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Social Policies and Adaptation to Extreme Weather: Evidence from South Africa

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Abstract

Can social policies assist households in coping with the effects of extreme weather events? We evaluate the role of the Indigent Program, an income-based social assistance program in South Africa that provided free electricity and water to poor households, in helping rural households adapt to drought conditions, using household-level panel data. We first analyse the impact of eligibility for the program on the likelihood of acquiring access to electricity and piped water, as well as on expenditure on these amenities, and find that program eligibility did not have a significant impact on these measures. While eligibility for the program was largely ineffective in increasing appliance adoption, electricity use, or welfare, we find that eligible households were more likely to use a borehole as their main water source, a result primarily driven by drought-affected households, suggesting a possible adaptation response facilitated by the program. In general, the benefits offered by the program may have only been marginal in facilitating significant adaptation responses, exacerbated by the fact that households in drought-affected areas may not have enough assets/wealth to purchase durables, or to make complementary investments. Policy implications relate to the effective design of policies to enable access and use of amenities such as electricity and water, and easing access to credit to facilitate adaptation responses, as climatic conditions intensify.

JEL Classification: O13: Q01: Q54

Keywords: Adaptation; Social policies; Electricity; Water; Droughts; Impact evaluation; South Africa

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1 Introduction

Adaptation has been recognised as an inevitable margin of response to extreme weather events and climate change; even if countries were to reduce emissions significantly in the coming decades, global warming is underway, and societies would need to adapt to the climate change that is already taking place. Recent research has hows that even if mitigation policies were followed, we may fail to achieve the targets set out in the Paris Agreement in 2015 (Diffenbaugh and Barnes, 2023). This further magnifies the importance of adaptation behavior, and an understanding of how to strengthen these responses.

Adaptation responses are even more pertinent for developing countries. Developing countries are known to be particularly vulnerable to climate change: firstly, it is documented that the economic effects of climate change are more intense and occur with higher frequency in these countries, partly due to geographical reasons (Tol, 2018; N.S. and Burke, 2019). Secondly, they lack resources, and often the institutional capacity, to withstand the negative effects of climate change, particularly the lower-income groups within these countries. Adaptation, thus, acquires a heightened importance in these settings. Adaptation behavior can take several forms in developing countries. Building resilience to climate change in low and middle-income countries involves developing stronger coping mechanisms within the rural (agricultural) sector (such as better irrigation, adoption of better seeds, etc.), as well as improving access to amenities (such as electricity and water), high-quality healthcare, finance, and telecommunications.

The question that then arises is, can policy play a role in reducing the vulnerability of households to climatic events? In this study, we evaluate the impact of a social policy meant to provide support to low-income households in South Africa, the Indigent Program, in enabling them to withstand the effects of a pervasive extreme weather event, namely drought. Sub-Saharan Africa experiences one-third of the world's droughts, and is vulnerable to extreme weather, due to its heavy reliance on rain-fed agriculture (IMF, 2021). South Africa has been vulnerable to droughts for almost the last four decades, and their frequency, intensity and duration is expected to increase as climate change advances (Meza et al., 2021). In recent years, droughts have been relatively pervasive events that have affected most, if not all, of the South African population (World Bank, 2023). For these reasons, we focus on droughts in this study.

The social program that we evaluate is the Indigent Program of South Africa. The Indigent Program primarily provides a certain amount of grid-based electricity (usually 50 KwH per household per month) and water (at least 6 kL per household per month) for low-income households in South Africa either for free, or at heavily subsidised rates.[1] Thus, this program was designed to enable poor households to use amenities more extensively. Theoretically, program eligibility may incentivise households lacking access to these services to acquire them (on the extensive margin). It may also compel households that already have an electricity or water connection at home to use these services more intensively (on the intensive margin). With greater use of electricity and water, households can theoretically use more appliances and water, that may directly help them in coping with the effects of events such as droughts. They

[1]The program also enables poor households to access free sewerage and sanitation services in some municipalities. In this paper, we choose to focus on the electricity and water provisions of the program. We think that this is an appropriate approach, given that a) it is implausible that subsidised sanitation services can help households in adapting to extreme weather events, and b) our data does not have detailed information on sewerage services or sanitation.

can also glean indirect benefits from these amenities, such as improvements in employment opportunities, quality of life, as well as welfare (as has been shown by Khandker et al. (2009, 2014) and Lipscomb et al. (2013) in the case of electricity, and Devoto et al. (2012) for access to water, particularly piped water services).

Electricity access and use is a promising means for poor households in developing countries to build resilience against extreme weather events and climactic shocks. As electricity consumption increases in response to climate change (Li et al., 2018), households often invest in appliances such as refrigerators, electric stoves, or ventilators and air conditioners that can enable them to cope with these shocks. Such durables enable households to directly deal with the effects of climate change: for e.g., fridges can help households to store food, in the midst of drought-conditions, that often lead to high food prices. Borehole pumps can facilitate drawing groundwater, and thus replenish reduced water supplies during times of drought. Moreover, given that several households still lack electricity access in Africa (World Bank, 2021), ensuring that most households have electricity connections is one means to strengthen adaptation. In this paper, we will focus on grid-based electricity access, even though decentralized solutions have emerged as a viable alternative in recent years.[2] Likewise, water use is also relevant in building the capacity to withstand climate shocks. Access to a clean and reliable water supply can theoretically improve health outcomes and life-satisfaction, and importantly also lead to considerable time-savings (Devoto et al., 2012). In the presence of extreme weather events such as droughts, access to a clean and reliable water supply is pivotal.

While one margin of adjustment for households, in response to events such as droughts, is to migrate (Albert et al. (2021), for example, show this using data from Brazil), for other households, acquiring electricity and water access, as well as use, remain an important means to adjust to the effects of climate change in the short-run, especially if climate-vulnerable households are unable to relocate without incurring significant costs (Delaporte and Maurel, 2016; Castells-Quintana et al., 2018). On the other hand, households who are intensely affected by climate events may theoretically be unable to reap these benefits, largely because extreme weather events may erode their assets, and thus their ability to invest in welfare-enhancing appliances, or make other investments that are needed to benefit from access to amenities (Lee et al., 2020a). We focus, in this study, on analysing these types of responses, given a low prevalence of migration in our sample.[3]

We have four key research objectives in this paper: firstly, we want to evaluate the impact of eligibility for the Indigent Program in facilitating access to grid electricity as well as piped water for rural South African households. Secondly, we would like to investigate whether program eligibility resulted in gains for households in terms of appliance ownership, or electricity or water use, behaviors which have adaptive potential. Thirdly, we want to analyse whether households who are affected by extreme weather events, such as droughts, experienced any of these benefits on being eligible for the program. Finally, and in more general terms, we would like to shed light on whether gaining access to, or spending on, electricity and water facilitated socioeconomic gains for households in rural South Africa, and whether these effects varied for

[2]Electrification may be extended either through centralized/grid-based, or through decentralized renewable-based solutions, the adoption of which, in particular, picked up between 2010 and 2019: the number of people connected to mini grids more than doubled during this period across developing countries (IEA et al., 2019). In this paper, we focus on grid-based electricity access.

[3]About 3-4% of the households migrated across districts in both the data samples that we use for our analysis, during the period of study.

drought-affected households.

If climate change attenuates the ability of households to benefit from electrification or from acquiring a water connection, policy should be designed not just to extend access to households, but it should also support households in purchasing appliances and energy services, or other ancillary services. A policy that enables vulnerable households to acquire affordable access to electricity could, theoretically, support households through these negative effects, and act as a buffer. However, it may only result in limited gains if households are unable to capitalize on acquiring a grid connection (by purchasing durable goods, for example). To the best of our knowledge, studies in the economic literature have not evaluated the relationship between extreme weather events and of electricity and water use as means of adaptation for households in developing countries, and thus have not been able to shed light on the role of policy in facilitating adaptation either.

We first use a regression discontinuity design (RDD)-based approach to understand whether the Indigent Program was effective in increasing electricity and piped water access among rural South African households, and whether receiving it incentivised households to spend on electricity and water. We evaluate this overall effect for rural households in the year 2017, and then evaluate the impact for households living in areas affected by droughts, and those areas relatively unaffected by them. South Africa experienced a severe drought in the year 2017, which makes this a suitable year for this analysis. We then estimate the effect of being eligible for the program on measures of appliance ownership, electricity and water use, as well as welfare to analyse whether the program may have yielded some benefits for households along these dimensions. We, again, do this analysis for all rural households, as well as separately for drought-affected as well as drought-unaffected households.

We find, using a reduced-form approach, that eligibility for the program did not significantly increase the likelihood of rural households acquiring access to electricity or piped water, or on their likelihood of spending on these amenities. These effects were observed for both households living in drought-struck areas, as well as for households that were relatively protected from drought conditions in the year 2017. However, our second set of reduced-form results show that Indigent Program-eligible households were more likely to use a borehole as their main source of water. We find that this effect was largely driven by drought-affected households, who were presumably more likely to a borehole pump to extract ground-water in response to drought conditions. This may have been one channel for drought-affected households to use the program to adapt to the effects of extreme weather. On the other hand, we find that eligible households were not significantly more likely to use electricity for functions such as lighting, cooking, or heating, and they were not more likely to own appliances such as fridges or electric cook-stoves, effects which are persistent for both drought-affected as well as drought-unaffected households. Furthermore, we do not find any evidence that program eligibility increased household consumption expenditure.

These results suggest to us the possibility that households may have used the program to acquire borehole pumps, in response to drought conditions in the year 2017. However, in order to provide evidence on whether amenities enable adaptation, it is important to use panel data to understand changes in behavior over time, in response to changing climatic conditions (Auffhammer and Mansur, 2014). In the second part of this study, we estimate the impact of acquiring access to both amenities, as well as spending non-zero amounts on both, on various household-level socioeconomic outcomes related to employment and health, using a staggered difference-in-difference approach and panel data over five years, and also analyse how these effects vary for drought-affected households. We adopt a staggered difference-in-difference methodology proposed by Chaisemartin and D'Haultfœuille (2020) to account for treatment times varying across households (since households could acquire access to amenities, or start to spend on them, in different periods).

We find that both access to electricity or piped water, as well as expenditure on them, increased the likelihood of households growing crops, and that this effect was driven by drought-unaffected households. We do not observe the same for drought-affected households. However, we also find that electricity or piped water access had a positive effect on monthly consumption expenditure, an effect that may have been slightly stronger for drought-affected households (even though insignificantly different from zero). We do not find any other significant employment or health-related gains for both sets of households.

Thus, drought-affected households are likely to have benefited from the Indigent Program, to the extent that it may have incentivised them to acquire borehole pumps to draw groundwater (even though we do not obtain evidence that they may have used this water to grow crops). However, we do not find consistent evidence that eligibility for the program, or electricity and water use, benefited this subgroup in any other way. In uncovering the reasons for these findings, we argue that the benefits offered by the program were marginal to engender any strong welfare gains. Households unable to afford appliances or to make complementary investments (such as in heating systems, or toilets) are likely to have been unable to benefit from this program, whether drought-affected or not. Given high unemployment rates in South Africa at the time (about 59% of our regression sample was unemployed), this can explain their inability to make investments, and thus, to benefit from the program. These effects may have been even stronger for drought-affected households, whose assets (such as land and livestock) were eroded due to droughts, which is likely to then undermine their intentions to purchase appliances or to use electricity or water extensively.

