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# Weather and Crime – Cautious Evidence from South Africa

## Abstract

*South Africa has one of the highest crime rates in the world. This paper examines the effect of weather shocks on various types of crime. Using a 12-year panel data set at monthly resolution on the police ward level, we observe a short-term effect of temperatures on violent crime, supporting the heat-aggression link suggested by psychological research. Furthermore, we find evidence for a subtle medium-term effect of weather on crime via droughts and agricultural income, which is in line with the economic theory of crime. Yet, we also emphasize often neglected but well-documented limitations to the interpretability of weather data and weather-induced mechanisms. Recognizing these limitations, we conclude with a cautious interpretation of our findings to inform police deployment strategies.*

*JEL-Codes: C33, O55, Q54, R11*

*Keywords: South Africa; weather; crime, income shocks*

*February 2022*

*1 Anna Bruederle, University of St. Gallen, Switzerland; Jörg Peters, RWI and University of Passau; Gareth Roberts, University of the Witwatersrand Johannesburg.* *- We are grateful for valuable comments by Emilie Bechtold, Roland Hodler, and Colin Vance.* *– All correspondence to: Jörg Peters, RWI, Hohenzollernstr. 1/3, 45128 Essen, Germany, e-mail: peters@rwi-essen.de*

## 1. Introduction

High crime rates are one of the biggest challenges South Africa has been facing since the end of apartheid in 1994. The country's homicide rate of 34 annual killings per 100,000 people is the sixth highest in the world and the highest in Africa.1 This incurs costs along various dimensions that Alda and Cuesta (2011) estimate to be as high as 5-15 percent of the country's GDP. Next to the direct costs and the human suffering caused to the victims and their relatives, South Africa's high crime rates discourage sustainable social and economic development of the country. While crime in South Africa certainly must be interpreted in its historical context of apartheid and the related conflicts, it is important to understand more immediate drivers of high crime rates. To the degree that socio-economic and environmental factors affect crime within South Africa, policy responses can be shaped.

Against this background, the present paper examines the effect of weather on crime in South Africa. Using a 2001-2012 panel of monthly crime statistics at the police ward level, we scrutinize short-term and medium-term effects of weather on various types of violent and property crime. For the short-term effects we investigate how temperature and rainfall affect crime within the same month, whereas for the medium-term effect we look at the effect of droughts on lagged crime incidences. We use monthly crime data recorded within the 1,158 police wards in the country, monthly time series of gridded temperature and rainfall data from the *Climatic Research Unit* (CRU) at the University of East Anglia, and a drought indicator derived from the *Global Standardized Precipitation-Evapotranspiration Index* (SPEI) database.

The most important theories conceptualizing the thinking about crime in social sciences are the economic theory of crime by Becker (1968), the strain theory introduced by Merton (1938), and the social disorganization theory by Shaw and McKay (1972). The strain theory and the social disorganization theories argue that features of the society's structure such as inequality, poverty, and racial heterogeneity influence people's propensity to commit crimes. They hence capture much of the historical perspective on crime in South Africa. The economic theory of crime in contrast models the utility of committing a crime or abstaining from doing so, considering the probability of being arrested, as well as the opportunity cost. Here, the short- and medium-term effects of weather come into play.

[1] Source: https://data.unodc.org/

Temperatures and rainfall might affect these components in at least three ways, two of which operate in the short term, one in the medium-term: The first short-term effect is that high temperatures immediately raise aggression. While psychologists have proposed various emotional and cognitive processes triggered by temperature (for a discussion, see Groves and Anderson, 2016), one version supported by most of the evidence is simple: Heat-induced discomfort makes people cranky and increases hostile affect, which in turn promotes aggressive thoughts and attitudes and, consequently, behavior (Anderson, 2001). This channel is substantiated empirically, including evidence from experimental and quasi-experimental field studies (Curtis et al., 2016; Gamble and Hess, 2012; Heilman et al. 2021, Heyes and Saberian 2019, Kenrick and MacFarlane, 1986; Vrij et al., 1994), and by laboratory experiments (Anderson et al., 2000; Baron and Bell, 1976).[2] Second and still in the short-term, weather shapes the circumstances which discourage or favor criminal behavior, such as the probability for perpetrators of being detected and hence the expected cost of committing a crime. For example, heavy rainfalls or extreme temperatures could lead to a lower density of people in public space or reduce police patrolling (see, e.g., Jacob et al., 2007). Reversely, high density of people in public space due to good weather could create a more favorable environment for committing a crime.

Third, income is an important channel through which weather affects the *relative* returns of crime in the medium-term. Recent evidence suggests a substantial effect of rainfall on economic growth rates (see Kotz et al. 2022) and of high temperatures on productivity (see Somanathan et al. 2021). Most notably, the agricultural sector in the Global South is heavily weather-dependent. Drought spells can reduce output and employment opportunities. This, in turn, might drive individuals into criminal ways of mending their livelihoods or decrease their opportunity cost of engaging in criminal activity (see, e.g., Blakeslee and Fishman, 2018). Rising inequality can additionally amplify the effect of weather shocks on crime (Manea et al. 2021, Kelly, 2000). In Colombia, Cortés et al. (2016) find that economic shocks (not induced by whether) have a more pronounced effect on property crime in regions with weak judicial and law enforcement institutions.[3]

Assuming that weather variation within spatial units over time is exogenous, we try to isolate the weather effects from other drivers of crime. We find that higher temperatures are associated with

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[2] Some studies observe a monotonic positive relationship between ambient temperature and crime (e.g., Bushman et al., 2005; Gamble and Hess, 2012), others an inverse U-shape, with a peak at around 23°C (e.g., Bell, 2005; Rotton and Cohn, 2000, 2004).

[3] Figure A1 in the appendix provides a stylized overview of the possible channels mediating weather effects on crime to which our empirical analysis refers.

increasing crime rates in the short term, while rainfall tends to decrease them. The temperature effect is more distinct for violent crimes than for property crimes, supporting the heat-aggression mechanism. Yet, we cannot rule out that other mechanisms are at work translating higher temperatures into higher crime rates. We also explore the medium-term effect of weather through droughts and, thus, income as a mechanism. Indeed, income related crime types such as robbery increase after growing seasons that had been affected by a drought. Crime levels do not go down until the end of the next agricultural cycle. This drought responsiveness is stronger in rural areas, where a larger share of livelihoods depends on agriculture.

The use of weather data is not without problems. Most notably, we reiterate the critique by Mellon (2021), who compellingly demonstrates that weather enters a complex causal network with many affected variables, making it difficult to interpret relationships between weather and one specific variable such as crime. We therefore use the theoretical background to structure our analysis and corroborate or contradict these theoretical linkages, but explicitly caution against perceiving our results as a clean test of a theory.[4] Further limitations to our analysis are related to issues with weather data summarized by Auffhammer et al. (2013), which we ponder in a dedicated section. While these caveats call for a cautious interpretation of our findings with respect to the above-mentioned theories, we conclude that – irrespective of which specific mechanism links weather to crime – our results suggest that weather could be effectively used in police deployment strategies.

## 2. Literature Review

We interpret our findings within the debate about criminal deterrence (see Chalfin and McCrary, 2017, for a recent review of the literature), which is a first-order policy priority because the costs of high crime rates in South Africa are immense. In addition to direct judicial, police and rehabilitation costs they also comprise health costs (Soares, 2006), and it is sometimes argued that high crime rates have adverse effects on the business environment (Grabrucker and Grimm, 2018). Our findings on the drought channel confirm that stable incomes and better employment opportunities can help deter people from turning towards criminal activities. Our suggestive evidence on the link between heat-aggression and violent crime, in contrast, implies that there is scope for ad hoc deterrence strategies

[4] Also note that, like most secondary data-based papers, we did not pre-specify our hypotheses. Yet, we emphasize that we comprehensively show all outcomes we tested and that we did not engage in any type of specification searching.

such as hot spot policing. Weather forecasts could be used in the prediction of short-term policing demands.

Our paper contributes primarily to the growing literature on the nexus between climate change, weather, and conflict (see Burke et al., 2009, 2015; Dell et al., 2014; Gleditsch, 2012; Hendrix and Salehyan, 2012; Hsiang et al., 2013; Miguel, 2005; Takahashi 2017). The overall picture that has emerged from this literature is that higher temperatures increase the probability of interpersonal violence, intergroup conflict, and criminal behavior. The effect of rainfall on social interaction is less well understood, but some studies in developing countries find negative rainfall shocks to increase conflict, mostly through effects on agriculture (see, e.g., Fjelde and Uexkull, 2012; Hodler and Raschky, 2014; Miguel et al., 2004). Moreover, there is a growing body of research on the weather-crime nexus in Mexico, a country suffering from high crime rates as well (see Baysan et al. 2019, Cohen and Gonzales 2018, and Garg et al. 2018).

