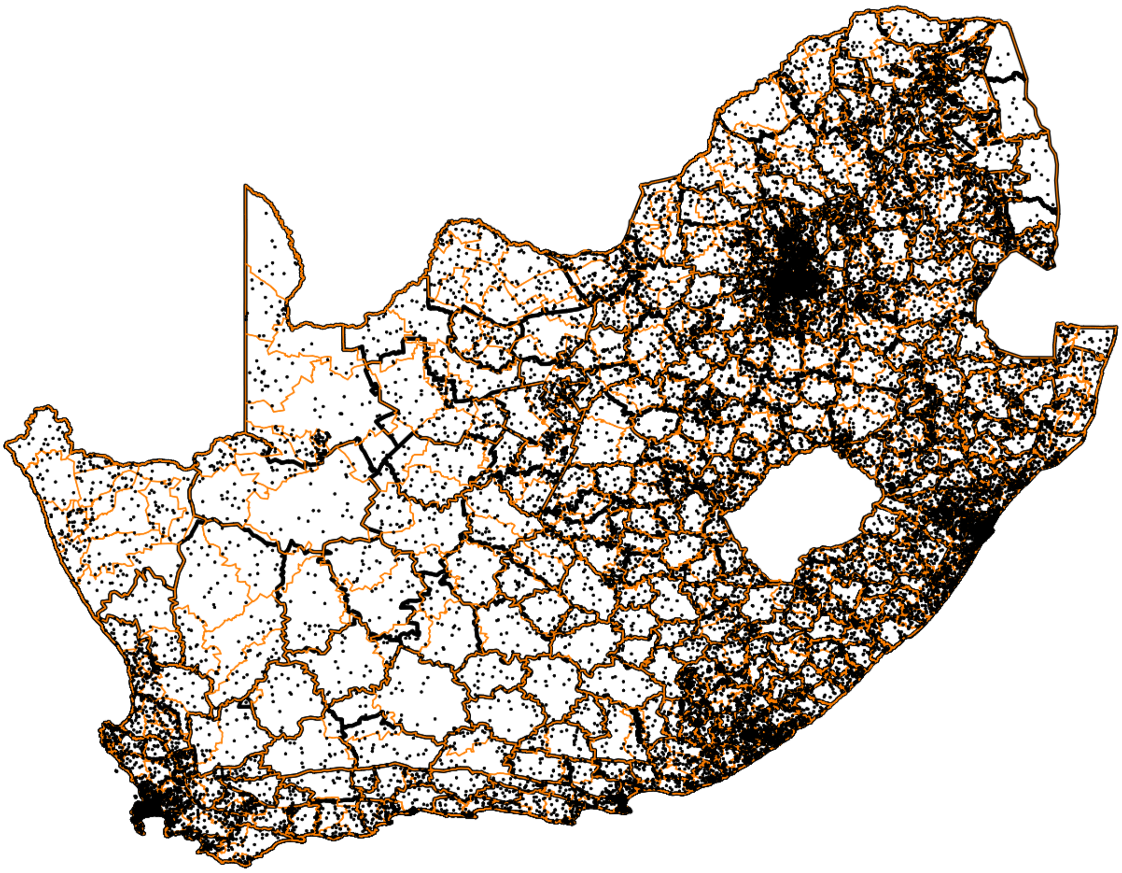
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Negative binomial fixed effects estimates. Standard errors are reported in parenthesis. The dependent variable is the incidence of crime at the level of MDs per 100,000 people. The coefficients have not been exponentiated. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group and percentage individuals who have moved in the past 10 years, MD-level averages of household characteristics such as average size, average number of rooms, percentage living in an informal dwelling, percentage with access to water on the household's premises, percentage who own a flush or chemical toilet, percentage who have their rubbish removed by authorities, percentage with access to electricity and finally, percentage of households who own their dwelling.