However, we also find that taking a loan did not increase the likelihood of households investing in appliances or using electricity or water, *except* for the use of boreholes, i.e., drought-affected households who took a loan were more likely to use a borehole, as compared to households that didn't borrow. Thus, the main positive effect of the program was largely driven by households who also borrowed. These findings resonate with other studies, which have also found that electricity access by itself may not yield significant socioeconomic gains, and may require further policy support to strengthen the ability of households to make additional investments (Burlig and Preonas, 2016; Lee et al., 2020b).

Borehole pump use is likely to be an important welfare-enhancer in the short-run, especially for drought-affected households. However, if a large number of households begin to draw on groundwater, drought conditions are likely to be exacerbated. We present suggestive evidence that higher rates of borehole adoption were associated with lower groundwater levels in our sample. While the effects on borehole adoption that we find in this paper are small, we recognize that they are likely to represent a form of 'mal-adaption', if pursued on a relatively large scale.

In terms of the literature, this paper seeks to bridge two relevant strands of studies in economics, 1) that has focused thus far on adaptation to climate change at a household level, and thus on the impact of climate change on various economic outcomes, and 2) on the determinants of electrification and access to water, and on their impact on economic outcomes.

A copious stream of literature has looked at the impact of climate change and extreme weather on several economic outcomes. This literature has largely focused on the effects of extreme temperature and rainfall on outcomes such as agricultural yields (Deschênes and Greenstone 2007; Schlenker and Roberts 2009; Schlenker and Lobell 2010): Auffhammer and Schlenker (2014) provide a comprehensive review, mortality (Deschênes and Greenstone 2011; Barreca et al. 2016), migration (Bohra-Mishra et al. 2014; Deschênes and Moretti 2009), conflict (Burke et al. (2015) provide a review), crime (Baysan et al., 2019) or health (Patz et al., 2005). Zivin et al. (2018) also find an effect for extreme temperature (particularly high temperatures) on test scores of children, using data from the US. A few studies have also found an association between extreme weather and energy use: for example, Auffhammer et al. (2017) found that extreme temperatures had had an effect on peak load electricity consumption in the US. As mentioned before, the literature on the use of electricity to adapt to the effects of climate change is relatively scant. Auffhammer and Aroonruengsawat (2011); Auffhammer and Mansur (2014); Rapson (2014); Davis and Gertler (2015); Davis et al. (2021) have evaluated the adoption of durables such as air-conditioners in response to extreme temperatures, both in industrialized countries as well as in a sample of developing countries. However, to the best of our knowledge, studies have not examined the effect of extreme weather either on the electricity access decision itself, or on how extreme weather alters the benefits that can be derived from electrification.

Another stream of literature relevant to this study has found ambiguous developmental effects of rural electrification (Jiménez (2017) provides a through review of many of these studies). Some of the early studies found that the effect of rural electrification on outcomes such as income and schooling can be positive (Khandker et al., 2009), and persistent (although diminishing) over time (Khandker et al., 2013). Khandker et al. (2009) also found, using cross-sectional survey data from Bangladesh, that rich households benefited more from acquiring electricity access, compared to poor households. Khandker et al. (2014) found that households in the highest quintile of income in India doubled their consumption expenditure relative to households in the middle quintile, on acquiring access to electricity. Dinkelman (2011) examined the developmental effects of electricity from a South African perspective, and found that rural electrification increased female employment, primarily through its role as a labor-saving technology shock at the household level that shifted female labour from home to outside work. She used land gradient as an instrument for electricity supply. In addition, Lipscomb et al. (2013) found that the effect of electrification on country-level development outcomes in Brazil (measured by housing values and the human development index) was also largely positive.

However, relatively recent papers that have used experimental or quasi-experimental identification approaches have found either a negative effect, or a non-effect for electrification in determining welfare outcomes. In a recent study, Lee et al. (2020b) provide experimental evidence to this tune from Kenya, whereby they find that electrification provided only marginal benefits to households at a relatively large cost, and Burlig and Preonas (2016) used regression-discontinuity and difference-in-difference based-designs to draw a similar conclusion using data from India. The latter study also found considerable heterogeneity in effect sizes, with larger villages benefiting more from electrification than smaller ones.

With respect to access to piped water, and the gains from it, the literature also finds heterogeneous effects: Devoto et al. (2012), for example found, using a randomised controlled trial in Morocco, that demand for private piped water connections was high, and households, while unlikely to experience gains in labor market participation or income, or experience significant health improvements, were likely to experience improvements in their quality of life, on acquiring a connection. Jalan and Ravallion (2003) use propensity score matching to find that access to piped water significantly reduced the risk of children in households developing diarrhoea, as well as reduced its duration. In a recent study, Fan and He (2023) also find improvements in infant health on using piped water in China, and they argue that the social benefits from extending piped water throughout rural China are greater than the costs.

The main contributions of this study, with respect to this literature, are two-fold: firstly, this is one of the first studies, to our knowledge, to conduct an evaluation of the Indigent Program, a vital social program for ensuring access to basic services among poor, rural households in South Africa. Secondly, it is the first study, to the best of our knowledge, to provide causal evidence on the role of a policy, and more specifically on electricity and water access and use, in enabling household adaptation to extreme weather conditions. While other studies have evaluated the adoption of appliances in response to changing climatic conditions, this is the first study to analyse how households facing extreme weather events can use amenities to obtain socioeconomic gains (if at all) that may help in coping with shocks such as droughts. The Indigent Program, theoretically, may have enabled households to build resilience to climate change and extreme weather, because it provided benefits in using amenities that are equipped to directly address these shocks. We test this hypothesis in the study, and thus are able to delineate policy requirements to enable household adaptation. We seek to identify the underlying mechanisms for these results in our analysis, using rich household-level panel data, and the main results of the study are robust to several specification as well as placebo checks.

An important point that is made through this study is that programs such as the Indigent Program in South Africa may have the potential to enable poor households to adapt to droughts, but they may need to be accompanied by policies that make it easier for households to purchase durable goods such as appliances. Extreme weather events have a direct effect on household assets, and thus may make it difficult for households to adopt welfare-enhancing goods. In the absence of financial assistance, households may not be able to benefit from acquiring electricity: it may not be enough to offer limited free electricity to households facing negative shocks in the form of extreme weather. Enabling households to make investments in appliances and energy services (such as for cooking or heating) may require additional, concerted policy efforts (for example, through other social welfare programs, subsidies, education and employment policies, as well as other adaptation policies such as crop insurance, natural disaster insurance, etc.).

The rest of this paper is organised as follows: in section 2, we present a background on the Indigent Program and on extreme weather in South Africa, section 3 includes a description of the data and methodology of the study, section 4 presents the main empirical results, and section 5 presents the policy implications and concludes.

2 Background

2.1 Impact of Extreme Weather in South Africa

Climate change has not left southern Africa untouched, with the region having already witnessed climate events that are both more extreme, as well as that have larger impacts, than the global average (Engelbrecht et al., 2015). South Africa has an overall warm climate, with cool temperatures characterizing high-altitude areas, and it is a relatively dry country (the fifth most water-scarce country in sub-Saharan Africa), being located within a 'drought belt'. Average annual precipitation in South Africa is about 464 mm, whereas average temperatures in South Africa range from 15℃ to 36℃ in the summer and -2℃ to 26℃ in the winter. The mean annual temperature for South Africa as a whole is 17.5℃ (Climate Change Knowledge Portal, 2021).

However, in the past years, extreme weather has become more common; on the one hand, parts of South Africa have experienced more frequent heatwaves and higher temperatures (van der Walt and Fitchett, 2021; Fitchett, 2021); on the other hand, variable rainfall has resulted in frequent droughts (Sousa et al., 2018). There is also a growing trend towards an increase in the intensity of rainfall events interspersed with prolonged dry spells, a sign of high inter-annual variability in precipitation. South Africa has also been vulnerable to El-Nino induced droughts (Malherbe et al., 2020), which, combined with the higher temperatures, have lead to increased evaporation and decreased stream flows, thereby exacerbating already existing water shortages (Climatelinks, 2017).

Climate change predictions show that by 2050, the interior parts of the country will witness significant warming (5-8°C), while the west and south of the country are likely to experience severe dry conditions (with the threat of wetter conditions along the eastern part of the country) (Zwane and Montmasson-Clair, 2016). It is thus clear that extreme weather events (such as droughts) pose a grave threat to South Africa's agriculture and water resources, food security, health, infrastructure, ecosystem services and biodiversity (Climatelinks, 2017). Agriculture in particular can be expected to suffer from the effects of climate change such as droughts, increased evaporation rates, changes in temperatures and proliferation of pests and diseases, which are likely to result in reduced yields. In particular, yields of staple crops such as maize and wheat are expected to decline by 2050.

2.2 Indigent Program in South Africa

Electrification rates in South Africa are higher than in other parts of sub-Saharan Africa; they increased from 35% in 1990 to 85% in 2019 (GNESD Energy Access Knowledge Base, 2019; World Bank, 2019), driven partly by the ending of the Apartheid regime in 1994 and the subsequent rise of a democratically-elected government, and partly by the cross-subsidisation from industrial users. Eskom, a state-owned entity, is the single largest generator/supplier and distributor of electricity in South Africa (generating almost 95% of its electricity), and incidentally, it alone is also responsible for almost half (42%) of South Africa's greenhouse gas emissions (Bloomberg Law, 2019). This is primarily because of South Africa's reliance on coal as a source of power: as of 2019, coal accounted for about 83% of installed capacity in South

Africa (58GW), followed by wind and solar (8%), and hydropower (6%), with the rest including nuclear, geothermal etc. accounting for less than 3% (USAID, 2023).

The Integrated National Electrification Plan (INEP) was launched in 2001, as a part of which Eskom as well as registered municipalities received funding from the Department of Energy (DEA) to extend both grid as well non-grid electricity access across South Africa (Energypedia, 2021). Under the INEP, the governments as well Eskom set a target of ensuring access to electricity for all formal households by 2025.

Remote areas of South Africa were prioritised to receive electricity access, and private firms were also encouraged to operate in these areas. While connection charges remained low (with the possibility to pay in installments available in many municipalities), the government realised that poor households were finding it difficult to be able to afford electricity use (GNESD Energy Access Knowledge Base, 2019). Thus, the Free Basic Electricity (FBE) scheme was introduced in 2004, with the national government providing the majority of the funding, and Eskom and the local governments plugging the gap to fund the remaining connections (Energypedia, 2021). Under this scheme, municipalities subsidized up to 50 KwH per month of electricity consumption of households (with many municipalities providing up to this much electricity for free, or at subsidised rates, to households every month).