Our paper is innovative in that hitherto there is not much evidence on the crime-weather relationship from Africa in general and South Africa in particular (see Chersich et al. 2019). Gates et al. (2019) use mortality data from official statistics in South Africa to examine the effect of temperature on homicide, with a daily resolution. They find that a one-degree increase in temperature is associated with a 1-2% increase in homicides. For the city of Tshwane (Pretoria) in South Africa, Schutte and Breetzke (2018) also investigate daily temperature and rainfall variation and observe a strong increase in violent crime rates in response to high temperatures, and to a lesser extent, rainfall. Manea et al. (2021) examine the interplay of housing conditions and crime, which is likely to be relevant for the weather-crime nexus as well.

The three most closely related papers from the international context are Ranson (2014), Rotton and Cohn (2003), and Blakeslee and Fishman (2018). Ranson (2014) uses a thirty-year panel on monthly crime and weather data in the US and finds a sizable effect of temperature on most types of violent and property crime. He does not find evidence for an effect of rainfall. Rotton and Cohn (2003) use time-series and state-level data for several decades in the US to study the association between temperature and crime. They find effects of temperature on some violent crime types, but not on murder rates.

In the context of the Global South, we complement Blakeslee and Fishman (2018), who use detailed annual district-level crime data from India and find that heat and drought increase all categories of crime in their records, with a larger impact on property crimes than on violent crimes. Blakeslee et al. (2021) examine daily crime statistics and weather data in India. They observe that violent crimes respond to both daily and seasonal temperature variation. Property crimes, in turn, only respond to seasonal variation. These results are consistent with psychological theories as well as the economic theory of crime. While we do not have the same timely resolution, our crime records at a monthly level also allow us to investigate in detail how crime rates fluctuate over the agricultural cycle in response to drought shocks. It hence provides strong evidence in support of agricultural income shocks as an underlying driver of criminal activity, which is in line with what Blakeslee and Fishman's (2018) and Blakeslee et al.'s (2021) analyses suggest.[5]

Moreover, our paper speaks to the growing literature on the determinants of crime in South Africa. Kynoch (2005) traces the origins of crime and conflict in the country back to its recent history and most notably the transition from apartheid to democracy. For example, those areas of the country that exhibited the most intense level of political conflict in the transition phase, KwaZulu-Natal and the townships of Johannesburg, also exhibited the highest levels of organized crime in the early and mid-2000s. Kynoch points at the low quality of public security forces and emphasizes that even ten years after the end of apartheid the population lacks trust in the police and the judiciary. These historical path dependencies and resulting limitations must be appreciated when interpreting our results. Bhorat et al. (2017), in contrast, examine the socio-economic determinants of different types of crimes in the country. They find that a rising income at the left tail of the distribution raises overall property crime rates but decreases them at the right tail of the distribution. The authors explain this with the increasing fear of loss as incomes rise and the associated willingness to defend newly acquired property. They do not observe socio-economic correlates for robbery crime, and unemployment is not correlated with crime either. Inequality, in turn, is highly correlated with crime according to their analysis, which is also in line with earlier findings by Demombynes and Oezler (2005).

[5] This medium-term analysis of drought effects on crime is also related to a paper by Harari and La Ferrara (2013), who study effects of agricultural production shocks on civil conflict in Africa. They exploit variation in the timing of drought shocks in the growing season of different crops, as well as spatial variation in crop cover across grid cells of 1 × 1 decimal degrees. Their results show that if drought negatively affects agricultural output, civil conflict incidence rises.

## 3. Data

### 3.1. Crime Data

Our crime data stem from the records of the South African Police Service.[6] As dependent variables we use counts of various types of serious crimes recorded by the police ($crime_{ipmy}$) that occurred within a police ward $i$ in province $p$ in calendar month $m$ of year $y$. Our data cover the period from January 2001 to March 2012. Figure A2 shows the 1,158 police wards in the country. Catchment areas range between 30 km$^2$ and 20,000 km$^2$, depending on the population density. Metropolitan municipalities are divided into several police wards, while rural police wards cover entire districts.

Each crime is coded into one of 35 categories, including various types of assault, murder, rape, sexual offence, various types of robbery, arson, malicious damage to property, burglary, and theft. **Error! Reference source not found.** in the appendix provides an overview of all crime categories as they are organized in the original data set, including for each category the total count over all police wards and over our full observation period. We analyze weather effects on all types of serious crimes as well as on aggregate crime variables:

- $totalcrimes_{ipmy}$: includes all crimes in our records;
- $murder_{ipmy}$: includes attempted murder and murder;
- $sexualcrimes_{ipmy}$: includes abduction, attempted sexual offences, contact sexual offences, rape, sexual assault, and sexual offences due to police action;
- $assault_{ipmy}$: includes common assault, and assault with the intent to inflict grievous bodily harm (note that it does not comprise sexual assault which is included under sexual crimes);
- $robbery_{ipmy}$: includes common robbery, robbery with aggravating circumstances, street or public robbery, bank robbery, robbery of cash in transit, robbery at residential and non-residential premises, carjacking, and truck-hijacking;
- $theft_{ipmy}$: includes theft of motor vehicles or motorcycles, theft out of or from motor vehicles, and stock theft;
- $burglary_{ipmy}$: burglary at residential premises;

[6] The data set was compiled by the Crime and Justice Hub, an initiative by the Governance, Crime and Justice Division of the Institute for Security Studies (ISS), South Africa.

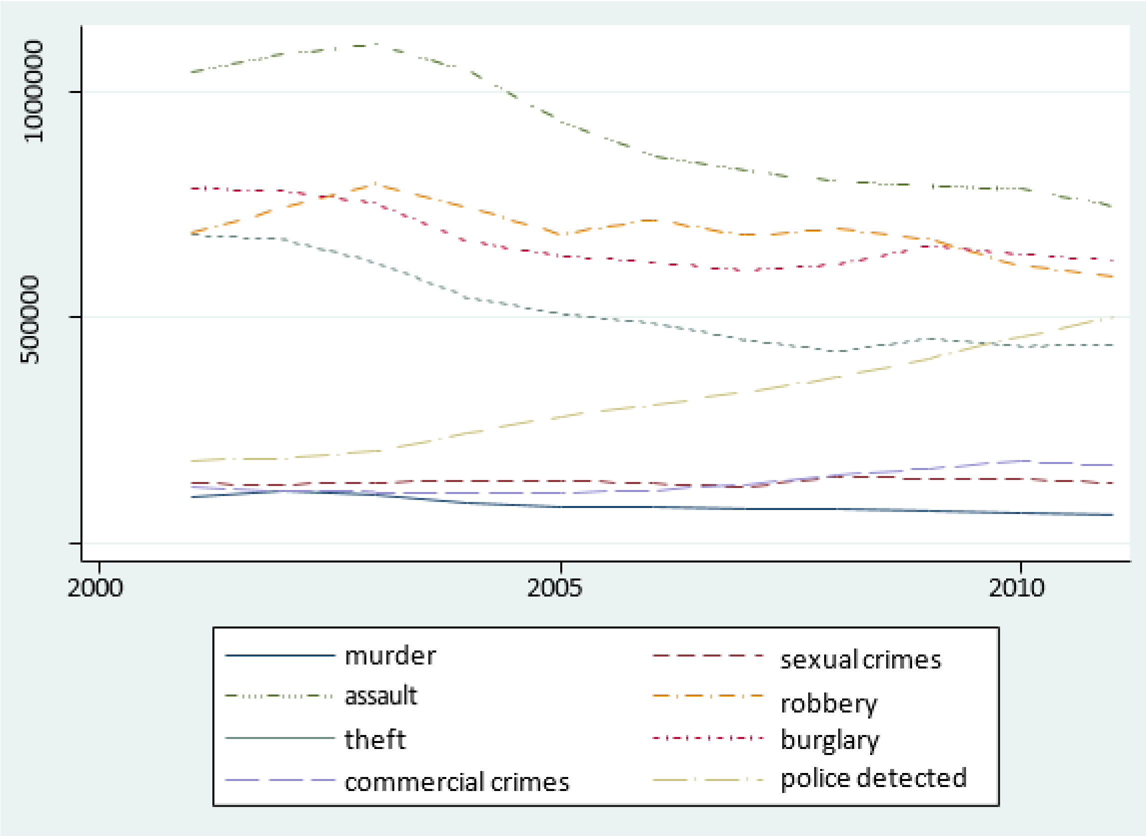
- $stealing_{ipmy}$: includes all crimes that involve the taking of property, i.e., all types of robbery, burglary, theft and commercial crime;[7]
- $nonstealing_{ipmy}$: includes all crimes that do not involve the taking of property, i.e., all serious crimes in our data that are not listed under "stealing";
- $commercial_{ipmy}$: commercial crime;
- $policedetect_{ipmy}$: includes all crimes heavily dependent on police action for detection (as defined by our original data set), which are illegal possession of firearms and ammunition, drug-related crime, and driving under the influence of alcohol or drugs.

