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Weather and Crime in South Africa

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Anna Bruederle, Jörg Peters, and Gareth Roberts[1]

Weather and Crime in South Africa

Abstract

South Africa has one of the highest crime rates in the world, incurring high cost for society. The present 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 demonstrate a short-term effect of warmer temperatures on violent crime and thereby offer support for the heat-aggression link as suggested by psychological research. Furthermore, we find evidence for a mid-term effect of weather on crime via agricultural income, which is in line with the economic theory of crime. Our findings have direct policy implications for the design of crime prevention strategies, in which weather forecasts could play an important role.

JEL Classification: C33, O55, Q54, R11

Keywords: South Africa; weather; crime; income shocks

December 2017

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1 Introduction

High crime rates are one of the biggest challenges that 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 pandemic 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 induced with 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 has to 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 mid-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 mid-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 that conceptualize the thinking about crime in the 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, taking into account the probability of being arrested, as well as the opportunity cost. Here, the short- and medium-term effects of weather come into play.

Temperatures and rainfall might affect these components in three ways, two of which operate in the short term, one in the mid-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 recent discussion, see Groves and Anderson, 2016), one version supported by most of the evidence is simple:

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

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 by psychological research mostly, including evidence from experimental and quasi-experimental field studies (Curtis et al., 2016; Gamble and Hess, 2012; 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 mid-term. Most notably, the agricultural sector is heavily weather-dependent. Drought spells can shrink output and employment opportunities. This, in turn, might drive individuals into criminal ways of mending their livelihoods or decreases their opportunity cost of engaging in criminal activity (see, e.g., Blakeslee and Fishman, 2017). Rising inequality can additionally amplify the effect of weather shocks on crime (Kelly, 2000). Figure 4 below provides an overview of the possible channels mediating weather effects on crime to which our empirical analysis refers.

We use this theoretical background to structure our analysis and examine effects of temperature, rainfall, and drought on various types of crime in order to investigate different mechanisms linking crime to weather. Exploiting exogenous variation within spatial units over time, we isolate the weather effects from other drivers of crime. Because of the exogeneity of weather to human behavior, correlations between weather and crime can be interpreted causally. We find that higher temperatures tend to increase 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, which supports the heat-aggression mechanisms. In a next step, we analyze the medium-term effects of drought in order to explore the role of income as a mediator between weather and crime. Indeed, income related crime types such as robbery increase after growing seasons affected by a drought spell. 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 depend on agriculture.

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

[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 ℃ (e.g. Bell, 2005; Rotton and Cohn, 2000, 2004).

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, 2016). 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 such as hot-spot policing. Weather forecasts could be used in the prediction of short-term policing demands.

Our paper contributes primarily to the 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 justice system. These historical roots and limitations certainly have to be appreciated when interpreting our results. Bhorat et al. (2017), in contrast, examine the socio-economic determinants of crime in the country and find that a rising income at the left tail of the distribution raises property crime rates, but decreases them at the right tail of the distribution. The rationale behind this is that, according to the authors, as incomes rise, individuals note their vulnerability and take action for protection. The authors do not observe socio-economic correlates for robbery crime, though, 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).

Moreover, our paper speaks to the growing literature on the nexus between climate change, weather, and conflict (see Dell et al., 2014; Hsiang et al., 2013; Burke et al., 2015, for recent overviews and Hendrix and Salehyan, 2012 and Miguel, 2005 for evidence from Africa). The overall picture that has emerged from this literature is that higher temperatures increase the probability of interpersonal violence, intergroup conflict, and criminal behaviour. 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).[3] Our paper is closely related to the work by Ranson (2014) and Blakeslee and Fishman (2017), but to the best of our knowledge is the first to study the crime-weather relationship in Africa. 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

[3]Short-term variation in weather is often used as an exogenous source of income variation and serves as an instrumental variable to help deriving causal effects on conflict outcomes; e.g. in Brückner and Ciccone (2011); Hodler and Raschky (2014); Miguel et al. (2004).

of violent and property crime. He does not find evidence for an effect of rainfall.[4] Blakeslee and Fishman (2017) 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. Our results confirm their finding on agricultural income shocks as a driver of the weather-crime relationship. Our medium-term analysis of drought effects on crime is also closely related to a paper by Harari and La Ferrara (2013)), which studies effects of agricultural production shocks on 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, conflict incidence rises.