These subsidies were only offered to households that were eligible, namely households that qualified as being 'indigent households'. Municipalities would set a household income threshold, and all households that earned less than this threshold were eligible for benefits. Likewise, in 2001, South Africa launched the Free Basic Water policy providing 6kL of free water per household per month, and along with the FBE, this was another component of what was collectively known as the Indigent Program. It is important to note that the provision of free water within this program is different from many other countries, where households still need to pay a fixed fee for the first units of water, while paying a zero marginal price (Szabo, 2015). It is important to note that the free water provision of the Indigent Program does not require households to have a private piped water connection: it is valid even for communal supplies of water, as long as they are within 200 metres of the households (Ruiters, 2018). This means that households could use their water allowance from the program to acquire both piped water, as well as water from a communal water supply. Water drawn from boreholes, on the other hand, is essentially free: households only needed to pay for the drilling costs, as well as electricity costs, if they use a borehole pump.

While municipalities are encouraged to provide free services to all eligible indigent households, a lack of funding or limited public resources have meant that some indigent households did not end up receiving their benefits. Each municipality has its own income-based threshold to determine the indigent status of households. They also have the freedom to decide how much to subsidise them (South African Government, 2021). In order to receive the benefits, households must first register themselves with the municipalities. Once their applications are approved, they are granted indigent status, but they are required to reapply for this status every year (since it is plausible that economic conditions might improve for households over time). Households need to submit certified copies of their proof of income if they are employed (or a sworn affidavit if unemployed) in order to be eligible for the program (along with identity documents, birth and death certificates, marriage and divorce certificates, etc.).

The 50 KwH free electricity allocation, while not a lot, was considered enough to "to run basic lighting, basic media access, basic ironing and boil water using an electrical kettle" (CRAM, 2021). Any consumption above 50 KwH per household per month is charged using a block-tariff regimen. Electricity connection fees in South Africa are also heavily subsidised: as of 2022, the Department of Energy subsidised 20A supplies, and therefore, either very low, or no connection fees, were charged in many municipalities for setting up a new point of delivery. Additional charges were valid, however, for upgrading connections, or adding connections. Water fees are also charged using a block-tariff, with any additional consumption beyond 6kL per household per month being charged at this rate.

3 Methodology and Data

3.1 Methodology

In this section, we describe the main empirical approaches used in this paper. As mentioned in the Introduction section, there are four main questions we are interested in answering in this study: firstly, what was the impact of eligibility for the Indigent Program in facilitating access to electricity as well as water for rural South African households? Secondly, did eligibility for the program result in households acquiring more appliances, or using electricity as their main energy source for different functions? Thirdly, do these effects materialize in a similar manner if households are affected by extreme weather events, such as droughts? Fourth, and more generally, does access to, or expenditure on, electricity and water facilitate socioeconomic gains for households, and how do these effects vary for drought-affected households? We explain the methodology adopted for answering each of these research questions in the sections below.

3.1.1 Impact of the Indigent Program on Socio-Economic Outcomes

First, we evaluate whether eligibility for the Indigent Program was successful in increasing 1) access to electricity, 2) access to piped water, 3) monthly expenditure on electricity, and 4) monthly expenditure on water for households in South Africa. This is a natural starting point to evaluate the program, because as mentioned in the previous section, eligible households could receive up to 50 KwH of free (grid) electricity, and up to 6kL of free water.[4] Theoretically, the program could have incentivised households without access to these amenities to acquire it. Households then have the option of either consuming the minimum amount of electricity and water for which they are eligible for free, or of consuming more than these thresholds, and spending on the additional units that they consume. Thus, even for households that have already acquired access, eligibility to the program is likely to loosen budget constraints, and it may allow them to spend more on these amenities, given that they receive an effective subsidy on their total consumption. For this reason, we consider these four outcome variables.

Next, we consider the impact of eligibility for the Indigent Program on a range of outcome variables related to the use of electricity and water, appliance adoption as well as welfare. These models help us to evaluate whether eligible households responded to the program, by

[4]We focus on the use of piped water, because while water collected from communal taps was also eligible for the benefits, we do not have municipality-level information in our data on how the costs are split across households, whether a meter is installed to measure consumption, etc.

either investing in durables that use electricity (such as fridges or electric cook-stoves), in using electricity as the main energy source for different functions (such as for lighting, heating and cooking), or in using water for different functions (such as by having a toilet at home, or pursuing subsistence agriculture). Importantly, we also estimate the impact of program eligibility on the use of boreholes as the main water source. Boreholes are ubiquitous in many parts of South Africa, and they provide households the possibility to draw on groundwater reserves, which may be a form of adaptation behavior in dry areas. As mentioned in the Background section, households do not pay any fees for the water acquired from a borehole. Thus, it is likely that if we find any effect of eligibility on borehole adoption, it will be driven by the free electricity provision of the policy. Lastly, we also evaluate the role of program eligibility on monthly consumption expenditure.

Given that households with monthly income less than a certain threshold were eligible for receiving benefits within the program, we employ a parametric reduced-form regression discontinuity design (RDD) approach for estimating these models. In this paper, we focus on deriving reduced-form RDD estimates rather than the local average treatment effect-based estimates. The two main reasons for this are, firstly, the reduced-form estimates are sufficient for us to assess the impact of the Indigent Program on both take-up of electricity and water services, as well as on other socioeconomic outcomes. Secondly, the literature suggests that reduced-form models are preferable with potential weak-instrument problems (Gerardino et al., 2017; Chernozhukov and Hansen, 2008; Feir et al., 2016). Weak instrument problems may arise due to several reasons in this setting. Firstly, eligibility for the program does not warrant that households will receive benefits from the program: households still need to go through the application procedure, and it is not certain that they will receive access even after submitting their documents, for instance, due to administrative or budget-related reasons. They may not even be aware of the benefits that they can receive, or they may have already acquired an electricity connection. Thus, we estimate reduced-form models to evaluate the program effects. In these estimations, we restrict the sample to the year 2017 (which was also a year of severe drought), the most recent year in our data, and we focus on districts with income thresholds of either 1601 Rand (87 USD) or 3201 Rand (175 USD). This data sample comprises households belonging to 24 different districts of South Africa.

Thus, the models that we estimate will be the following:

$$\begin{aligned} A_{i,j} &= \alpha_0 + \alpha_1 Z_i + \alpha_2 f(I_i) + \alpha_3 Z_i f(I_i) + \alpha_4 X_i + \nu_j + \mu_{,ji} \\ Y_{i,j} &= \beta_0 + \beta_1 Z_i + \beta_2 f(I_i) + \beta_3 Z_i f(I_i) + \beta_4 X_i + \lambda_j + \epsilon_{i,j} \end{aligned} \tag{1}$$

where the 'i' subscript denotes households, and 'j' denotes the district of residence. As equation (1) shows, we are firstly interested in estimating the effect of program eligibility on the likelihood of households either acquiring electricity and piped water access, as well as spending on these services. A_i denotes a vector of these four outcome variables, while Z_i is an indicator variable for monthly household income being less than the threshold that qualifies the household for the Indigent Program. I_i denotes the running variable, namely the negative of the normalized household income (the threshold value minus the income, with values above zero denoting households eligible for the program) in a narrow bandwidth around the threshold, and $X_{i,t}$ denotes other household and head-of-household specific covariates. ν_j and λ_j denote district fixed-effects, while $\mu_{i,j}$ and $\epsilon_{i,j}$ denote residuals. In the second part of equation (1), $Y_{i,j}$ denotes a vector of other socioeconomic outcomes (related to household welfare, durable ownership, and electricity and water use).

We consider two bandwidths in our main specifications for these models, namely 1000 Rand (55 USD) and 2000 Rand (109 USD), which have been chosen based on the income thresholds for the program in 2017 (namely, 1601 and 3201 Rand), with the former being our preferred bandwidth. In our main specifications, we use a linear polynomial in the running variable (following Gelman and Imbens (2019)), and we also employ a flexible functional form, whereby the effect of the running variable can be different, depending on program eligibility, i.e., we introduce an interaction term between Z_i and $f(I_i)$. We also use clustered standard errors. Additionally, we control for the district of residence, gender, age and educational attainment of the household head, household size, home ownership and whether the household receives any rental income. As robustness checks, we also use varying orders of polynomials, alternative functional forms, and non-parametric approaches.

These models will firstly be estimated for the overall sample of rural households in the year 2017. We will then estimate them by subgroup, i.e., we will estimate these models for households living in areas affected by drought, and for households unaffected by drought. For this analysis, we will construct and use a binary indicator for living in a drought-affected area (exact definition provided in the next subsection).

Assumptions of RDD

In this subsection, we discuss the conditions for the validity of the RDD estimation methodology, as well as the assumptions that need to be satisfied. The two main conditions that need to be satisfied to be able to apply the RDD methodology are a) the availability of a continuous running variable, and b) a clearly-defined cutoff point (or threshold). In our case, both of these assumptions are satisfied, given that the running variable is household income, and that we are able to obtain information on the thresholds at the district level for households in the 24 districts included in the data sample for 2017, which was either 1601 Rand or 3201 Rand. Households with monthly incomes lower than these thresholds were eligible for the Indigent Program, and thus for receiving up to 50 KwH of free electricity per month as well as 6kL of water per household per month.

The two main assumptions that need to be satisfied for the validity of the RDD methodology are a) that the distribution of potential outcomes varies continuously with the running variable around the threshold, and that there is no "manipulation" in the running variable, and b) that individuals close to the cutoff are very similar, on average, in terms of both observables and unobservables. While we can test for similarity in observables between treated and control groups, we need to assume similarity in unobservables, which is plausble given the relatively narrow bandwidth within which the RDD estimates are valid. We will discuss these two assumptions, and their relevance to our data, in the subsection below.

Assumption 1: No manipulation of the running variable

Either households themselves, or administrators of the program, can invalidate the assumption of continuity of the running variable, if they either strategically manipulate the running variable to be just below the cutoff (to receive free electricity or water in this case), or if the running variable is not determined exogenously due to other reasons, and this may create a discontinuity (or bunching to the right of the cutoff) in the distribution of the running variable.

Plausibly, households may have incentives to manipulate their incomes to receive the benefit of free electricity or water. Most municipalities have criteria for households to qualify as indigent households, and they need to submit certified copies of their proof of income if they are employed (or a sworn affidavit if unemployed) in order to be eligible for the program (along with identity documents, birth and death certificates, marriage and divorce certificates, etc.). This can, conceivably, make manipulation more difficult (or costly), in this setting. However, it is difficult to obviate the possibility that households (or even local administrative officials) would not manipulate incomes to be considered eligible for the program.