Figure 1 shows how annual crime counts have developed over our sample period. The occurrence of assault, robbery, theft, and burglary has decreased, most notably during the years 2003 to 2012. Some crimes are mainly detected through police checks ($policedetect$). These crime types have increased markedly in the records over our sample period, which may be related to increases in police force capacities. Commercial crimes have also increased over time. The frequency of murder and sexual crimes has remained roughly constant over our sample period.

Clearly, reported crimes can only be interpreted as a proxy for actually committed crimes. Problems of misreporting, deliberate or otherwise, and under-reporting are well recognized by the South African Police Service (Brodie, 2013). We are interested in effects on actually committed crime, which we do not directly observe. Our analysis rests on the assumption that difference between reported and actually committed crimes are uncorrelated with the weather. Certain weather conditions, however, might influence reporting of crimes, for example because weather affects people's ability and willingness to travel. However, we expect that weather would then lead to postponing the filing of the complaint rather than to not filing a complaint at all. In addition, our data comprises crimes reported through phone calls that we do not expect to be sensitive to the weather. We are thus confident that weather effects on reporting are not a major concern for the validity of our analysis.

[7] This aggregate is not equivalent to the commonly used term *property crime*, because *property crimes* do not include any violent crimes that involve the taking of property, such as robbery.

**Figure 1: Crime rates**




Moreover, it is well established that the probability of a crime being reported to the police varies considerably across different types of crime. Murder and homicide, for example, are generally difficult to manipulate for obvious reasons. Other crime categories for which we assume police records to be reasonably accurate include those involving theft or damage of property, because such incidents are usually reported to the police in order to submit insurance claims (Brodie, 2013). By contrast, sexual offences, including rape, generally tend to be under-reported (Statistics South Africa, 2017). Such underreporting must be taken into account when interpreting the weather effects for particularly sensitive crime types and when comparing the effect sizes between sensitive and less sensitive ones.

To examine the weather-income-crime nexus we will focus on crime prevalence in rural areas, because this is where income is most weather sensitive. To distinguish rural from urban contexts, we create an indicator variable $rural_{ip}$ which equals one if less than 50 percent of the area of police ward $i$ in province $p$ was classified in 2013 as *city* or *city region* according to settlement types defined by the

*South African Council for Scientific and Industrial Research* (CSIR), and zero otherwise. Our data source is the digital map of settlement types, version of April 2013, available from the *CSIR Geospatial Analysis Platform*,[8] which we combine with police ward boundaries in ArcGIS software to derive $rural_{ip}$ indicator values for each police ward. Of all the police wards in our sample, 75 percent are classified as rural.

### 3.2. Weather data

To construct our main explanatory variables, we use the updated monthly time series of gridded climate variables *CRU TS3.22* produced by the *Climatic Research Unit* (CRU) at the University of East Anglia (Harris et al., 2014). CRU constructs this data set from monthly observations at meteorological stations (50 in South Africa), which are interpolated into grid cells of 1.5× 0.5 decimal degrees, covering the global land surface. At South Africa's latitude, these cells correspond to approximately 55 × 45 km. The use of interpolated grids rather than station data allows us to include the full sample of police wards in our analysis (which might yet lead to measurement errors, see Section 7 for a discussion). We spatially aggregate the cell-level values of the weather variables to the level of the police ward $i$ in province $p$, for each calendar month $m$ of year $y$, using ArcGIS software. We include the following weather variables in our analysis:

- $maxtemp_{ipmy}$: monthly average daily maximum temperature;
- $mintemp_{ipmy}$: monthly average daily minimum temperature;
- $rainydays_{ipmy}$: number of rainy days per month.

The data set unfortunately does not contain information on daily temperature, monthly peak temperature, or combined heat-humidity. In addition, we use a drought indicator based on the *Global Standardized Precipitation- Evapotranspiration Index* (SPEI) database (Beguería et al., 2014). The SPEI index uses as input variables monthly precipitation and potential evapotranspiration data from the CRU time series. It measures the current balance between precipitation and potential evapotranspiration. Like the CRU climate data, the SPEI data set is available as a monthly time series

[8] http://www.gap.csir.co.za

with a 0.5 × 0.5 decimal degrees spatial resolution. Since we are interested in drought conditions during the local growing season specifically, we use the variable

- $drought_{ipy}$: share of growing season affected by drought,

as provided in the PRIO-GRID data set (Tollefsen et al., 2012). More precisely, this variable is defined as the share of months of the growing season starting in year $y-1$ and ending in year $y$ in police ward $i$ in province $p$ that are affected by consecutive drought. A month is flagged as a drought month if its SPEI value is at least 1.5 standard deviations below the local long-term historical average.[9] The growing season is the growing season for the cell's main crop, defined in the *MIRCA2000* data set (Portmann et al., 2010). For example, if the growing season in one grid cell spans five months from October of year $y-1$ to February of year $y$, and the SPEI value in that grid cell falls below -1.5 during October and November of year $y-1$, the share of growing season affected by drought would be 2/5 = 0.4 for year $y$ for that cell. As for the other weather variables, we aggregate the cell-level values of this growing-season drought indicator to the level of the police ward using ArcGIS software. Unlike the temperature and rainfall variables, by definition, the drought indicator has a time resolution of calendar years rather than months.

We obtain a large balanced panel data set, with 1,158 police wards in the cross-sectional dimension and 135 consecutive months in the time dimension, which makes 156,330 observations. Table 1 provides summary statistics of our weather variables.

**Table 1: Summary statistics of weather variables**

| Variables | (1)<br>N | (2)<br>Mean | (3)<br>SD | (4)<br>Min | (5)<br>Max |
|---|---|---|---|---|---|
| $maxtemp_{ipmy}$ | 152,550 | 25.0 | 4.2 | 9.3 | 38.5 |
| $mintemp_{ipmy}$ | 152,550 | 11.3 | 5.1 | -5.6 | 22.9 |
| $rainydays_{ipmy}$ | 152,550 | 7.1 | 5.1 | 0.0 | 27.2 |
| $drought_{ipy}$ | 152,550 | 0.03 | 0.08 | 0.00 | 0.60 |

*Notes: See the main text for descriptions and sources of all variables.*

[9] If a growing season is affected by more than one streak of drought, only the longest streak of drought enters this share.

## 4. Empirical specification and identification

We use two different specifications for our short-term and medium-term analysis, respectively. First, we exploit variation in weather over time within spatial zones. In our baseline specification we regress the logarithm of crime counts $ln(crime_{ipmy})$ in police ward $i$ in province $p$ in calendar month $m$ of year $y$ on one or several weather variables $weather_{ipmy}$ in the same location and at the same time, on a police ward fixed effect $\alpha_i$, a calendar-month-by-province fixed effect $\gamma_{pm}$, and a year fixed effect $\beta_y$:

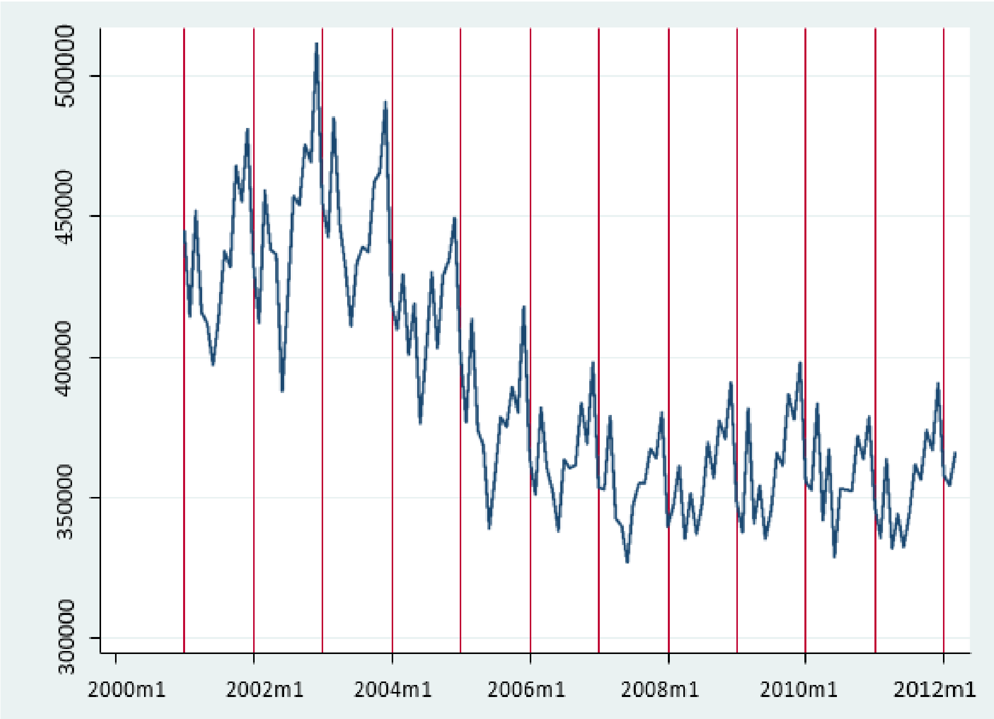
$$\ln(crime_{ipmy}) = \delta weather_{ipmy} + \alpha_i + \gamma_{pm} + \beta_y + E_{ipym} \quad (1)$$

$crime_{ipmy}$ can be the count of all serious crimes ($totalcrimes_{ipmy}$), or only crimes of certain types ($murder_{ipmy}$, $sexualcrimes_{ipmy}$, etc.). We use logarithmic transformations of the crime counts because they exhibit right-skewed distributions, and it turns out that the log-transformation helps to symmetrize residuals in our main regressions. We can then interpret the coefficient $\delta$ on our weather variables as percentage changes in crime counts due to unit changes in our weather variables.

By including the set of fixed effects, we capture the effect of local extraordinary weather events that stand out against the longer-term climate conditions within the police ward, against seasonality patterns within the province, and against weather fluctuations from year to year affecting the whole country. The police ward fixed effects absorb observed and unobserved time-invariant spatial characteristics, including long-term climate conditions, which are likely to be correlated with local contemporary weather and criminal behavior. The year fixed effects difference out any variation over time that is common to all police wards, including country-wide trends and shocks in weather and in criminal behavior, as well as any possible change in central crime reporting conventions. The calendar-month-by-province fixed effects account for province-specific seasonality. Figure 2 shows that there is indeed substantial seasonal variation in criminal activity in our data. Monthly total crime peaks in the last months of the year and has its lowest levels during the months May, June and July (during the local winter season). We control for seasonality because we want to disentangle the effects of weather from those of other seasonal conditions such as hours of daylight, cultural and religious festivals and public holidays, and agricultural cycles, but also potential seasonal patterns in how police forces are being deployed. Some of these conditions vary across regions of South Africa, which is why we choose to control for a calendar-month-by-province interaction.

Our coefficient $\delta$ on the weather variable hence must be interpreted as the effect of a January (February, March, etc.) that is exceptionally hot or cold, or, wet or dry, given the average long-term local climate, the long-term climate conditions for January (February, March, etc.) within the province, and the country-wide annual weather trend. Assuming weather is exogenous and the fixed effects allow us to isolate the effect of weather from other drivers of criminal behavior, the coefficient $\delta$ could be interpreted as the causal effect of weather on crime.[10]

**Figure 2: Seasonality in criminal activity**




*Notes: Figure shows trends in total monthly counts (indicated on the vertical axis) of crimes of all types in our records, over our sample period running from 2001 to 2012 (along the horizontal axis). The (red) vertical lines mark months of January.*

Because weather variation occurs over spatial areas with an extent beyond that of police wards (see Auffhammer et al. 2013), we adjust standard errors for spatial correlation between police wards. We follow the methodology of Hsiang (2010) based on non-parametric covariance matrix estimation and a uniform spatial weighting kernel function (as recommended in Conley, 1999; and Conley and Molinari, 2007), with a distance cut-off at 500 km (meaning that spatial correlation is assumed to be

[10] For a general discussion on the use of panel fixed effects regressions for estimating effects of weather on economic and social outcomes, see Dell et al. (2014).

zero beyond 500 km). We also account for autocorrelation within individual police wards over time, up to a 24 months lag.

In a second specification, we analyze effects of drought during the local growing season on lagged crime to explore the plausibility of an income mechanism. We use $drought_{ipy}$ as our main explanatory variable for this part of the analysis and reduce our sample to rural police wards only (i.e., police wards with $rural_{ip} = 1$ as defined in Section 2). The growing season for locally dominant crops in South Africa runs roughly from October to March, with slight variations across the different agro-climatic zones (see Portmann et al., 2010). We regress crime during each quarter of year $y$ on $drought_{ipy}$. As in our main specification, we also control for police ward fixed effects, year fixed effects and calendar-month-by-province fixed effects. We introduce as additional controls $mintemp_{ipmy}$ and $rainydays_{ipmy}$. This is because temperature and rainfall during the months January to March of year $y$ are clearly correlated with $drought_{ipy}$; and adding these controls helps us to isolate drought effects from more immediate weather effects as examined in the previous section.

As crime variables, we now focus on $stealing_{ipmy}$, in which we aggregate all crime types that involve the taking of property (robbery, burglary, theft, and commercial crime); and on $nonstealing_{ipmy}$, an aggregate of all crime types that do not involve the taking of property. While negative income shocks, by decreasing people's opportunity cost of engaging in criminal activity, may encourage all types of crime according to Becker's (1968) economic theory of crime, we hypothesize effects to be stronger for crimes that involve the taking of property. This is because we expect resource-acquisition in response to economic distress as the main driver of these types of crime, on top of the decreased opportunity cost that Becker suggests. We also separately analyze effects on the various types of crime which we used as dependent variables in Section 4.1.

As in our main specification, we use logarithmic transformations of crime counts and adjust standard errors for spatial correlation between police wards, using a uniform spatial weighting kernel function and a distance cut-off at 500 km, and for serial correlation within police wards, up to a 24 months lag.

## 5. Short-term effects of temperature and rainfall

### 5.1. Effects on total crime counts

We investigate the short-term weather effects on criminal activity by regressing crime on weather within the same month. Possible channels which may mediate these effects, and the crime types which we expect to be affected, are illustrated in Figure A1 in the appendix. As a starting point, we examine effects on total crime and use ln $(totalcrimes_{ipmy})$ as a dependent variable, accounting for police ward, calendar-month-by province and year fixed effects. Results are presented in Table 2. We first regress the aggregate crime variable separately on daily maximum temperature (column 1); daily minimum temperature (column 2); and the number of wet days in the month (column 3). Second, we include daily minimum temperature and the number of wet days in the month jointly in the same regression (column 4). We find that total crime increases with temperature and decreases with rainfall. Both daily maximum and minimum temperature have a positive effect on total crime. All weather coefficients are statistically significant at the 1 percent-level.

**Table 2: Short-term weather effects on total crime**

| Dependent variable: ln($totalcrime_{ipmy}$) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $maxtemp_{ipmy}$ | 0.0137*** | | | |
| | (0.00235) | | | |
| $mintemp_{ipmy}$ | | 0.0195*** | | 0.0209*** |
| | | (0.00358) | | (0.00368) |
| $rainydays_{ipmy}$ | | | -0.00453*** | -0.00523*** |
| | | | (0.00112) | (0.00115) |
| Observations | 152,550 | 152,550 | 152,550 | 152,550 |
| R-squared | 0.008 | 0.008 | 0.008 | 0.009 |
| Police ward FE | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. All variables are described in the main text. Standard errors are robust to autocorrelation within police wards up to a 24-months lag, and to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

Our coefficients imply that a one standard deviation rise in the daily maximum temperature within an average month of the year (a rise by 2.7 degrees Celsius) increases total crime counts by 3.7 percent.