## A.3 Robustness to Variations of the Inequality Index

| | VIOLENT CRIMES Log of crime per 100,000 people | | | | | | | | PROPERTY CRIMES Lof of crime per 100,000 people | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All Violent Crimes | | Aggravated Assaults | | Murders | | Rapes | | All Property Crimes | | Thefts out of Vehicles | | Residential Burglaries | |
| | (1) | | (2) | | (3) | | (4) | | (5) | | (6) | | (7) | |
| **Variations index specification** | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total | Direct | Total |
| **Benchmark: FA on type of dwelling, access to water, type of toilet and fuel/energy for lighting, cooking and heating** | | | | | | | | | | | | | | |
| Housing inequality index | 0.085*** | 0.109*** | 0.094*** | 0.124*** | -0.030 | -0.038 | 0.124*** | 0.135*** | 0.099*** | 0.124*** | 0.345*** | 0.522*** | 0.086** | 0.105** |
| | (0.029) | (0.037) | (0.031) | (0.041) | (0.044) | (0.055) | (0.037) | (0.040) | (0.030) | (0.038) | (0.058) | (0.093) | (0.035) | (0.043) |
| | (8) | | (9) | | (10) | | (11) | | (12) | | (13) | | (14) | |
| **PCA on type of dwelling, access to water, type of toilet and fuel/energy for lighting, cooking and heating** | | | | | | | | | | | | | | |
| Housing inequality index | 0.099*** | 0.126*** | 0.122*** | 0.158*** | -0.014 | -0.018 | 0.147*** | 0.160*** | 0.108*** | 0.133*** | 0.371*** | 0.549*** | 0.103*** | 0.125*** |
| | (0.030) | (0.039) | (0.032) | (0.042) | (0.046) | (0.057) | (0.038) | (0.041) | (0.032) | (0.039) | (0.061) | (0.092) | (0.036) | (0.044) |
| | (15) | | (16) | | (17) | | (18) | | (19) | | (20) | | (21) | |
| **FA on type of dwelling, access to water, type of toilet and fuel/energy for lighting** | | | | | | | | | | | | | | |
| Housing inequality index | 0.109*** | 0.139*** | 0.156*** | 0.200*** | -0.008 | -0.010 | 0.159*** | 0.173*** | 0.101*** | 0.124*** | 0.423*** | 0.610*** | 0.105*** | 0.127*** |
| | (0.032) | (0.040) | (0.034) | (0.043) | (0.048) | (0.060) | (0.040) | (0.043) | (0.033) | (0.041) | (0.066) | (0.095) | (0.038) | (0.045) |
| | (22) | | (23) | | (24) | | (25) | | (26) | | (27) | | (28) | |
| **FA on type of dwelling, access to water and type of toilet** | | | | | | | | | | | | | | |
| Housing inequality index | 0.098*** | 0.125*** | 0.148*** | 0.190*** | 0.024 | 0.030 | 0.125*** | 0.138*** | 0.081** | 0.101** | 0.304*** | 0.458*** | 0.084** | 0.102** |
| | (0.031) | (0.040) | (0.033) | (0.043) | (0.047) | (0.059) | (0.039) | (0.044) | (0.033) | (0.041) | (0.064) | (0.098) | (0.037) | (0.045) |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each cell is a different regression: 7 dependent variables × 4 index measurements (including the benchmark specification). Errors are reported in parenthesis. Crime is assumed to be spatially correlated with the level of crime in a district's first-order neighbor. Errors are assumed to be correlated with those of all other neighbors inversely proportional to the distance between districts. All specifications include the following covariates: year dummies, density (1,000 people per $km^2$), MD-level averages of individual characteristics such as population-group, education, percent unemployed, percent discouraged and percent individuals who have moved in the past 10 years, and MD-level averages of household characteristics such as average size, average number of rooms, percent living in an informal dwelling, percent with access to water on the household's premises, percent who own a flush or chemical toilet, percent who have their rubbish removed by authorities, percent with access to electricity and finally, percent of households who own their dwelling.