The standard approach to evaluate whether there are discontinuities in the running variable is the McCrary test (McCrary, 2008). The discontinuity estimate for our sample, according to this test, is equal to 0.547. Thus, we cannot reject the null hypothesis of no discontinuity in the monthly income at the threshold at the 5% level. On using the approach of local polynomial density estimators proposed in Cattaneo et al. (2020), the value of the T-statistic is 0.399 corresponding to a P-value of 0.69 on using our preferred bandwidth of 1000 Rand, and conventional standard errors, which implies that the null hypothesis of no manipulation of the assignment variable cannot be rejected. Thus, even though theoretically we cannot completely rule it out, empirical evidence suggests that the risk of a discontinuity in the probability distribution at the threshold may be low in this case. Figures A1 and A2 in Appendix A illustrate the results of the McCrary test as well as of the manipulation test proposed by Cattaneo et al. (2020) graphically.

Potential sorting, or manipulation of the running variable, does not necessarily invalidate the RDD methodology, unless it is very precise and widespread. Lee and Lemieux (2010) argue that as long as agents are unable to precisely manipulate the running variable (even if they have some imprecise control), in the RDD framework we can assume that the "variation in treatment near the threshold is randomized as though from a randomized experiment" (Lee and Lemieux, 2010). There is no evidence from our data that sorting, in this case, is done precisely or on a large scale. Furthermore, the results of both statistical tests confirm that there is no discontinuity in the running variable at the threshold, which validates the use of the RDD approach.

Assumption 2: Individuals on either side of the cut-off are very similar to one another

In order to test this assumption, we compare some household-level pre-determined characteristics in the vicinity of the cutoff, to examine whether they are locally balanced. Figure A3 in Appendix A shows some of these scatter plots. As these graphs suggest, there is no significant discontinuity in baseline covariates such as the gender of the head of the household (panel a)), age of the head of the household (panel b)), whether the household own their home (panel c)), or the level of educational attainment of the household head (panel d)). This points to the fact that the assumptions of local randomization may be met, in our case. Furthermore, in Table A1 in the Appendix, we provide the results of parametric RDD estimations, where we evaluate the reduced-form local effects of program eligibility on different socioeconomic covariates. These models are also estimated with local linear polynomials, using a bandwidth of 1000 Rand and 2000 Rand, and robust standard errors. We find that eligibility for the program was not associated with a significant change in most of the main socioeconomic variables, except for the likelihood of households living in a modern dwelling on using a bandwidth of 2000 Rand, i.e, Indigent Program eligible households were less likely to be living in a modern dwelling. However, in all other estimations, we find that eligibility for the program was not a significant determinant of any other socioeconomic covariates.

3.1.2 Impact of Electricity and Water on Socio-Economic Outcomes

The reduced-form RDD models help us to understand the role of eligibility for the Indigent Program on both electricity and water access, as well as on other outcomes related to the use of these amenities, in the most recent year of the NIDS data, 2017. This analysis enables us to understand the role that social policies can play in facilitating behavior that may have enabled households to build resilience to extreme weather events such as droughts. However, as the literature on the effects of climate change highlights, adaptation behavior is better modelled with the use of panel data methods that capture changes in behavior (and climate) over time.

To this end, one approach could be to use a staggered difference-in-difference methodology to evaluate the effect of program eligibility on different socioeconomic outcomes (given that it is likely that different households are 'treated' at different times). However, directly comparing eligible to ineligible households using this methodology is unlikely to be very fruitful, given that eligible households are also poorer by definition. Another possibility is to compare households that have access to electricity or piped water (or spend on either of these amenities), and those that do not. On controlling for Indigent Program eligibility, this empirical approach would yield estimates of the impact of acquiring (or spending on) these amenities on socioeconomic outcomes over time. By estimating this model separately for drought-affected households, we would be able to distinguish the role of amenities in facilitating adaptation behavior. Furthermore, we will be able to control for time-invariant unobserved heterogeneity across households, and obtain estimates of the impact of electricity or water access over the full support of household incomes (as opposed to the local effects we derived using the RDD model). The model that is estimate using this methodology is the following:

$$Y_{i,j,t} = \beta_0 + \beta_1 A_{i,t} + \beta_2 C_{j,t} + \beta_3 X_{i,t} + \eta_i + \mu_t + \epsilon_{i,j,t} \tag{2}$$

where $Y_{i,j,t}$ denotes a socioeconomic outcome for household 'i' living in district 'j' in year 't'. $A_{i,t}$ could denote one of two possible treatment variables, firstly whether household 'i' either had electricity access in period 't', or had access to piped water in period 't', and secondly whether household 'i' either spent on electricity or spent on water. $C_{j,t}$ denotes a district-specific time trend, $X_{i,t}$ denotes household-specific covariates, whereas η_i and μ_t denotes household and year fixed effects, respectively. $\epsilon_{i,j,t}$ denotes the residual term.

The coefficient of interest in this model is β_1, which represents the average treatment effect on the treated. Given that households acquired access at different points in time, using the classical diff-in-diff model that assumes a common treatment period across all units, in this setting, may result in biased estimates (Baker et al., 2022; Athey and Imbens, 2022; Chaisemartin and D'Haultfœuille, 2020, 2022). We thus choose to estimate a staggered diff-in-diff model following the methodology of Chaisemartin and D'Haultfœuille (2020).

First, we estimate a model evaluating the current effect of access to electricity/piped water (or positive spending on these amenities) on outcomes for households whose treatment status changes between period 't-1' and period 't'. The Chaisemartin and D'Haultfœuille (2020) estimator is a weighted average over time periods and over treatment values, of the effect of treatment on outcomes for households whose treatment changes from 0 to 1 compared to households whose treatment status stayed at 0 in both time periods, and for households whose treatment changes from 1 to 0, compared to households whose treatment status stayed at 1 in both time periods. Next, we also estimate this model by only considering households whose treatment status changed from 0 to 1 between period t-1 and period t, compared to households whose treatment status remained at 0 in both time periods. We call the first set of results the 'òverall" results, whereas the second set of results are for "switchers into treatment".

As outcome variables $Y_{i,j,t}$ in these estimations, we use measures of employment and health-related outcomes for the head of the household, as well as the log of monthly consumption expenditure. These measures are chosen to capture the broader gains from electricity or piped water access along various socioeconomic dimensions for households.

3.2 Data

3.2.1 Household data

The source for the household data used in this study is the National Income Dynamics Study (NIDS) panel dataset, collected by the Department of Planning, Monitoring and Evaluation and implemented by the Southern Africa Labour and Development Research Unit based at the University of Cape Town (DataFirst and University of Cape Town, 2021).

The NIDS dataset comprises information on a sample of South African households since 2008, with five years of data available (for the years 2008, 2010, 2012, 2014 and 2017).[5] The data has national coverage, and it spans all nine provinces, and all 52 districts (including 44 district municipalities, and 8 metropolitan municipalities) of South Africa in terms of geographic scope. The sample is nationally representative (CRAM, 2020), and comprises individuals who were contacted about once in two years, and asked questions about their income and employment status, ownership of durables and assets, educational activities, as well as other socioeconomic information.

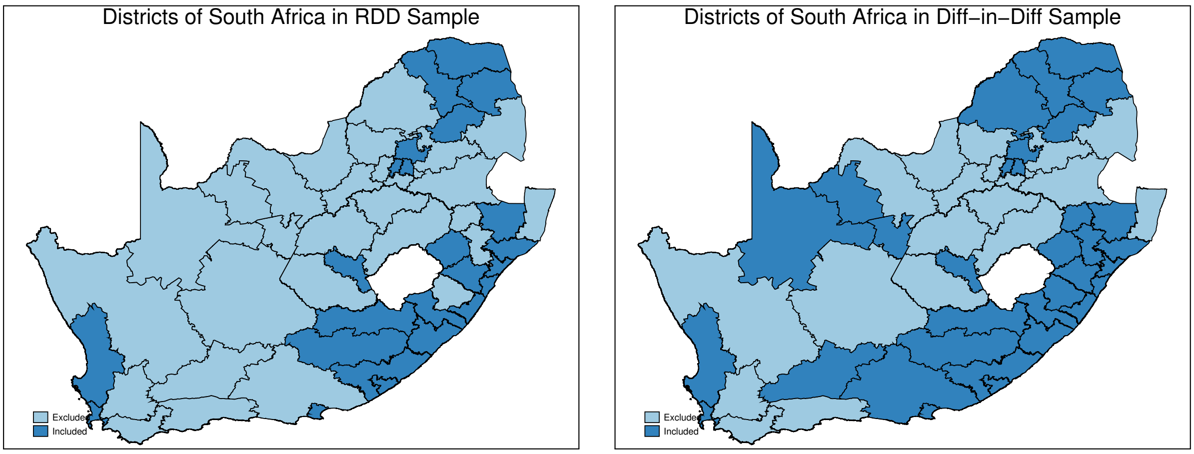
While the data contains information on households as well as their individual members, households are the unit of analysis for this study. It is plausible that households can split over time (for e.g., members can move out of their homes to start their own families), or they can reunite (if household members decide to move in together at a later date). In general, household members who split from their original household in a particular year are said to form their own households, and are treated as constituting a separate household from then on, in our analysis. If at some later point they move in with their 'original' household again, the newly-formed household is set to not exist from that year on.

As mentioned in Section 1, the sample for this study is focused on non-urban or rural households; this implies that we select those households that are categorised in the NIDS data as either living on farms, or in 'traditional' areas, in line with the nomenclature used in the Census 2011 in South Africa (Laldaparsad, 2021). According to this definition, farm households are

[5] An additional survey was also conducted in 2020 with a sub-sample of individuals from the 2017 survey, but this data has not been used in this paper. This is because the focus of the survey was on the coronavirus pandemic and its impact on individuals and households, and thus information on some of the important variables that I use in this study was not collected during this round of survey.

those that are involved in subsistence or commercial farming, whereas traditional households are those that live in rural areas that fall under the jurisdiction of traditional authorities (or erstwhile 'traditional chiefs'). The final sample is obtained after cleaning this data, taking into account non-missing values of the important socio-economic variables, and top-trimming the sample for outliers (i.e., dropping the observations having normalised income exceeding the 99th percentile). Note that the final data set is an unbalanced panel. Figure 1 shows a map of South Africa, with the districts that are included in the RDD analysis described in the previous subsection, shown in a darker shade of blue in figure (a), and the same for the diff-in-diff sample in figure (b). The rates of inter-district migration in our sample are relatively low: in the RDD sample, about 4% of the households changed their district of residence between 2014 and 2017 (i.e., in consecutive years in our data), whereas this share is 3% in the diff-in-diff sample. For this reason, we do not believe that the risk of migration in response to droughts is likely to bias our results.

There are two sets of explanatory variables that are used in the models in this paper; those captured at a household level, i.e., the information in these variables is common across all individuals in a household (such as whether the household has access to grid electricity), as well as some variables that capture information that may vary across individuals in a household (such as gender, age, etc.). For the latter category of variables, we collect information only on the heads of the households. The explanatory variables in the main models include some standard socioeconomic controls (such as for household size, gender of the head of the household, whether the household owns their home, etc.) as well as other important individual and household level controls (more details on these variables are provided in section 3.2.3 below). The data on the income thresholds for Indigent Program eligibility was collected from the Stats South Africa website, from the 'Non-financial census of municipalities' files for each respective year (Statistics South Africa, 2021).