A rise in the daily minimum temperature by one standard deviation within an average month of the year (again a rise by 2.7 degrees Celsius) increases total crime counts by 5.3 percent. Our daily maximum temperature variable captures daytime temperature peaks, and our daily minimum temperature variable captures nighttime temperatures (so, a higher *mintemp* value indicates a warmer night), both averaged across the month. The results then suggest that warmer nights drive criminal behavior more strongly than warmer days. The coefficient on the number of wet days is negative and statistically significant at the 1%-level. In Column (3), i.e., when we do not control for temperature, our coefficient implies that an increase in the number of wet days by one standard deviation in an average month of the year (an increase by 4.3 days) decreases the total crime count by 1.9 percent.

In Column (4) we include both the daily minimum temperature and the number of wet days per month in the same regression. All weather coefficients are still statistically significant at the 1%-level and slightly higher in magnitude than when not controlling for other weather variables. This means the positive effect of warmer temperatures at night on crime is even more pronounced when we take the negative effect of rainy days into account; and the negative effect of rainy days on crime is even more pronounced when we account for rises in nighttime temperature.

As a robustness check for these results, we run a placebo test by replacing our contemporary weather variables with the corresponding weather variables in the 12 months lead period, otherwise employing the same model specification. If our interpretation of short-term weather fluctuations as exogenous drivers of crime is correct, then this lead-period weather variable should have no effect. Indeed, we find that weather in period *t+12* has no effect on crime in period *t* (see Table A2 in the appendix).[11]

### 5.2. Effects on specific types of crime

Next, we break down the total number of crimes by type and regress these on daily minimum temperature and number of wet days, again including police ward, calendar-month-by-province, and

[11] In the remainder of the paper, we present results corrected for spatial correlation only. Only accounting for spatial correlation in our main results increases standard errors by up to one third as compared to no correction at all. Accounting for serial *and* spatial correlation increases standard errors by not more than 6 percent (meaning that significance levels for our main results are unaffected).

year fixed effects.[12] Specifically, we compare effects for four types of violent crimes: murder or attempted murder, sexual crimes of any type, assault, and robbery; and for four types of property crimes: theft, burglary, commercial crime, and crimes heavily dependent on police action for detection. Results are presented in Table 3.

**Table 3: Short-term weather effects on various types of crime**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Dependent variable | ln(mur-der) | ln(sexual-crimes) | ln(assault) | ln(robbery) | ln(theft) | ln(burg-lary) | ln(comer-cial) | ln(police-detect) |
| mintemp | 0.015*** (0.0047) | 0.032*** (0.0048) | 0.028*** (0.0038) | 0.012** (0.0055) | 0.0068 (0.0046) | 0.015*** (0.0040) | -0.0040 (0.0056) | 0.0078 (0.0077) |
| rainydays | -0.0039** (0.0017) | -0.0034** (0.0016) | -0.0068*** (0.0011) | -0.0059*** (0.0019) | -0.0033** (0.0014) | -0.0033*** (0.0012) | -0.0027 (0.0018) | -0.0049* (0.0026) |
| Obser-vations | 152,550 | 152,550 | 152,550 | 152,550 | 152,550 | 152,550 | 152,550 | 152,550 |
| R-squared | 0.008 | 0.015 | 0.022 | 0.004 | 0.002 | 0.004 | 0.002 | 0.007 |
| Police ward FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Calender-month-by-province FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

We find that a rise in daily minimum temperature tends to drive crime counts upwards, and the number of wet days reduces crime counts. Beyond this, interesting differences across the types of crime become perceivable. The effects of rising temperatures are statistically significant for all four violent crime types, and for burglary. The temperature effect is strongest for sexual crimes: A one standard deviation increase in minimum temperature increases sexual crimes by more than 8.6 percent. By contrast, theft, commercial crimes, and crimes detected by police action appear not to be affected by rises in temperature according to our data. The negative coefficients on the number of wet days in a month are statistically significant at 1%- or 5%-levels for most crime types. For commercial

[12] For conciseness, we only present results from regressions that include both weather variables as explanatory variables. The pattern of results when regressing the various crime variables on each weather variable separately is very similar to what we found in regressions of total crime (presented in Table 2): Daily maximum temperature has slightly weaker effects on crime than daily minimum temperature; and coefficients on daily minimum temperature and number of wet days, when included separately, are both slightly smaller in magnitude, but statistically significant at the same level.

crime, there is no statistically significant effect of rainfall; and for crimes detected by police action, the effect is only marginally significant. The negative effect of rainy days is most pronounced on assault, which decreases by 2.9 percent with 4.3 additional rainy days in a month, which corresponds to one standard deviation within an average month of the year.

Our findings are consistent with the presence of a heat-aggression channel. This channel predicts effects of rising temperatures on violent crimes, but not necessarily on property crimes, which is exactly what we find. The negative effect of rainfall on all types of crime could be interpreted as a hint to an opportunity channel: Rainfall might lower the density of people in public space and thereby the opportunity to commit crimes. Similarly, the (weak) effect on crimes detected by police action could be interpreted as a hint towards reduced police patrol activity during rainy weather. We acknowledge, though, that different mechanisms might be at play in parallel mediating the link between temperature, precipitation, and crime (e.g., drunk driving might be less frequent on rainy days). Yet, especially the absence of any weather effect on commercial crimes is reassuring that some of the suggested channels are indeed at work.

To check for possible non-linearities we take advantage of the large number of observations in our data set allowing the application of non-parametric techniques. More specifically, we compute local polynomial smoothing plots for each crime type on temperature and rainy days. Overall, these plots confirm the findings from our parametric estimations and show approximatively linear relationships between crime and temperature as well as rainfall on the weather variable ranges in which our data are dense enough to estimate the relationship locally (see the Online Appendix for further explanations and results).

As a first conclusion, criminal behavior in South Africa is highly responsive to variation in temperature, and less so to variation in rainfall, in the short term. Higher temperatures tend to increase, higher rainfall tends to decrease criminal activity.

## 6. Medium-term effects: Weather and droughts

In this section, we examine weather effects that materialize through droughts and hence an income channel (see also Figure A2 in the appendix). Compared to the short-term relationship considered in the previous section this effect might well occur with a substantial time lag between weather shocks and responses in criminal behavior. If drought conditions decrease agricultural yields, people whose livelihoods depend on agriculture may be unable to set aside sufficient resources and experience economic distress several months after the end of the growing season, as they run out of savings. If, in turn, such weather-induced economic distress drives some people into criminal behavior, we expect the effect of drought during the growing season to materialize at some point during the second, third or fourth quarter of the same year.

Table 4 presents results for the specifications with $stealing_{ipmy}$ (panel A) and $nonstealing_{ipmy}$ (panel B) as dependent variables. Columns (1) to (8) show regression results for sub-samples by quarter of the year, for each quarter with and without controlling for temperature and rainfall. We find that $stealing_{ipmy}$ increases in years when the growing season was affected by drought, and this effect occurs in the quarters after the end of the growing season only. The effect is largest for the months July to September (columns 5 and 6). An increase in $drought_{ipy}$ by one standard deviation (i.e., by 0.08) increases crimes that involve the taking of property by around 2 percent – the effect is statistically significant but its size economically modest. Drought does not increase crime during the first quarter of the year, while the growing season is still ongoing. Crimes that do not involve the taking of property also increase during the second to fourth quarter following a drought-affected growing season, but the effect is smaller and not statistically significant. We interpret these estimates as suggestive evidence in support of an agricultural income channel linking crime outcomes to weather conditions.

To further scrutinize the plausibility of this interpretation, we run the same regressions as in Table 4, but replace drought during the current year's growing season by drought during growing seasons in the two previous years. Table 5 shows that drought during the growing season in year $y-1$ continues to have a statistically significant effect on $stealing_{ipmy}$ precisely up to the first quarter of year $y$ (panel A of Table 5, columns 1 and 2, first row). In fact, the size of the effect of drought during the growing season in year $y-1$ is highest in the first quarter of the following year $y$, which is around the time when yields from the new growing season become available. In the second quarter of year $y$, the effect is still positive but no longer statistically significant (columns 3 and 4); and in the third and fourth quarter, the effect fades away (columns 5 to 8). Drought during the growing season in year $y-2$ does not affect crime in year $y$. For crimes that do not involve the taking of property, the coefficient for a drought in one of the two previous years is not statistically significant (panel B of Table 5).