The remainder of this paper is organized as follows: Section 2 describes our crime and weather data, and Section 3 our empirical strategy. Sections 4 and 5 present our results, and Section 6 concludes.

2 Data

2.1 Crime data

Our crime data stem from the records of the South African Police Service.[5] 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 1 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.

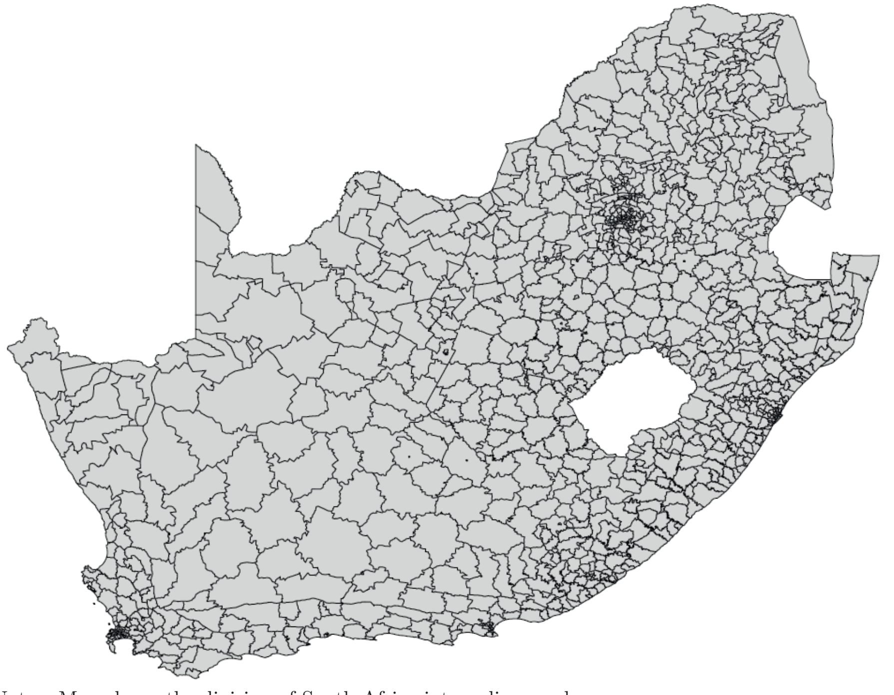
Each crime is coded into one of 35 categories, including various types of assault, murder, rape, sexual offence, various types of robbery, arson, malicious damage to property, burglary, and theft. Table A.1 in the Appendix provides an overview of all crime categories as they are organized in the original 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;

[4] In a related empirical approach, but focussing on the effect of air pollution rather than weather, Herrnstadt and Muehlegger (2015) exploit daily variation in wind directions in Chicago and find that higher levels of air pollution increase rates of violent crime, but not of property crime. This is consistent with evidence from psychology suggesting that air pollution causes discomfort which itself leads to antisocial behaviour.

[5] 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. See https://www.issafrica.org/crimehub/about

Figure 1: South African police wards



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

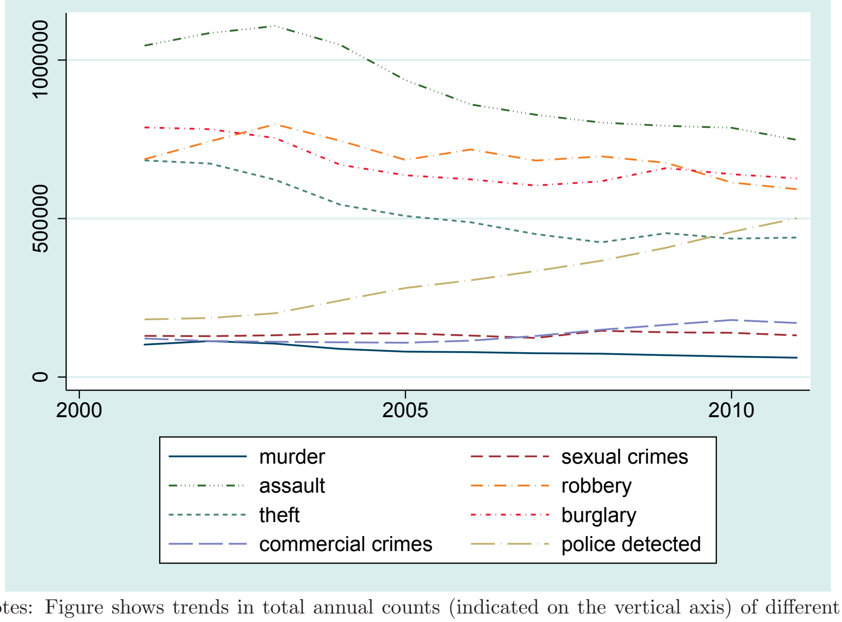
- $murder_{ipmy}$: includes attempted murder and murder;
- $sexualcrimes_{ipmy}$: includes abduction, attempted sexual offences, contact sexual offences, rape, sexual assault, and sexual offences due to police action;
- $assault_{ipmy}$: includes common assault, and assault with the intent to inflict 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, car-jacking 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;
- $stealing_{ipmy}$: includes all crimes that involve the taking of property, i.e., all types of robbery, burglary, theft and commercial crime.[6]