(a) RDD Sample

(b) Diff-in-Diff Sample

Figure 1: Districts Included in RDD and Diff-in-Diff Samples

3.2.2 Drought Data

In this study, we construct and use one main extreme weather-related variable, namely an indicator for droughts. As control variables in some models, we also use indicators for hot and cold temperature. More details are provided on the data sources for these three variables below.

There are several methods to measure droughts, as well as drought intensity. The simplest type of index compares the amount of rainfall in a specific time-frame to the historical average, or counts the number of days in a year without any precipitation. However these measures do not provide any information on the intensity, duration or the relative severity of the drought. Another commonly used measure is the Standarized Precipitation Index (SPI), which relates actual precipitation to the median historical precipitation over several time periods. While this is a more advanced measure than the previous ones, it is also uni-dimensional like the other measures, in that it only focuses on rainfall as a predictor of drought.

One of the most common indices to measure drought is the Palmer Drought Severity Index (PDSI) (PennState University, 2022). The PDSI is defined to measure both the duration and intensity of long-term drought based on time series of precipitation, temperature, as well as data on water content. It also takes into account soil/surface characteristics of each location. Thus, not only is it a more holistic measure to pick up the effects of global warming (through potential evapotranspiration), but it is also useful at quantifying long-term drought (NCAR Climate Data Guide, 2021). However, one of the limitations of this measure is that it may not be as comparable across relatively large regions as the SPI; the self-calibrating PDSI (scPDSI) is a variant of the PDSI that partially alleviates this concern (Wells et al., 2004). We use the self-calibrating PDSI as our measure of drought. This data is drawn from the Climatic Research Unit (CRU) TS 4.05 database, which provides scPDSI values from 1901-2020 at a 0.5° latitude and longitude resolution (Climatic Research Unit, 2021). The scPDSI typically varies between -4 and 4, with a value of -4 (or lower) denoting extreme drought conditions, and a value of 4 (or more) denoting extremely wet conditions (Wells et al., 2004). In the main regression models evaluating the heterogeneous effects for drought-affected households, this index is converted to a indicator variable for drought incidence, denoting whether the scPDSI is less than the median value for our data sample, namely -2.48 (summary statistics for this variable, and others, are provided in the next sub-section). Details on how we create the drought variable are presented in Appendix B, along with details of the data sources, as well as the variable creation for temperature and rainfall measures that we use in some regressions.

3.2.3 Descriptive Statistics

In this subsection, we provide descriptive statistics on the main outcome variables, as well as on the assignment variable and the drought indicator. Table 1 provides these summary statistics. We present these statistics for the data samples used for both the RDD analysis, as well as for the diff-in-diff analysis. In Table A2 in the Appendix, we provide summary statistics for the main covariates used across different models in this paper.

About 85% of the sample had access to grid electricity in the RDD sample, whereas this share was about 74% in the diff-in-diff sample. Thus, many households in both samples had electricity access, whereas piped water adoption rates are relatively lower, at 40% and 39% in both samples, respectively. We find stark differences between the two amenities in terms of average rates of spending as well: while 81% of households spent a non-zero amount on electricity last month in the RDD sample, only 3% of these households spent on water. Appliance adoption rates are moderate, at about 71% and 59% for fridges, and 79% and 65%

Table 1: Descriptive Statistics of Important Variables

Variables	RDD Sample Mean	Standard Deviation	Minimum	Maximum	Obs.	Diff-in-Diff Sample Mean	Standard Deviation	Minimum	Maximum	Obs
Household has access to grid electricity	0.845	0.362	0	1	2,197	0.744	0.436	0	1	8,018
Household has access to piped water	0.400	0.490	0	1	2,197	0.386	0.487	0	1	8,034
Household spent non-zero amount on electricity last month	0.812	0.390	0	1	2,191	0.690	0.463	0	1	7,934
Household spent non-zero amount on water last month	0.032	0.177	0	1	2,194	0.047	0.211	0	1	7,879
Consumption expenditure (Rand, deflated) last month	2,345.09	5,413.92	9,968.77	200000	2,197	2,182.303	4,116.66	2,296.76	200000	8,036
Ownership of a fridge	0.709	0.455	0	1	2,195	0.586	0.493	0	1	8,032
Ownership of an electric-stove	0.785	0.411	0	1	2,197	0.653	0.476	0	1	8,032
Use electricity as the main energy source for lighting	0.883	0.321	0	1	2,197	0.762	0.426	0	1	8,030
Use electricity as the main energy source for cooking	0.684	0.465	0	1	2,197	0.567	0.495	0	1	8,034
Use electricity as the main energy source for heating	0.499	0.500	0	1	2,193	0.431	0.495	0	1	8,029
Use borehole on the property as the main water source	0.042	0.200	0	1	2,197	0.035	0.184	0	1	8,034
Whether household has a flush toilet	0.105	0.307	0	1	2,197	0.104	0.305	0	1	8,032
Whether household participated in subsistence agriculture	0.315	0.465	0	1	2,195	0.287	0.453	0	1	8,031
Whether anyone in household employed in last month	0.415	0.493	0	1	2,196	0.414	0.493	0	1	8,032
Household head self-employed in the last month	0.066	0.249	0	1	2,111	0.061	0.239	0	1	7,534
Anyone in household grew crops in the last year	0.155	0.362	0	1	2,197	0.169	0.375	0	1	8,036
Household head satisfied with their life	0.368	0.482	0	1	2,108	0.344	0.475	0	1	7,395
Household head has asthma	0.031	0.173	0	1	2,072	0.034	0.181	0	1	7,426
Household head has tuberculosis	0.054	0.226	0	1	2,030	0.061	0.239	0	1	7,334
Eligible for Indigent Program (normalized income >0)	0.404	0.491	0	1	2,197	0.330	0.470	0	1	8,036
Household living in drought-affected area (Binary variable)	0.660	0.474	0	1	2,197	0.515	0.500	0	1	8,036

Notes: The summary statistics reported are calculated for the regression sample of households that lived in rural areas in 2017, whose normalised monthly income is within the 99^{th} percentile of the distribution (RDD Sample), and for rural households whose monthly income was within the 99^{th} percentile of the distribution (Diff-in-Diff Sample).

for electric cook-stoves. Furthermore, the total monthly (deflated) household consumption expenditure is about 2345 Rand per month (about 129 USD)[6]. This measure is commonly used to approximate well-being in quasi-experimental studies on developing countries (Burlig and Preonas, 2016; Topalova, 2010; Banerjee et al., 2015).

We find some heterogeneity in the use of electricity for different functions: for instance, 88% of households used electricity as the main lighting source in the RDD sample, while only about 50% used it as the main heating source, and 68% used it for cooking. These three variables are important outcome measures, because as has been confirmed in the literature, households in developing countries often use multiple sources of energy at the same time (also known as fuel-stacking) (Cheng and Urpelainen, 2014). By focusing on the use of electricity as the main source of energy for these three important activities, we are better able to identify the effect of the Indigent Program on electricity use at a household level.

We find that about 4% of households in the RDD sample used a borehole as their main water source, whereas about 11% of households had a flush toilet in their house, both of which are low. We also find that only about 42% of households had someone employed in the last month, suggesting generally high levels of unemployment in this sample. In general, we find that about 40% of households were eligible for the Indigent Program in 2017 (33% in the diff-in-diff sample), while about 66% of households were living in drought affected areas in 2017 (about 52% in the diff-in-diff sample). These relatively high shares of drought-affected households, especially in 2017, suggest that drought is likely to have been a pervasive threat to many rural households in South Africa. With respect to the health-related outcome measures, we find that about 3% of household heads stated that they had asthma (the incidence of which often increases due to the use of inefficient or firewood-powered cook-stoves, as opposed to electric cook-stoves), about 5% had tuberculosis (a disease that is often transmitted by the consumption of contaminated water) whereas about 37% of household heads were satisfied with their lives (life satisfaction index greater than or equal to 5, where a score of 1 denotes very dissatisfied, while 10 denotes very satisfied).

In Table A2, we present summary statistics on the covariates used in the estimations. The mean monthly deflated household income was about 3719 Rand (deflated to 2010 prices) (about 205 USD), whereas the mean asset holdings for these households are about 218700 Rand (or about 12061 USD). However, it is important to note that we do not have information on the asset holdings for all households in this sample, due to several missing observations.

The mean household size for the sample was about 5 individuals, whereas a relatively high share of (about 76% of households) owned their homes. About 67% of the sample lived in a 'modern dwelling' (a house or brick structure on a separate yard/farm, in a flat or apartment in a block of flats, or in a cluster or semi-detached house). We also have information on some socioeconomic characteristics of the heads of the households; about 70% of them are female, and their average age is about 51 years. Moreover, most household heads have limited educational attainment, having only either completed high-school or a lower grade in school (about 78%). About 74% of household heads spoke either in the Zulu or Xhosa languages while completing the survey, which indicates the main ethnicity of these households. About 45% of households had a bank account, whereas only about 2.8% of households earned rental income. Lastly, we also collected information on the sum of nighttime lights at the district-level, and the

[6] 1 Rand = 0.055 USD, as of 22nd March, 2023.

mean value is about 15.546, which is relatively low, and suggests low levels of electricity use in this sample. The nighttime lights measure uses satellite data to infer gains in electrification, and also has been shown to be closely related to the level of economic development of areas (Addison and Stewart, 2015; Nordhaus and Chen, 2015; Bluhm and Krause, 2022).

In terms of the extreme weather variables, as we mentioned earlier, we about 66% of the sample lived in areas of drought: we define this indicator as taking the value 1 when the household lives in a district having a scPDSI score less than the median value for the whole sample, which is -2.48 in our data. A PDSI value between -2.99 to -2 denotes moderate drought, between -3.99 to -3 denotes severe drought, and less than -4 denotes extreme drought (National Drought Mitigation Center, 2022). Thus, we call households living in areas of moderate to extreme drought as 'drought-affected' households. In our RDD sample, about 42% of households live in areas of severe or extreme drought according to this definition (this share is about 25% in the diff-in-diff sample). In terms of the temperature variables, we find that the average measure of cooling-degree days was about 0.26 for our sample, whereas the average heating degree-days measure was slightly higher, at about 3.099 in the RDD sample. These two temperature variables are used as covariates in some estimations.

4 Empirical Results

4.1 Impact of Indigent Program on Socio-Economic Outcomes: Reduced-Form RDD Results

In this section, we present the main flexible parametric RDD-based empirical results in which we evaluate the effect of eligibility for the Indigent Program on various outcomes. The first set of results evaluate the impact of program eligibility on electricity and water access as well as expenditure, using four outcome variables: having grid electricity access, having a piped water connection, spending a positive amount on electricity in the last 30 days, and spending a positive amount on water in the last 30 days. Given that the Indigent Program provided eligible households a certain amount of free electricity and water, these are relevant measures to understand if the program was successful in meeting its objectives. Table 2 presents these results, whereas the reduced-form results for the other socioeconomic outcome variables are presented in Table 3. As described in the Methodology section, these models are estimated for households in the year 2017, the most recent year of data in the NIDS dataset, and using a local linear polynomial in the running variable, and robust standard errors.[7] The running variable is the normalised income of the household, and it is defined as the indigent program threshold minus the monthly household income (given that households below the income threshold are considered as treated), and the sample comprises households living in non-urban areas of South Africa ('traditional' areas as well as commercial farms). In Tables 2 and 3, we present the results of models estimated by including basic covariates (including household size, a dummy for home ownership, a dummy for whether the household receives any rental income, educational attainment, age and gender of the head of the household, and district fixed effects) and using two different bandwidths, 1000 Rand and 2000 Rand.