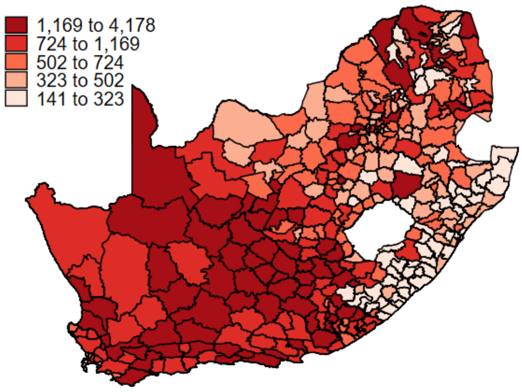
## A.4 Merger Between Magisterial Districts and Police Districts



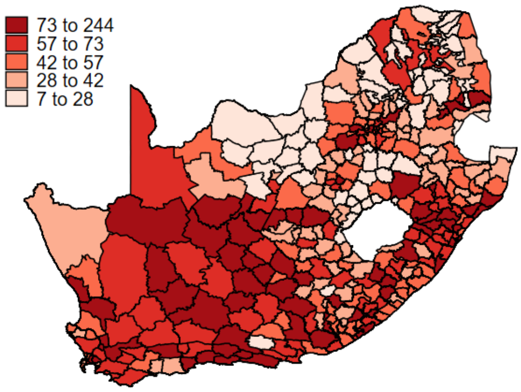
The black, thick contour is that of the magisterial districts (MDs). The orange, thin contour describes the police districts. Each police district is populated with several randomly generated points. For police districts that cross several MDs, of the total number of points, we count the points that fall in each MD and we distribute the crimes of that police district to its respective MDs proportionally.

## A.5 Spatial Distribution of Variables (1996–2011 Means)

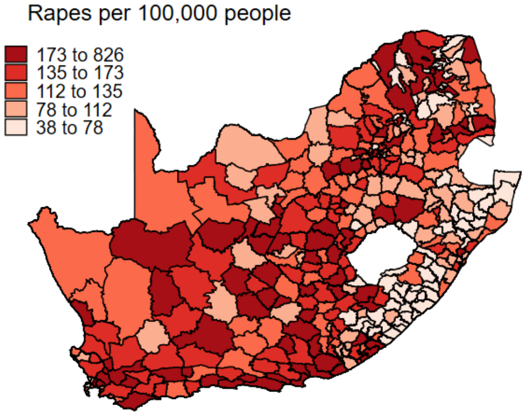
Aggravated assaults per 100,000 people



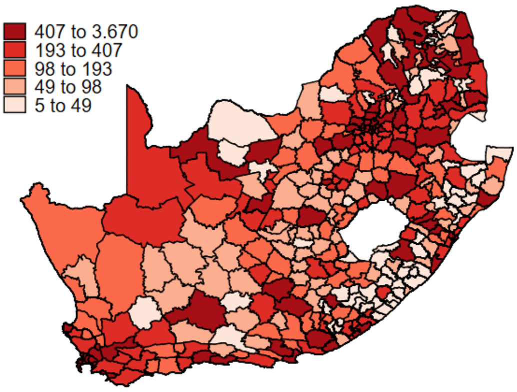

Murders per 100,000 people



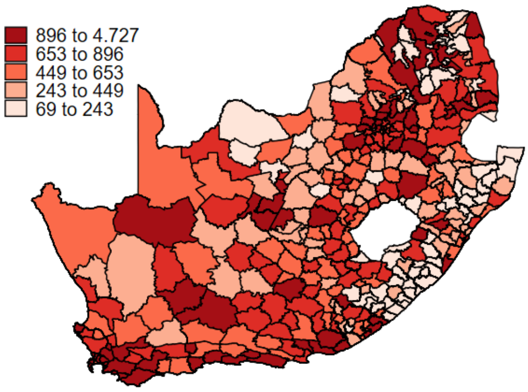

Rapes per 100,000 people




Thefts out of Vehicles per 100,000 people




Residential Burglaries per 100,000 people




Housing Conditions Inequality Index (Factor Analysis)