[6]This aggregate is not equivalent to the commonly used term *property crime*, because *property crimes*

- $nonstealing_{ipmy}$: 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 2 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.

Figure 2: Crime trends



Notes: Figure shows trends in total annual counts (indicated on the vertical axis) of different types of crime in our records for our sample period running from 2001 to 2012 (along the horizontal axis). Crime types are described in the main text.

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

do not include any violent crimes that involve the taking of property, such as robbery.

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 differences between reported and actually committed crimes are uncorrelated with the weather. Certain weather conditions, though, 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 comprise 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.

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 has to 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.

In order 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 settlements 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,[7] 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.

2.2 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, which are interpolated into grid cells of 0.5 × 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. We

[7]http://www.gap.csir.co.za)

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.

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 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.[8] 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 $\frac{2}{5} = 0.4$ 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 Geographic Information System (GIS) 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.

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

Table 1: Summary statistics of weather variables

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) 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
$drought_{ipmy}$	152,550	0.03	0.08	0.00	0.60

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

3 Empirical specification and identification

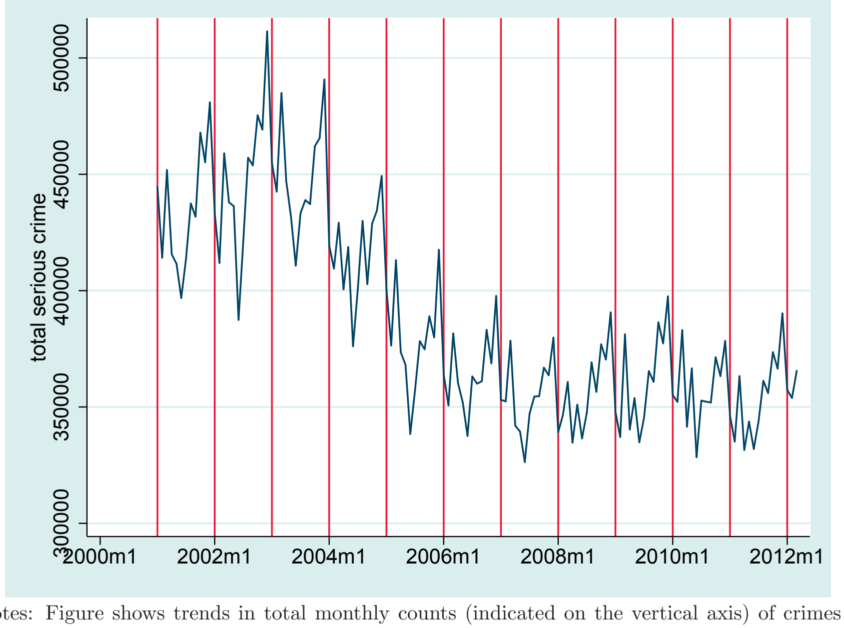
We use two different specifications for our short-term and mid-term analysis, respectively. First, we exploit exogenous variation in weather over time within spatial zones. In our baseline specification we regress the logarithm of crime counts $ln(crime_{ipmy})$ in police ward i in province p in calendar 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 α_i, a calendar-month-by-province fixed effect γ_{pm}, and a year fixed effect β_y:

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

$crime_{ipmy}$ can be the count of all serious crimes ($totalcrime_{ipmy}$), 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 δ on our weather variables as percentage changes in crime counts due to unit changes in our weather variables.