[7]Results of using alternative RDD specifications, including non-parametric methods, are presented in the Robustness Checks sub-section.

4.1.1 Impact on Electricity and Water Access and Expenditure

Table 2 presents the estimation results evaluating the impact of program eligibility on electricity and water access and expenditure. Panel A presents the results for the overall sample, whereas panels B and C present the results by subgroup, i.e., for drought-unaffected and drought-affected households, respectively. In columns (7) and (8), we present the p-values testing the null hypothesis that the coefficients derived in each model are equal for the two subgroups (drought-affected and unaffected households), for the models estimated using a bandwidth of 1000 Rand and 2000 Rand respectively.

From the reduced-form results in panel A of Table 2, we get strong evidence that eligible households were not significantly more likely to either acquire electricity access compared to non-indigent households, or to acquire access to piped water. We also observe this for spending a non-zero amount on both electricity and water. Furthermore, the insignificance of program eligibility on these measures is confirmed for both bandwidths. Thus, the overall results of panel A seem to suggest that the local effects of program eligibility on both access, as well as on expenditure on these amenities, were statistically insignificant, despite the fact that almost 15% of households still did not have electricity access, and 60% of households did not use piped water even as recently as 2017.

In panels B and C of Table 2, we report the findings of the subgroup-specific estimations, using the same flexible parametric RDD methodology as for the overall sample results. These models are estimated for drought-unaffected households, as well as drought-affected households, defined using the binary drought indicator described in the Data section. While we find some evidence that there is a positive effect of eligibility on non-zero expenditure on electricity and on water in drought-unaffected areas (at a bandwidth of 2000 Rand), the effects for drought-affected households are insignificant across specifications in panel C. Thus, in general, the results of panel B suggest that at the threshold, households living in drought-unaffected areas with income levels just *below* the income threshold may have been more likely to spend a non-zero amount on electricity and on water, compared to households with incomes just above the threshold (we only observe this on using a bandwidth of 2000 Rand).

However, an important point to note about this finding is that the differences in the coefficients between the two sub-groups of households are insignificant for all variables, except for electricity expenditure (p-values reported in columns (7) and (8)). This means that eligible households in drought-affected areas were less likely to spend on electricity, compared to eligible households in drought-unaffected areas, at the 10% level of significance using a bandwidth of 1000 Rand, and at the 5% level at a bandwidth of 2000 Rand. On the other hand, we do not obtain significant differences between subgroups for the other three outcome variables. At a bandwidth of 2000 Rand, we also observe that households in drought-affected areas were less likely to spend on water, compared to households in drought-affected areas (with a p-value of 0.054, provided in column (8)).

This reduced-form evidence provides support in favor of the notions that a) eligibility for the program may not have adequately incentivised households to acquire electricity access or piped water, at least in 2017, and b) households living in drought-unaffected areas may have been more likely to spend on electricity, and weakly more likely to spend on water in response to being eligible for the Indigent Program, compared to drought-affected households. Drought-affected households may have found it difficult to spend on electricity or water, if droughts affected their assets and incomes (as we will later see in Table A5); for instance, acquiring an electricity connection requires households to pay connection fees as well as additional charges, which they may not be able to afford. Acquiring a piped water connection also requires paying some upfront costs. Furthermore, they may have been dissuaded by the additional cost of purchasing appliances or electricity or water-based services, and thus perceived lower utility from acquiring electricity or piped water access. These findings weaken the 'amenities as adaptation' argument partially, even though it is difficult to rule out entirely, given the insignificance of these results.

4.1.2 Impact on Other Socioeconomic Outcomes

Table 3 presents the estimation results evaluating the impact of program eligibility on other socioeconomic outcomes related to electricity and water use. As before, panel A presents the results for the overall sample, whereas panels B and C present the results by subgroup, i.e., for drought-unaffected and drought-affected households, respectively. Again in columns (7) and (8), we present the p-values testing the null hypothesis that the coefficients for the different models are equal for drought-affected and unaffected households, at bandwidths of 1000 and 2000 Rand respectively.

In panel A of Table 3, we present the overall reduced-form results for program eligibility on a range of other socioeconomic outcome variables. Column (1) includes the results on using the optimal bandwidth, whereas column (2) includes the results for double this bandwidth. In these models, we include the same covariates as in the reduced-form models in Table 2. In column (1), we find that at the overall level, eligible households were more likely to use a borehole as their main source of water. Eligible households were almost 4 percentage points more likely to use a borehole, compared to ineligible households (column (1), panel A), a finding also confirmed in column (2). Interestingly, we find from panels B and C that this finding is driven mostly by drought-affected households. Drought-affected households were about 4 percentage points more likely to use a borehole as their main water source, in response to program eligibility in columns (5) and (6), compared to ineligible households. On the other hand, we do not find this effect for drought-unaffected households in columns (3) and (4) (even though the effects are not significantly different from one another as indicated by the p-values in columns (7) and (8), due to the noisy estimates for drought-unaffected households).

This suggests that one possible outlet through which eligible households in drought-affected areas were capitalizing on the benefits of the Indigent Program was through the adoption of electric borehole pumps. Borehole pumps offer households the possibility to acquire water for private use in drier areas, which may yield short-term gains, however, this may also be considered to be a form of 'mal-adaptation' in this setting, given that large-scale adoption of borehole pumps may exacerbate drought conditions, by further reducing groundwater levels. Theoretically, a borehole pump may either be a hand-operated pump, or an electric one. Both are commonly used in the South African scenario, however we can infer, based on these findings, that free electricity may have increased the adoption of electric borehole pumps.[8]

Besides the use of a borehole as the main water source, we do not find any significant effects for program eligibility on any other outcome variable, either at the overall level, or by sub-group.

[8]The NIDS dataset does not provide information on whether the household used a hand pump or an electric borehole pump.

Table 2: Reduced-Form Parametric RDD Results: Electricity and Water

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access to grid electricity	0.006	0.006	0.048	0.078	-0.012	-0.025	0.548	0.143
	(0.046)	(0.033)	(0.084)	(0.057)	(0.054)	(0.041)		
Observations	1016	1508	292	486	724	1022		
Access to piped water	-0.007	0.001	-0.03	0.024	-0.020	-0.029	0.935	0.539
	(0.053)	(0.038)	(0.107)	(0.073)	(0.062)	(0.046)		
Observations	1016	1508	292	486	724	1022		
Spent on electricity	0.005	0.019	0.142	0.135**	-0.044	-0.025	0.088	0.024
	(0.046)	(0.034)	(0.095)	(0.058)	(0.053)	(0.041)		
Observations	1016	1504	292	486	724	1018		
Spent on water	0.003	0.017	0.032	0.056**	-0.006	-0.0003	0.284	0.054
	(0.013)	(0.011)	(0.033)	(0.027)	(0.013)	(0.011)		
Observations	1016	1508	292	486	724	1022		

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on electricity access, piped water access, expenditure on electricity (dummy variable) and expenditure on water (dummy variable) using the parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Households were not significantly more likely to increase their likelihood of owning potentially useful appliances such as fridges, or electric cook-stoves on being eligible for the Indigent program, despite one in four households not already owning these appliances in our sample. Thus, it appears that the 50 KwH of free electricity offered by the program did not compel eligible households to adopt these appliances, compared to ineligible households. This effect persists for both drought-unaffected and affected households. Furthermore, the differences between both subgroups for these variables are insignificant as well.

Furthermore, we observe that assignment to the program did not lead to a significant increase in the likelihood of households using electricity as the main energy source for lighting, but given that by 2017, 88% of households in our sample were already using electricity as the main lighting source, this can be justified. However, at a bandwidth of 2000 Rand, we find that the effect of program eligibility on drought-affected households was significantly less than that on drought-unaffected households at the 10% level, as we can see in column (8). We also observe the insignificance of program eligibility on the use of electricity for cooking, as well as heating purposes. On further examining the heterogeneous effects across drought-affected and unaffected households, we find that there were no significant differences between the subgroups in the use of electricity for heating or cooking. As the literature on energy-stacking suggests, households typically use multiple sources of fuel at the same time, especially when costs, access and/or reliability may be a constraint. Thus, it is still plausible that eligible households may be using a limited amount of electricity for lighting, cooking or heating, but as these results suggest, they were not using it as the main source of energy. For instance, households in South Africa living near coal mines or coal-fired power stations (in the interior) are likely to opt for coal as a heating source, whereas in the eastern coastal areas, they prefer to use paraffin (Buthelezi et al., 2019).

In Table A3 in the appendix, we evaluate the effect of program eligibility on the likelihood of households using wood as the main energy source for cooking, using the same econometric methodology. We find that eligible households were almost 13 percentage points more likely to use wood as the main cooking source (column (1)). In column (2), the effect size is weaker (with a p-value of 0.122). Moreover, we find that drought-affected households were 14 percentage points more likely to use wood to cook on being eligible for the Indigent program at the bandwidth of 1000 Rand, even though we cannot infer that this effect is significantly different compared to the effect for drought-unaffected households (the p-value is 0.754 in column (7)). Thus, the findings of panel A are likely to be driven by drought-affected households using wood more extensively for cooking purposes. This suggests that drought-affected eligible households may have been "saving" the potential electricity-related benefits that they could obtain from the Indigent Program for some other purpose, and using wood instead of electricity to cook. There is some evidence to suggest, for instance, that during droughts, rural communities often rely on sales of firewood to help them adapt to the negative income effects (Quandt (2021) provided qualitative evidence from Kenya, whereas Bailey et al. (2019) used survey data from Eswatini to also show this). This implies that households may have access to relatively cheaper firewood during droughts, which may compel them to use firewood more extensively instead of electricity.

To investigate whether households may have benefited from the free water allocation provided in the program, in Table 3 we evaluate the impact of program eligibility on the likelihood of households acquiring a toilet, or pursuing subsistence agriculture. Households that received up to 6 kL of free water per month may, theoretically, have found it beneficial have a toilet in the house, or they may have used water to help them grow crops. We do not find any significant effects of program eligibility on either of these outcomes at the overall level. We also do not find any differences between drought-unaffected and affected households, for these effects.