**Table 4: Medium-term effects of drought during most recent growing season on crime**

| | (1)<br>Jan-Mar | (2)<br>Jan-Mar | (3)<br>Apr-Jun | (4)<br>Apr-Jun | (5)<br>Jul-Sep | (6)<br>Jul-Sep | (7)<br>Oct-Dec | (8)<br>Oct-Dec |
|---|---|---|---|---|---|---|---|---|
| Panel A - Dependent variable: *ln*($stealing_{ipmy}$) | | | | | | | | |
| $drought_{ipy}$ | 0.107<br>(0.117) | 0.070<br>(0.119) | 0.225**<br>(0.090) | 0.218**<br>(0.091) | 0.256**<br>(0.113) | 0.250**<br>(0.114) | 0.240**<br>(0.105) | 0.241**<br>(0.106) |
| $mintemp_{ipmy}$ | | -0.006<br>(0.009) | | 0.012*<br>(0.006) | | 0.0129*<br>(0.007) | | 0.011<br>(0.008) |
| $rainydays_{ipmy}$ | | -0.004**<br>(0.002) | | -0.006**<br>(0.002) | | 9.66e-05<br>(0.003) | | -0.001<br>(0.002) |
| Observations | 30,240 | 30,240 | 27,720 | 27,720 | 27,720 | 27,720 | 27,720 | 27,720 |
| R-squared | 0.003 | 0.003 | 0.002 | 0.003 | 0.001 | 0.001 | 0.001 | 0.002 |
| Panel B - Dependent variable: *ln*($nonstealing_{ipmy}$) | | | | | | | | |
| $drought_{ipy}$ | -0.0599<br>(0.131) | -0.100<br>(0.133) | 0.066<br>(0.111) | 0.056<br>(0.111) | 0.133<br>(0.105) | 0.128<br>(0.103) | 0.114<br>(0.125) | 0.108<br>(0.124) |
| $mintemp_{ipmy}$ | | 0.008<br>(0.008) | | 0.019***<br>(0.007) | | 0.026***<br>(0.007) | | 0.0125<br>(0.008) |
| $rainydays_{ipmy}$ | | -0.004**<br>(0.002) | | -0.007***<br>(0.003) | | -0.010***<br>(0.003) | | -0.005**<br>(0.002) |
| Observations | 30,240 | 30,240 | 27,720 | 27,720 | 27,720 | 27,720 | 27,720 | 27,720 |
| R-squared | 0.002 | 0.002 | 0.003 | 0.003 | 0.005 | 0.007 | 0.023 | 0.023 |
| Police ward FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. Samples include only rural police wards ($rural_{ip}$ = 1). Sub-samples in columns (1) and (2) include calendar months January to March; sub-samples in columns (3) and (4) include calendar months April to June; sub-samples in columns (5) and (6) include calendar months July to September; and sub-samples in columns (7) and (8) include calendar months October to December. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

**Table 5: Medium-term effects of drought during previous growing seasons on crime**

| | (1) Jan-Mar | (2) Jan-Mar | (3) Apr-Jun | (4) Apr-Jun | (5) Jul-Sep | (6) Jul-Sep | (7) Oct-Dec | (8) Oct-Dec |
|---|---|---|---|---|---|---|---|---|
| Panel A - Dependent variable: *ln*(*stealing$_{ipmy}$*) | | | | | | | | |
| $drought_{ipy-1}$ | 0.360*** | 0.346*** | 0.149 | 0.156 | -0.001 | -0.006 | -0.037 | -0.035 |
| | (0.121) | (0.121) | (0.112) | (0.113) | (0.106) | (0.106) | (0.107) | (0.107) |
| $drought_{ipy-2}$ | -0.002 | 0.0047 | -0.060 | -0.057 | 0.036 | 0.041 | -0.098 | -0.094 |
| | (0.127) | (0.128) | (0.087) | (0.087) | (0.102) | (0.102) | (0.098) | (0.0100) |
| $mintemp_{ipmy}$ | | -0.006 | | 0.011* | | 0.008 | | 0.005 |
| | | (0.009) | | (0.006) | | (0.008) | | (0.010) |
| $rainydays_{ipmy}$ | | -0.003 | | -0.005** | | -0.002 | | -0.001 |
| | | (0.002) | | (0.003) | | (0.003) | | (0.002) |
| Observations | 25,183 | 25,183 | 22,665 | 22,665 | 22,662 | 22,662 | 22,663 | 22,663 |
| R-squared | 0.004 | 0.004 | 0.003 | 0.003 | 0.001 | 0.001 | 0.001 | 0.001 |
| Panel B - Dependent variable: *ln*(*nonstealing$_{ipmy}$*) | | | | | | | | |
| $drought_{ipy-1}$ | 0.146 | 0.138 | 0.124 | 0.134 | 0.152 | 0.133 | -0.002 | 0.006 |
| | (0.097) | (0.099) | (0.137) | (0.137) | (0.114) | (0.112) | (0.119) | (0.117) |
| $drought_{ipy-2}$ | 0.098 | 0.108 | 0.036 | 0.044 | -0.021 | 0.006 | -0.0302 | -0.018 |
| | (0.093) | (0.092) | (0.095) | (0.095) | (0.089) | (0.089) | (0.077) | (0.076) |
| $mintemp_{ipmy}$ | | 0.018** | | 0.027*** | | 0.030*** | | 0.012 |
| | | (0.008) | | (0.008) | | (0.007) | | (0.009) |
| $rainydays_{ipmy}$ | | -0.006*** | | -0.008*** | | -0.009*** | | -0.005** |
| | | (0.002) | | (0.003) | | (0.003) | | (0.002) |
| Observations | 25,183 | 25,183 | 22,665 | 22,665 | 22,662 | 22,662 | 22,663 | 22,663 |
| R-squared | 0.002 | 0.002 | 0.004 | 0.005 | 0.005 | 0.007 | 0.023 | 0.024 |
| Police ward FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. Samples include only rural police wards ($rural_{ip}$ = 1). Sub-samples in columns (1) and (2) include calendar months January to March; sub-samples in columns (3) and (4) include calendar months April to June; sub-samples in columns (5) and (6) include calendar months July to September; and sub-samples in columns (7) and (8) include calendar months October to December. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

When we extend the sample to include also urban areas and run the same regressions as those presented in Table 4, the estimated coefficients lose statistical significance (in spite of an increase in sample size by 35 percent; see Table A3 in the appendix). We now only find a weakly statistically significant $drought_{ipy}$ coefficient in the third quarter (of similar magnitude as for the rural subsample) for $stealing_{ipmy}$. We interpret this as another hint towards the hypothesized income-crime channel.

We furthermore break down the analysis by types of crime and run the same regressions as those presented in odd columns of Table 4 (where we do not control for temperature and rainfall). Results are presented in Table A4 in the appendix, where the number of each column (1) to (2) corresponds to the quarter of the year. We find that drought during the growing season of year $y$ has negative effects on murder and on sexual crimes, which are weakly statistically significant for quarters 2 and 4, respectively. Also, we find a strong positive and statistically significant effect of drought during the growing season of year $y$ on robbery during the quarters 2 to 4 of year $y$. In fact, the results in Table A4 suggest that the effect of drought on crimes that involve the taking of property, which we found above, are mainly driven by this strong response on robbery.

## 7. Data-related caveats

In this section, we discuss several well-known but often neglected caveats related to the type of data we use and caution against overinterpretation of our findings. To start with, we did not register or pre-specify our data analysis and are hence subject to concerns about specification searching, $p$-hacking, and multiple hypothesis testing (see Christensen and Miguel 2018). While registering secondary data-based and non-experimental studies is possible but very uncommon (see Burlig 2018, Janzen and Michler 2021), we nevertheless hereby declare that we have not engaged in specification searching or tested outcome variables other than those shown in the paper.

Mellon (2021) makes a very compelling case against using weather as an instrumental variable (IV) because it is hard to argue that it affects a certain economic outcome only through the endogenous variable of interest. Based on a systematic literature review he finds that the social science literature has used weather as a driver for 176 different outcome variables. Even if only a subset of these relationships applies to a certain context in which a weather IV is used, Mellon (2021) demonstrates that this will severely bias results. He also stresses that this bias does not materialize in papers using reduced-form equations like ours. Nevertheless, even in reduced-form approaches "interpreting the mechanism behind these total effects will be challenging" (Mellon 2021, p.25). A cautious interpretation of our results would be to focus on implications for police deployment, as we do in the conclusion, and abstain from drawing inference on the theories outlined in the introduction.