By including police ward and year fixed effects we capture the effect of extraordinary weather events, not the effect of weather conditions per se. Our estimates therefore constitute a conservative estimate of the weather-crime relationship. 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 criminal behavior, and any possible changes in central crime reporting conventions. The calendar-month-by-province fixed effects account for province-specific seasonality. Figure 3 shows that there is indeed substantial seasonal variation in criminal activity in our data. Monthly total crime counts peak in the last months of the year, and have their 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. Some of these conditions vary across regions of South Africa, which is why we choose to control for a calendar-month-by-province interaction.

Figure 3: 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.

By including these fixed effects, we estimate the effect of weather deviations from the province-specific average for a given calendar month over our 11 (or 12) years observation period. The coefficient δ hence must be interpreted as the effect of a January (February, March, etc.) that is exceptionally hot or cold, wet or dry, given the average conditions for January (February, March, etc.) in the province. Because weather is exogenous and the fixed effects allow us to isolate the effect of weather from other drivers of criminal behavior, the coefficient δ can be interpreted as the causal effect of weather on crime.[9]

Because weather variation occurs over spatial areas with an extend beyond that of police wards, 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 zero beyond 500 km).

In a second specification, we analyze effects of drought during the local growing season

[9]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).

on lagged crime in order 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, 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.

4 Short-term effects of temperature and rainfall

4.1 Total crime

We investigate the short-term weather effects 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 4. 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%-level.

Table 2: Short-term weather effects on total crime

	(1)	(2)	(3)	(4)
	Dependent variable: $ln(totalcrime_{ipmy})$			
$maxtemp_{ipmy}$	0.0137***			
	(0.00236)			
$mintemp_{ipmy}$		0.0195***		0.0209***
		(0.00341)		(0.00348)
$rainydays_{ipmy}$			-0.00453***	-0.00523***
			(0.00110)	(0.00112)
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

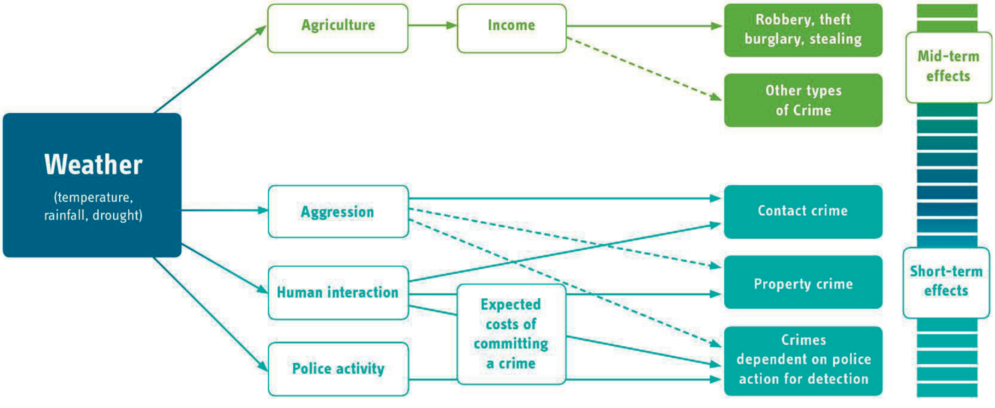
Notes: Linear fixed effects regressions on a panel of monthly observations of South African police wards, running from January 2001 to March 2012. All variables are described in the main text. Standard errors are robust to spatial correlation, with a uniform spatial weighting kernel function and a distance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

We exclude the wet days variable in Column (1) and (2). Here, 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. It is plausible to interpret daily maximum temperature as a proxy for daytime temperature peaks and daily minimum temperature as a proxy for nighttime temperature. 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 daily mean 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 of similar order of 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.

Figure 4: 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 those channels that are discussed in this paper.

4.2 Crime types

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 year fixed effects.[10] 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.

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: As daily minimum temperature rises by one standard deviation within an average month of the year, sexual crimes surge by more than 8.6 percent. By contrast, theft, commercial crimes and crime detected by police action appear not to

[10]For conciseness, we present here only 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.

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 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 would predict 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 and 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 these channels are indeed at work.

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.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable	$ln(murder_{ipmy})$	$ln(sexualcrimes_{ipmy})$	$ln(assault_{ipmy})$	$ln(robbery_{ipmy})$	$ln(theft_{ipmy})$	$ln(burglary_{ipmy})$	$ln(commercial_{ipmy})$	$ln(policedetect_{ipmy})$
$mintemp_{ipmy}$	0.0150***	0.0316***	0.0282***	0.0122**	0.00677	0.0145***	-0.00398	0.00784
	(0.00474)	(0.00480)	(0.00375)	(0.00549)	(0.00463)	(0.00403)	(0.00560)	(0.00768)
$rainydays_{ipmy}$	-0.00389**	-0.00339**	-0.00684***	-0.00593***	-0.00329**	-0.00334***	-0.00268	-0.00492*
	(0.00171)	(0.00158)	(0.00112)	(0.00189)	(0.00143)	(0.00121)	(0.00178)	(0.00255)
Observations	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
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. 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.