Lastly, we do not find that eligibility for the program resulted in any changes in the log of monthly consumption expenditure of households, and there were no significantly different effects for drought-affected and unaffected households in this regard either. This finding resonates with some recent studies that have shown that electricity access may not necessarily lead to large improvements in welfare for rural households (Burlig and Preonas, 2016; Lee et al., 2020b). In Table A3 in the Appendix, we investigate whether we observe the same effect for consumption expenditure net of electricity spending (given that we found that eligible drought-unaffected households were more likely to spend a non-negative amount on electricity in Table 2 than drought-affected households). Indeed, we do not obtain any significant results from these estimations. The impact of program eligibility appears on both monthly consumption expenditure, as well as on consumption expenditure net of electricity spending, appears to have been weak.

To summarize the results of this section, we observe that at the overall level, households eligible for the Indigent program were not more likely to either acquire electricity access or piped water access, and eligibility for the program did not lead to an increase in the likelihood of households spending a non-zero amount on either water or electricity. There is some evidence, however, that eligible households in drought-unaffected areas spent on electricity (and also water), whereas we do not find this effect for drought-affected households. Furthermore, in general the effect of eligibility on the likelihood of spending a non-zero amount is higher for drought-unaffected households, compared to drought-affected households.

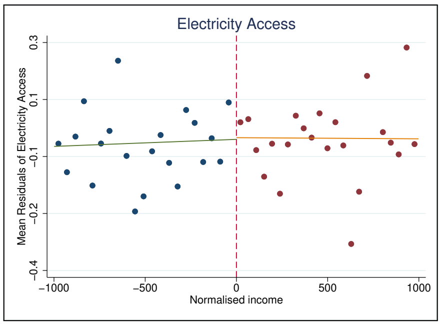
We also learnt that eligibility for the program did not lead to any significant welfare gains (or losses) in terms total consumption expenditure at the overall level. Based on our results, it also did not facilitate the adoption of appliances such as fridges or electric cook-stoves, or the use of electricity for lighting, cooking or heating, and it did not result in households having a toilet in their home, or participating in subsistence agriculture. However, drought-affected households eligible for the program were **more** likely to use a borehole as their main source of water, which suggests that they were may have been using an electric borehole pump to draw on groundwater, which could enable them to cope with drought conditions, at least in the short-run.

We present some of the overall reduced-form results in graphical form in Figure 2. These RD plots are based on a linear polynomial, within an bandwidth of 1000 Rand, while controlling for the same set of covariates that were included in the regression models in Tables 2 and 3. The weak (or non-existent) effect of eligibility on electricity access, access to piped water, expenditure on electricity, expenditure on water, and on the log of consumption expenditure, is clear from these plots. We also find a positive effect of eligibility on borehole adoption, even though the effect size appears to be small. We provide RD plots for the other outcome variables in Figure A5 in the Appendix, and while some of the effects appear to look relatively large (compared to others), such as for the use of electricity for cooking or heating, these effects are not significant as we saw in Table 3. Thus, even with these graphical results, we do not find any positive effects of eligibility for the Indigent Program on socioeconomic outcomes, except on borehole adoption.

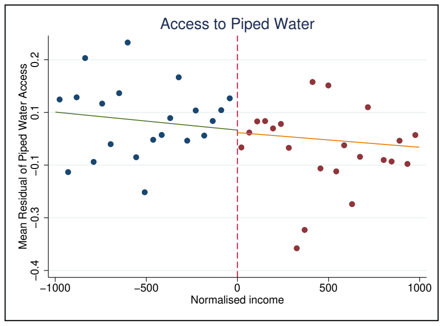
Table 3: Reduced-Form Parametric RDD Results: Other Socioeconomic Outcomes

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Use a borehole as main water source	0.040*	0.026*	0.042	-0.005	0.044**	0.043***	0.976	0.245
	(0.023)	(0.015)	(0.064)	(0.038)	(0.022)	(0.016)		
Observations	1016	1508	292	486	724	1022		
Own a fridge	-0.069	-0.047	-0.044	0.017	-0.081	-0.076	0.77	0.276
	(0.057)	(0.040)	(0.107)	(0.069)	(0.067)	(0.050)		
Observations	1016	1508	292	486	724	1022		
Own an electric cook-stove	-0.025	-0.027	0.051	0.032	-0.055	-0.048	0.406	0.337
	(0.053)	(0.038)	(0.113)	(0.070)	(0.059)	(0.045)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for lighting	-0.031	0.0001	0.009	0.079	-0.049	-0.028	0.518	0.076
	(0.040)	(0.029)	(0.077)	(0.049)	(0.046)	(0.035)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for cooking	-0.080	-0.031	-0.080	0.024	-0.089	-0.059	0.947	0.363
	(0.056)	(0.041)	(0.117)	(0.077)	(0.065)	(0.049)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for heating	-0.057	-0.003	0.017	0.081	-0.096	-0.06	0.407	0.129
	(0.057)	(0.041)	(0.119)	(0.079)	(0.066)	(0.049)		
Observations	1014	1506	292	486	722	1020		
Having a toilet	-0.0005	0.006	0.028	-0.015	-0.007	0.017	0.467	0.366
	(0.028)	(0.019)	(0.033)	(0.026)	(0.035)	(0.024)		
Observations	1016	1508	292	486	724	1022		
Subsistence Agriculture	-0.018	-0.024	0.099	0.034	-0.058	-0.039	0.217	0.41
	(0.055)	(0.039)	(0.110)	(0.075)	(0.064)	(0.047)		
Observations	1015	1507	292	486	723	1021		
Log of monthly net consumption expenditure	0.002	-0.021	-0.008	0.081	0.008	-0.024	0.903	0.266
	(0.050)	(0.038)	(0.120)	(0.084)	(0.054)	(0.043)		
Observations	1016	1508	292	486	724	1022		

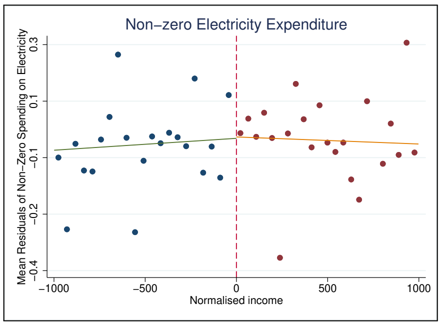
Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on various socioeconomic outcomes using the flexible parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.



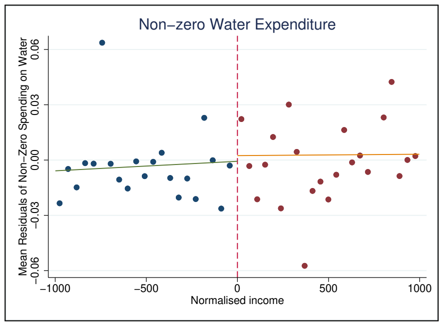
(a) Electricity access



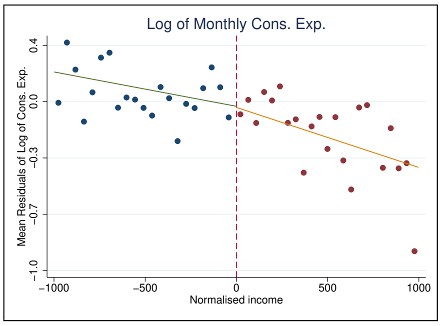
(b) Access to piped water



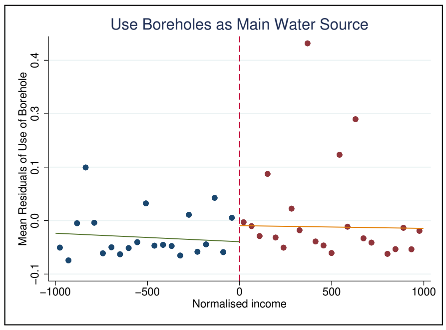
(c) Spent non-zero amount on electricity



(d) Spent non-zero amount on water



(e) Log of consumption expenditure



(f) Use of borehole as main water source

Figure 2: RD Plots for Electricity Access and Main Outcome Variables

4.2 Effect of Indigent Program on Socioeconomic Outcomes: Staggered Diff-in-Diff Approach

As we learnt in the previous section, the Indigent program did not lead to significant improvements in the likelihood of households acquiring electricity access or access to piped water, and while it may have increased the likelihood of households spending on electricity and water, this was only observed in drought-unaffected areas. The questions that then arise are whether electricity or piped water access or expenditure a) wielded any socioeconomic benefits to rural households, and b) whether drought-affected households were able to benefit from the program in any way.

This section includes the results of the staggered diff-in-diff estimations evaluating the effect of access to electricity and piped water, as well as expenditure on electricity and water, while controlling for program eligibility, on socioeconomic outcomes related to measures of welfare, health and employment. As described in the Methodology section, these models are estimated using the Chaisemartin and D'Haultfœuille (2022) approach. In columns (1) and (2) of Table

A4 in the Appendix, we use a treatment indicator equalling one if the household spent a non-zero amount on electricity or on water in that year, and zero otherwise, whereas in columns (3) and (4) we define this indicator equal to one if the household either had access to grid electricity, or had access to piped water, and equal to zero otherwise. In columns (1) and (3), we present the results of estimating the average treatment effect on households that changed their treatment status for the first time in the present time period compared to the previous one (compared to not-yet-switchers), and in columns (2) and (4), we provide the results of specifically estimating the effects on households that changed their treatment status from zero to one i.e., for households 'switching in' to treatment in the present time period, compared to the non-switchers. In all estimations, we control for eligibility for the Indigent Program. In our main specifications, we report contemporaneous average treatment effects, and we provide other specification checks in the Appendix. In panel A of Table A4, we report the overall model results, and in panels B and C, we report the results of estimating the model for the subgroups of drought-unaffected and drought-affected households, respectively.

We find that spending a non-zero amount on either electricity or on water (or both) resulted in an increase in the likelihood of growing crops (an effect that is significant at the 1% level), compared to households that did not change their treatment status between period 't-1' and period 't'. Furthermore, we also observe that spending on either of these services may have led to some welfare improvements: household heads were more likely to state that they were satisfied with their lives, in response to spending on either of these services. These two findings are also confirmed for households that switched in to treatment (in column (2)), i.e. for households whose treatment status changed form 0 in period 't-1' to 1 in period 't', compared to households that had treatment status 0 in both periods (or households that neither spent on electricity nor water in both periods). On the other hand, we learn that spending a non-zero amount on either electricity or water did not lead to any significant changes in health (measured by indicator variables for the prevalence of asthma or tuberculosis among household heads), in self-employment, or in overall welfare (measured by the log of monthly consumption expenditure). The coefficients on these variables are insignificant both in column (1), as well as in column (2).

From columns (3) and (4) of panel A, we learn that having access to electricity, or to piped water (or to both), also resulted in an increase in the likelihood of households growing crops compared to households whose treatment status did not change. While we do not find the same effect for life satisfaction as we did in columns (1) and (2), we observe that households with access to at least one of the two services were more likely to experience an increase in consumption expenditure. In column (4), we find that households that switched from treatment status 0 to 1 between periods 't-1' and 't', i.e., they went from not having access to either service, to having it for at least one of them, experienced an increase in the likelihood of growing crops: these households were 8.9 percentage points more likely to grow crops, compared to the non-switchers. They were also more likely to spend more, i.e., they experienced approximately an 8.6 % increase in consumption expenditure. We do not find similar effects for the other health and employment measures in columns (3) and (4).