Furthermore, Auffhammer et al. (2013) enumerate five typical pitfalls related to gridded weather data and demonstrate that the CRU data used here are prone to these pitfalls. First, there are inconsistencies between different weather data sets. They deliver consistent results when looking at averages across space, but not for deviations from the mean value over time, which is what we look at. This is induced by measurement errors and potentially aggravated when these data are used in regression models with fixed effects. One important source of a measurement error is due to a purely statistical reason because weather data and economic variables are observed on different spatial levels: The temperature and rainfall data used in this paper was originally collected on a higher spatial level than the crime data. There are 1,158 wards in our data set, but the weather data is derived from 50 stations. As described in Section 3.2, the CRU gridded data is derived by interpolation between these stations. Hence, the weather data on the ward level, our explanatory variable, suffers from a measurement error that is unknown but certainly not zero. Using explanatory variables with measurement error in a regression model usually leads to an attenuation bias in the estimated coefficient towards zero, so the actual effect of weather on crime could be higher (see also Auffhammer et al. 2012). As Dell et al. (2014) note, this measurement error is typically more pronounced for rainfall than for temperature, because precipitation varies much more between small spatial units. Auffhammer et al. (2013) recommend doing robustness checks across different weather data sets, which is beyond the scope of the present paper. Yet, the evidence presented in Gates et al. (2019) and Schutte and Breetzke (2018) draws on other data sources and broadly confirms the patterns we observed.

The second pitfall listed in Auffhammer et al. (2013) refers to another source of measurement error that can be induced by weather stations entering and exiting the sample because they are turned on or off or because recordings are missing. If a station located near a warmer ward exits (or enters) the sample, temperature in that ward falsely appears to decrease (increase). This is of even greater concern if these entries and exits are also correlated with crime, our dependent variable. Auffhammer et al. (2013) also stress that this measurement error problem is worse for countries with very few stations. The 50 stations in South Africa are probably good for African comparison, but their prevalence is still below what can be found in industrialized countries. Since we have no information about stations entering or exiting our sample, though, we cannot conduct robustness checks in this direction and resort to flagging this as a potential serious caveat.

The third pitfall in Auffhammer et al. (2013) points at the correlation of precipitation and temperature. Only including one of the two variables therefore leads to a combined effect. We examined this in our results section by estimating regression models which include each weather variable separately, and a model which includes both temperature and rainfall. The estimates from the combined model confirmed estimates from the separate models (see Table 2).

The fourth pitfall emphasizes spatial correlation typically present in gridded weather data sets and calls for correcting standard errors accordingly; otherwise significance levels are inflated. We applied this correction in our analyses and, indeed, the correction increased the standard errors by up to one third. The fifth pitfall is related to the measurement error pitfalls one and two. This one is again more difficult to account for in that it states that placement of additional weather stations could be correlated with economic or political shocks that also affect the variables of interest, crime rates in our case. We have no indication for station placement that is endogenous to crime, but we cannot rule this out either.

Beyond concerns about the weather data, we already mentioned potential issues of crime misreporting in Section 3.1. We have applied the robustness checks and considerations discussed in Brodie (2013) and stress that our key results hold also for the more serious types of crime, for which misreporting is unlikely. We acknowledge, though, that misreporting in the data is a source of uncertainty.

## 8. Conclusions

This paper has examined the relationship between weather and crime in South Africa over a 12-year period. Our results suggest that weather has a short-term effect on crime, with the strongest effect for increasing temperatures on violent crime. Property crime, in contrast, does not respond to changes in temperature. Rainfall has a negative effect on both violent and property crime, which is less pronounced than the effect of warm temperatures, though. These patterns are in line with the heat-aggression hypothesis. A noteworthy limitation to our analysis is that the monthly resolution of our crime data does not allow us to detect potential effects of short-term peaks in temperature or rainfall. We are hence unable to accurately capture the heat-aggression effect. Moreover, it is also possible that other mechanisms are at work, for example people are likely to go out more in warm weather. Recent evidence from Mexico, for example, suggests that higher alcohol consumption and time allocation play an important role (Cohen and Gonzales 2018). Weather is also related to pollution, which has been found to affect crime rates as well (Bondy et al. 2020). We are unable to probe deeper into what exactly translates temperature into aggression.

In our medium-term analysis, we observe patterns for an income channel that mediates the weather-crime relationship. More specifically, we find that drought spells during the growing season induce a modest increase in crimes that involve the taking of property in rural areas. In line with theoretical expectations, this effect becomes blurred as we extend the sample to urban areas, where livelihoods are less agriculture dependent.

Our findings on the short-term relationship can contribute to discussions about crime prevention. The heat responsiveness of crime incidences could be used to sensitize the public through media campaigns. Moreover, the strong effect that warmer temperatures have on violent crime suggests that weather forecasts might be incorporated into policing allocation plans (see as well Chersich et al. 2019). In a similar vein, Schutte and Breetzke (2018) recommend "identifying communities that are more prone to crime under certain meteorological conditions and allow stakeholders to target these neighbourhoods and plan interventions accordingly." This recommendation holds irrespective of the specific mechanism underlying our findings and hence also when accounting for many of the caveats discussed in Section 7.

Indeed, a growing literature has shown for other countries, mostly the US, that hot-spot policing and a general increase in visible police presence have clear deterrence effects (see Braga et al., 2012, for a review of the literature). Admittedly, this evidence is coming from countries with different institutional set-ups, for example more flexible police forces, and in which potential offenders may have different discount rates than in South Africa. We therefore call for more work probing into these linkages in the specific South African context. Our lessons might be taken on board in the future thinking and the design of upcoming research on how to improve prevention policies in South Africa.

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## 10. Appendix

**Table A1: Total crime counts by category over the sample period**

| Crime category | Total count |
|---|---|
| 1. VIOLENT CRIME | 17,011,490 |
| 1.1 Murder | 418,327 |
| 1.2 Total Sexual Crimes | 1,511,887 |
| 1.2.1 Abduction | 64,781 |
| 1.2.2 Attempted sexual offences | 32,072 |
| 1.2.3 Contact sexual offence | 67,486 |
| 1.2.8 Rape | 411,691 |
| 1.2.9 Sexual Assault | 59,886 |
| 1.2.10 Sexual offences due to police action | 5,482 |
| 1.3 Attempted murder | 507,537 |
| 1.4 Assault with the intent to inflict grievous bodily harm | 5,130,302 |
| 1.5 Common assault | 5,102,969 |
| 1.6 Common robbery | 1,672,408 |
| 1.7 Robbery with aggravating circumstances | 2,668,062 |
| 1.7.1 Street/public robbery, bank robbery, robbery of cash in transit | 1,870,689 |
| 1.7.2 Trio | 767,908 |
| 1.7.2.1 Robbery at residential premises | 278,518 |
| 1.7.2.2 Robbery at non-residential premises | 189,801 |
| 1.7.2.3 Carjacking | 299,589 |
| 1.7.3 Truck hijacking | 29,465 |
| 2. CONTACT-RELATED CRIME | 3,340,400 |
| 2.1 Arson | 172,338 |
| 2.2 Malicious damage to property | 3,168,062 |
| 3. PROPERTY-RELATED CRIME | 13,392,025 |
| 3.1 Burglary at non-residential premises | 1,521,958 |
| 3.2 Burglary at residential premises | 6,039,212 |
| 3.3 Theft of motor vehicle and motorcycle | 1,819,876 |
| 3.4 Theft out of or from motor vehicle | 3,246,791 |
| 3.5 Stock-theft | 764,189 |
| 4. CRIME HEAVILY DEPENDENT ON POLICE ACTION FOR DETECTION | 3,603,281 |
| 4.1 Illegal possession of firearms and ammunition | 331,862 |
| 4.2 Drug-related crime | 2,305,844 |
| 4.3 Driving under the influence of alcohol or drugs | 965,575 |
| 5. OTHER SERIOUS CRIME | 13,603,227 |
| 5.1 All theft not mentioned elsewhere | 10,467,713 |
| 5.2 Commercial crime | 1,519,591 |
| 5.3 Shoplifting | 1,615,923 |
| 6. OTHER CRIME CATEGORIES | 1,456,762 |
| 6.1 Culpable homicide | 269,236 |
| 6.2 Public violence | 24,580 |
| 6.3 Crimen injuria | 998,623 |
| 6.4 Neglect and ill-treatment of children (incl. underage victims of crimes e.g.) | 95,753 |
| 6.5 Kidnapping | 68,570 |