5 Mid-term effects: Weather and droughts

In this section, we examine weather effects that materialize through an income channel. 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. More specifically, we test if droughts induce criminal behavior (see also Figure 4). If drought conditions diminish agricultural yields, people whose livelihoods depend on agriculture may be unable to set aside sufficient resources to sustain them up to the next harvest. They may then 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) and (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. 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 evidence in support of an agricultural income channel linking crime outcomes to weather conditions.

To further scrutinize whether this interpretation is plausible, 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).

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). We now only find a weakly statistically significant coefficient on in $drought_{ipy}$ for the third quarter (of similar magnitude as for the rural sub-sample) for $stealing_{ipmy}$. We interpret this as another hint towards the hypothesized weather-agricultural income-crime channel, which would predict the drought effect on crime to be more pronounced in rural areas, where a larger share of livelihoods depend on agriculture.

We now 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), now using specific crime types as dependent variables. Results are presented in Table 6, 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 6 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.

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

	(1) Jan-March	(2) Jan-March	(3) Apr-Jun	(4) Apr-Jun	(5) Jul-Sept	(6) Jul-Sept	(7) Oct-Dec	(8) Oct-Dec
	Panel A - Dependent variable: $ln(stealing_{ipmc})$							
$drought_{ipy}$	0.107	0.0702	0.225**	0.218**	0.256**	0.250**	0.240**	0.241**
	(0.117)	(0.119)	(0.0897)	(0.0905)	(0.113)	(0.114)	(0.105)	(0.106)
$mintemp_{ipmy}$		-0.00643		0.0120*		0.0129*		0.0107
		(0.00856)		(0.00634)		(0.00701)		(0.00836)
$rainydays_{ipmy}$		-0.00402**		-0.00552**		9.66e-05		-0.00127
		(0.00164)		(0.00237)		(0.00278)		(0.00180)
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: $ln(nonstealing_{ipmc})$							
$drought_{ipy}$	-0.0599	-0.0998	0.0664	0.0558	0.133	0.128	0.114	0.108
	(0.131)	(0.133)	(0.111)	(0.111)	(0.105)	(0.103)	(0.125)	(0.124)
$mintemp_{ipmy}$		0.00844		0.0193***		0.0262***		0.0125
		(0.00771)		(0.00737)		(0.00665)		(0.00795)
$rainydays_{ipmy}$		-0.00417**		-0.00681***		-0.00982***		-0.00510**
		(0.00194)		(0.00258)		(0.00288)		(0.00225)
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-March	(2) Jan-March	(3) Apr-Jun	(4) Apr-Jun	(5) Jul-Sept	(6) Jul-Sept	(7) Oct-Dec	(8) Oct-Dec
	Panel A - Dependent variable: $ln(stealing_{ipmc})$							
$drought_{ipy-1}$	0.360***	0.346***	0.149	0.156	-0.00108	-0.00600	-0.0368	-0.0347
	(0.121)	(0.121)	(0.112)	(0.113)	(0.106)	(0.106)	(0.107)	(0.107)
$drought_{ipy-2}$	-0.00172	0.00466	-0.0594	-0.0573	0.0357	0.0412	-0.0983	-0.0936
	(0.127)	(0.128)	(0.0873)	(0.0868)	(0.102)	(0.102)	(0.0976)	(0.0990)
$mintemp_{ipmy}$		-0.00571		0.0106*		0.00771		0.00499
		(0.00899)		(0.00632)		(0.00782)		(0.00971)
$rainydays_{ipmy}$		-0.00261		-0.00526**		-0.00165		-0.00139
		(0.00161)		(0.00264)		(0.00280)		(0.00199)
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: $ln(nonstealing_{ipmc})$							
$drought_{ipy-1}$	0.146	0.138	0.124	0.134	0.152	0.133	-0.00190	0.00599
	(0.0965)	(0.0986)	(0.137)	(0.137)	(0.114)	(0.112)	(0.119)	(0.117)
$drought_{ipy-2}$	0.0980	0.108	0.0357	0.0440	-0.0213	0.00564	-0.0302	-0.0177
	(0.0927)	(0.0919)	(0.0945)	(0.0954)	(0.0889)	(0.0885)	(0.0765)	(0.0762)
$mintemp_{ipmy}$		0.0176**		0.0265***		0.0304***		0.0116
		(0.00780)		(0.00765)		(0.00735)		(0.00881)
$rainydays_{ipmy}$		-0.00589***		-0.00763***		-0.00938***		-0.00505**
		(0.00179)		(0.00290)		(0.00278)		(0.00243)
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.

Table 6: Medium-term effects of drought during most recent growing seasons on various types of crime

	(1) Jan-March	(2) Apr-Jun	(3) Jul-Sept	(4) Oct-Dec
	Dependent variable: $ln(murder_{ipmc})$			
$drought_{ipy}$	-0.169	-0.322*	-0.203	-0.131
	(0.186)	(0.194)	(0.201)	(0.209)
	Dependent variable: $ln(sexualcrimes_{ipmc})$			
$drought_{ipy}$	0.0444	-0.0773	0.0572	-0.319*
	(0.165)	(0.191)	(0.188)	(0.179)
	Dependent variable: $ln(assault_{ipmc})$			
$drought_{ipy}$	-0.0902	0.134	0.0733	0.132
	(0.185)	(0.138)	(0.136)	(0.147)
	Dependent variable: $ln(robbery_{ipmc})$			
$drought_{ipy}$	0.284	0.463**	0.707***	0.399**
	(0.208)	(0.206)	(0.173)	(0.199)
	Dependent variable: $ln(theft_{ipmc})$			
$drought_{ipy}$	0.244	0.154	0.198	0.0578
	(0.177)	(0.172)	(0.203)	(0.183)
	Dependent variable: $ln(burglary_{ipmc})$			
$drought_{ipy}$	0.0664	0.0977	0.127	0.207
	(0.141)	(0.129)	(0.151)	(0.152)
	Dependent variable: $ln(commercial_{ipmc})$			
$drought_{ipy}$	-0.0955	-0.138	-0.00120	-0.0162
	(0.237)	(0.199)	(0.202)	(0.235)
	Dependent variable: $ln(policedetect_{ipmc})$			
$drought_{ipy}$	0.0298	0.0499	0.203	0.346
	(0.232)	(0.230)	(0.250)	(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.

6 Conclusions

This paper has provided evidence on 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 found for increasing temperatures on violent crime. Property crime, in contrast, does not respond to temperature. Rainfall has a negative effect on both violent and property crime, which is however less pronounced than the effect of warm temperatures. This finding is in line with the heat-aggression hypothesis. A limitation to our analysis yet is that the monthly resolution of our crime data does not allow for detecting effects of short-term peaks in temperature or rainfall. We are hence certainly unable to capture the full heat-aggression effect.

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

Our findings have very tangible policy implications. The evidence of an agricultural income-crime channel demonstrates that better non-agricultural job opportunities and insurances to smooth income shocks can be helpful components of a holistic crime prevention strategy. For obvious reasons, however, such measures will only bear fruits in the longer term. As regards strategies to curb crime rates in the nearer future, the strong effect that warmer temperatures have on violent crime suggests that weather forecasts might be incorporated into policing allocation plans. This recommendation holds irrespective of the specific mechanism; even if it is not the heat-aggression channel that mediates weather and crime, because of weather being exogenous the relationship can be interpreted as causal. Hence, during exceptionally hot weather episodes, more police could be deployed, especially at neuralgic locations. 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 and in which potential offenders may have different discount rates than in South Africa. More work, including experimental research, is needed to probe into these linkages in the specific South African context. Our lessons might be taken on board in the future thinking and the design of future research on how to improve prevention policies in South Africa.

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Appendix

Table A.1: 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
1.7.1,4,5 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 A.2: Medium-term effects of drought during most recent growing season on crime, including urban and rural police wards

	(1) Jan-March	(2) Jan-March	(3) Apr-Jun	(4) Apr-Jun	(5) Jul-Sept	(6) Jul-Sept	(7) Oct-Dec	(8) Oct-Dec
	Panel A - Dependent variable: $ln(stealing_{ipmc})$							
$drought_{ipy}$	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: $ln(nonstealing_{ipmc})$							
$drought_{ipy}$	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.