*Notes: Table lists the crime categories as they appear in the original records from the South African Police Service, and the total counts of each crime category over our sample period, which is January 2001 to March 2012.*

**Table A2: Placebo test of short-term weather effects on total crime: Effects of 12 months lead weather variables**

| Dependent variable: *ln(totalcrime$_{ipmy}$)* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| maxtemp$_{ipmy+1}$ | -0.00113<br>(0.00273) | | | |
| mintemp$_{ipmy+1}$ | | -0.000764<br>(0.00155) | | 0.0000023<br>(0.00180) |
| rainydays$_{ipmy+1}$ | | | -0.00198<br>(0.00136) | -0.00198<br>(0.00151) |
| Observations | 138,814 | 138,814 | 138,814 | 138,814 |
| R-squared | 0.012 | 0.012 | 0.012 | 0.012 |
| Police ward FE | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2011 (since 12-months lead weather variables are available only up to 2011). All variables are described in the main text. Standard errors are robust to autocorrelation within police wards up to a 24 months lag, and to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

**Table A3: Medium-term effects of drought during most recent growing season on crime, including urban and rural police wards**

| | (1) Jan-Mar | (2) Jan-Mar | (3) Apr-Jun | (4) Apr-Jun | (5) Jul-Sep | (6) Jul-Sep | (7) Oct-Dec | (8) Oct-Dec |
|---|---|---|---|---|---|---|---|---|
| Panel A - Dependent variable: $ln(stealing_{ipmy})$ | | | | | | | | |
| $drought_{ipy}$ | 0.112 | 0.0265 | 0.250 | 0.236 | 0.278* | 0.270* | 0.241 | 0.239 |
| | (0.156) | (0.156) | (0.161) | (0.159) | (0.160) | (0.160) | (0.155) | (0.154) |
| $mintemp_{ipmy}$ | | 0.0156* | | 0.0183*** | | 0.0123* | | 0.0223** |
| | | (0.00944) | | (0.00658) | | (0.00684) | | (0.00948) |
| $rainydays_{ipmy}$ | | -0.00768*** | | -0.00555 | | 0.000353 | | -0.00161 |
| | | (0.00233) | | (0.00357) | | (0.00309) | | (0.00209) |
| Observations | 40,680 | 40,680 | 37,290 | 37,290 | 37,290 | 37,290 | 37,290 | 37,290 |
| R-squared | 0.002 | 0.003 | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 |
| Panel B - Dependent variable: $ln(nonstealing_{ipmy})$ | | | | | | | | |
| $drought_{ipy}$ | 0.00362 | -0.0890 | 0.121 | 0.102 | 0.174 | 0.158 | 0.149 | 0.143 |
| | (0.151) | (0.152) | (0.144) | (0.142) | (0.141) | (0.139) | (0.148) | (0.146) |
| $mintemp_{ipmy}$ | | 0.0279*** | | 0.0258*** | | 0.0254*** | | 0.0266*** |
| | | (0.00859) | | (0.00652) | | (0.00648) | | (0.00947) |
| $rainydays_{ipmy}$ | | -0.00804*** | | -0.00706** | | -0.00692** | | -0.00516** |
| | | (0.00219) | | (0.00292) | | (0.00281) | | (0.00228) |
| Observations | 40,680 | 40,680 | 37,290 | 37,290 | 37,290 | 37,290 | 37,290 | 37,290 |
| R-squared | 0.001 | 0.003 | 0.002 | 0.003 | 0.005 | 0.006 | 0.017 | 0.017 |
| Police ward FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES |

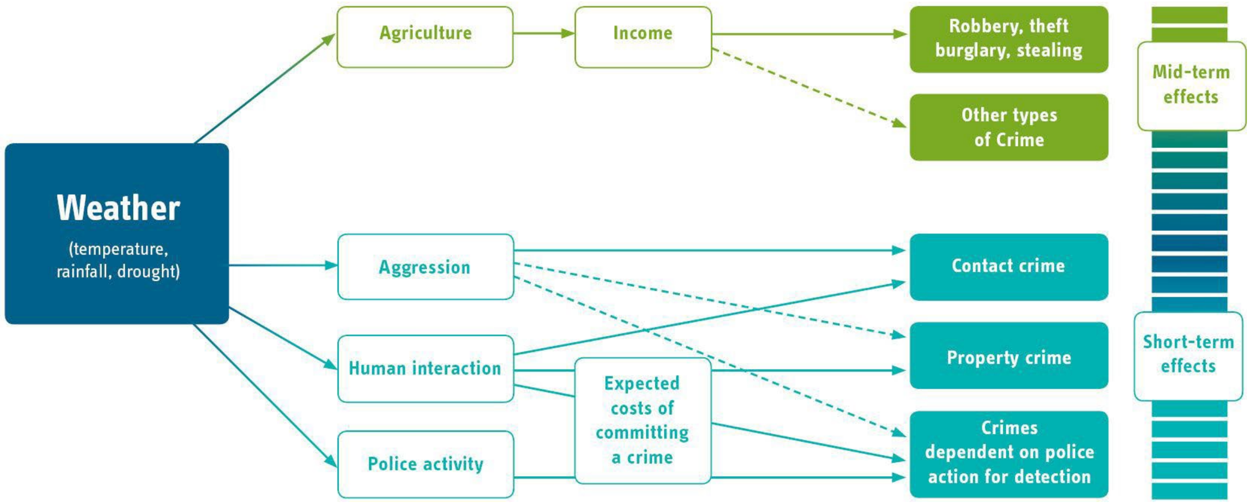
*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. Samples include both urban and rural police wards. Sub-samples in columns (1) and (2) include calendar months January to March; sub-samples in columns (3) and (4) include calendar months April to June; sub-samples in columns (5) and (6) include calendar months July to September; and sub-samples in columns (7) and (8) include calendar months October to December. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

**Table A4: Medium-term effects of drought during most recent growing seasons on various types of crime**

| | (1)<br>Jan-Mar | (2)<br>Apr-Jun | (3)<br>Jul-Sep | (4)<br>Oct-Dez |
|---|---|---|---|---|
| Dependent variable: *ln*(*murder*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | -0.169<br>(0.186) | -0.322*<br>(0.194) | -0.203<br>(0.201) | -0.131<br>(0.209) |
| Dependent variable: *ln*(*sexualcrimes*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | 0.0444<br>(0.165) | -0.0773<br>(0.191) | 0.0572<br>(0.188) | -0.319*<br>(0.179) |
| Dependent variable: *ln*(*assault*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | -0.0902<br>(0.185) | 0.134<br>(0.138) | 0.0733<br>(0.136) | 0.132<br>(0.147) |
| Dependent variable: *ln*(*robbery*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | 0.284<br>(0.206) | 0.463**<br>(0.173) | 0.707***<br>(0.199) | 0.399**<br>(0.208) |
| Dependent variable: *ln*(*theft*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | 0.244<br>(0.177) | 0.154<br>(0.172) | 0.198<br>(0.203) | 0.0578<br>(0.183) |
| Dependent variable: *ln*(*burglary*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | 0.0664<br>(0.141) | 0.0977<br>(0.129) | 0.127<br>(0.151) | 0.207<br>(0.152) |
| Dependent variable: *ln*(*commercial*$_{ipmy}$) | | | | |
| drought$_{ipy}$ | -0.0955<br>(0.237) | -0.138<br>(0.199) | -0.00120<br>(0.202) | -0.0162<br>(0.235) |
| Dependent variable: ln(policedetect$_{ipmy}$) | | | | |
| drought$_{ipy}$ | 0.0298<br>(0.232) | 0.0499<br>(0.230) | 0.203<br>(0.250) | 0.346<br>(0.271) |
| Observations | 30,240 | 27,720 | 27,720 | 27,720 |
| Policeward FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Calendar-month-by-province FE | YES | YES | YES | YES |

*Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. Samples include only rural police wards (rural$_{ip}$ = 1). Sub-samples in column include calendar months January to March; sub-samples in column (2) include calendar months April to June; sub-samples in column (3) include calendar months July to September; and sub-samples in column (4) include calendar months October to December. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance cut-off at 500 km. ***, **, * indicate significance at the 1, 5 and 10%-level, respectively.*

**Figure A1: Overview of mechanisms**




*Notes: This graphic outlines various channels mediating the effects of weather on different crime types in the short and medium term. The graphic focusses on channels discussed in this paper.*

**Figure A2: South African police wards**

*Notes: Map shows the division of South Africa into police wards.*