Thus, it seems that electricity and water access as well as expenditure may have supported households in participating in agricultural activity. What are, then, the effects of these amenities on adaptation behavior, i.e., did electricity and water help South African households in adapting to extreme weather conditions, such as drought? We test this in panels B and C of Table A4.

We find that spending on either electricity or on water did not result in a higher likelihood of life satisfaction, or in an increase consumption expenditure in drought-unaffected areas (as is evident from panel B). Furthermore, the other effects are also insignificant, both for the overall sample (in column (1)), as well as for the switchers into treatment (in column (2)). On the other hand, yet again, we find that spending on electricity or water led to an increase in the likelihood of households participating in growing crops, as observed in column (1), even though this effect is insignificant when we focus on the switchers in column (2), who are the relevant group for this analysis. Having access to either electricity or piped water also led to an increase in the likelihood of growing crops for these households, and unlike in columns (1) and (2), this effect was also prevalent when we focus on the group of switchers in column (4). While we find that in column (3), drought-unaffected household heads experienced a decrease in the likelihood of having asthma, this result is weak in column (4).

On the other hand, we observe that in drought-affected areas (panel C), households did not experience any material gains in welfare (i.e., in consumption expenditure), or in employment or health outcomes, from spending on electricity or water. The results also suggest that acquiring access to either service did not yield any significant benefits for drought-affected households: this finding is consistent across outcome variables, and in both columns (3) and (4). We only find a positive effect for life satisfaction among household heads, on spending on electricity or water in column (2). In general, the subgroup analysis results of this section show us that the effects for drought-affected households are not only insignificant by themselves, but they are also insignificantly different from the effects for drought-unaffected households. We only obtain significant differences between the two subgroups for the variable on someone in the household growing crops in the last year (significant at the 5% level in column (1)), and for the likelihood of the household head having tuberculosis (the difference in coefficients being significant at the 10% level in column (1)).

Thus, to summarize these findings, we obtain evidence that non-zero electricity or water expenditure as well as access to electricity or piped water increased the likelihood of participating in agricultural activities such as growing crops, and that this effect was mostly driven by drought-unaffected households. We do not obtain any evidence to suggest that drought-affected households experienced similar gains (even though the effects are insignificantly different for the two groups). Findings related to an increase in consumption expenditure seem to be weak in general across both subgroups, and we do not find evidence that either expenditure on these services, or access to them, resulted in improvements in other measures of employment or health for households. Thus, it appears that electricity and piped water access, or use, may have resulted in some benefits for households in this context, namely participation in agricultural activity, but they may not have been extensive, and they may have favored drought-unaffected households.

4.3 Mechanisms

The findings of the RDD results suggest that the Indigent Program may have had only a weak, and limited effect on increasing the likelihood of households acquiring electricity access or access to piped water, or on households spending on either of these services; furthermore, any positive effects were largely driven by drought-unaffected households. Furthermore, households living in drought-affected areas were not significantly more likely to adopt important appliances in response to being eligible for the program, and they were also not more likely to use electricity as the main energy source for lighting, cooking and heating purposes, compared to ineligible households. They were, however, significantly more likely to use a borehole as their main source of water, which suggests that the program may have somewhat increased resilience to droughts in these areas, at least in the short-run.

On the other hand, the staggered diff-in-diff results suggest that the effects of both a household switching from not having access to both services to having access to at least one, and the effect of households switching from not spending on both services to spending on at least one of them, were relatively strong (and positive) for participation in agricultural activity, i.e., in growing crops, but not for other measures of welfare or employment. On the basis of theses estimations, we were also able to infer that drought-affected households experienced weaker gains, compared to drought-unaffected households, even though the gains were not considerable for either subgroup.

To place these results in context, a few questions can be raised. Firstly, how have droughts influenced the socioeconomic outcomes of households? Secondly, why was the Indigent Program less successful in assisting drought-affected households? In this section, we focus on trying to disentangle the mechanisms for the main results of this paper for drought-affected households.

4.3.1 Effect of Extreme Weather on Socioeconomic Outcomes

In the first set of results, we provide suggestive evidence to evaluate the effect of drought on some important measures of household welfare. These models are estimated using household and year fixed effects and province time-trends, with standard errors clustered at the household level. We also control for temperature extremes in these models.

Theoretically, climatic events such as droughts can have devastating consequences on households in low-income countries. In addition to the primary effect of creating a shortage of water, droughts can thwart means of livelihoods for many households, especially of those engaged in agriculture and allied activities, due to lower yields, or disease/death of livestock. Moreover, in rural areas, given the nature of market spillovers, it is also plausible that households not directly engaged in agriculture will also be affected by climate change (Egger et al. (2021) provide experimental evidence of such general-equilibrium effects from Kenya). For example, they might find it difficult to buy goods and services, or inputs for their businesses, either because of supply shortages, or increased market prices for both food and non-food commodities. Droughts can create significant economic and financial problems for low-income residents such as indebtedness, while also increasing health risks such as malnutrition as well as risks of conflict and displacement (FAO, 2023).

Broadly speaking, and in line with intuition, the results of Table A5 in the Appendix suggest that living in a drought-prone area has a negative effect on most socioeconomic outcomes for rural households in South Africa. In column (1), we see that households living in drought-affected areas are likely to have lower consumption expenditures: each unit decline in the scPDSI is associated with a decline in consumption of 3.1% (this effect is significant at the 5% level). While the scPDSI variable is insignificant in the model with the log of monthly income as a dependent variable (column (2)), households living in drought affected areas (having a lower scPDSI score) are less likely to be employed (column (3)). However, each unit decline in the

DSI is associated with an increase in the likelihood of a household member being involved in subsistence agriculture by 1.8 percentage points (column (4)).

While the NIDS dataset contains information on household assets, this information is missing for several households. In column (5), we see that households living in relatively wetter areas (having higher DSI values) are likely to have larger asset holdings, compared to households living in drier areas. On focusing on specific types of assets, we do not find that households living in drought-affected areas were less likely to own livestock. In columns (7) and (8), we find that lower values of the DSI have an insignificant effect on vehicle ownership, and a positive effect on the likelihood of owning agricultural land.

In column (9), we observe that the onset of drought conditions has a significant (and negative) effect on the likelihood of acquiring electricity access, i.e., households living in drought-affected areas are less likely to have a grid electricity connection than households living in relatively wetter areas. Given that almost 85% of the electricity supply in South Africa is generated via coal-fired power stations (USAID, 2023), it is unlikely that this effect is driven by the effect of drought on the production of power in hydroelectric power plants, which constitutes only about 6% of installed capacity in South Africa. On the other hand, droughts are also known to affect coal-fired electricity generation, and it is difficult to rule out the effect that extreme weather may have on electricity supply. Having said that, our variable captures whether or not households have access to grid electricity, and not whether they receive a regular supply of electricity[9]. Thus, it is plausible that this finding reflects the fact that households living in drought-affected areas were less likely to acquire electricity access, even though we cannot rule out that the supply of electricity may also be lower in these areas.[10]

Column (10) shows us that lower values of the DSI are associated with higher likelihoods of having access to piped water, i.e., households living in drought-affected areas were more likely to use piped water as their main source of water. While this may seem counter-intuitive, studies have shown that in some areas of Africa, piped water may be relatively cost-effective in the presence of droughts (Godfrey and Hailemichael, 2017).[11] Furthermore, the results of columns (11) and (12) pinpoint that drought conditions did not have an effect on the likelihood of households spending on water, but it likely resulted in lower likelihoods of spending on electricity: each unit decline in the DSI is associated with a 3.1 percentage point decline in the probability that households spent on electricity. Thus, drought conditions seem to have influenced demand and expenditure on both services in different ways, in this setting.

[9] The South African government has made significant efforts to extend electricity access in recent years, with several policies targeting rural electrification (Meyer and Overen, 2021)

[10] This is further confirmed by an estimation of the same model using "whether the household lives in an area having street lighting" as a dependent variable. We find that living in a drought-prone area has no significant effect on this likelihood, suggesting that we do not have evidence that drought-affected areas are less likely to have electricity access in general than other areas. These results can be provided on request.

[11] Interestingly, and in line with the RDD results, we also find that drought conditions are associated with an increase in the likelihood of households using boreholes as their main source of water. While this may be a useful solution for coping with droughts, and is commonly observed in drought conditions in Africa (MacAllister et al., 2020), it is unclear whether it is viable in the long-run. These results can be provided on request.

4.3.2 Analysis of Main RDD and Diff-in-Diff Findings

The first finding from the RDD model was that the responsiveness of households to the Indigent Program, in terms of acquiring electricity access or access to piped water, was weak in areas affected by drought (Table 2). This may be due to several reasons. Firstly, given that the benefits offered by the program were limited to 50 KwH of free electricity per month and 6 kL of free water per month, it is plausible that this did not significantly tip the scales in favor of take-up of these services. Secondly, as seen in Table A5, drought-affected households were less likely to acquire electricity access and to spend on electricity in particular, likely driven by the impact of droughts on household incomes and assets. These two factors together may explain the limited impact of the indigent program in enhancing uptake of electricity and piped water among these households.

To explore whether the 50 KwH allocation of free electricity may have been low, in Table A6 in the appendix, we report the proportion of households who spent a positive amount on electricity use in the last month, and the proportion of households that had access to electricity, by assignment to treatment, and by drought status, across the years in our sample. The total number of observations corresponding to each subgroup are also presented. We find that among households who lived in drought-affected areas, and were eligible for the program, on average about 70% of households reported having access to electricity. Somewhat surprisingly, this share is lower, at 65%, in drought-unaffected areas, whereas ineligible households on average have higher shares of electricity access, in line with expectation. Among drought-affected households that had access to electricity, and were also eligible for the program, 86% of them reported having spent a positive amount on electricity in the last month. This suggests that a) almost 30% of households eligible for the program did not acquire access, and b) most households, on acquiring electricity, were actually spending something on electricity, suggesting that they may have been using more than the free electricity bonus. This indicates that 50 KwH may have been a low amount of free electricity to incentivize households without access to switch to acquiring it.

On the other hand, we find that among eligible households residing in drought-affected areas, about 30% of households had access to piped water (as with electricity, this share is relatively higher for ineligible households). However, among households with piped water access that lived in drought-affected areas, it appears that only less than 4% of households spent on water. To put this share in perspective, about 9% of eligible households living in drought-unaffected areas spent on water, and even among ineligible households in drought-unaffected areas, this share was only about 12%. These statistics reflect the fact that in general, simply having piped water access did not compel many households to spend on water, and this proportion was even lower for drought-affected households. This may have been the case because rural households could acquire water from additional sources (such as surface water runoffs, boreholes, rainwater harvesting, etc.), possibly without paying for it. It may also reflect the fact that 6kL of free water may have been sufficient for many households' monthly water consumption. It is difficult, given the data, to verify the reasons for this low water expenditure share.

The second main finding from the previous section was that households eligible for the Indigent program living in drought-affected areas were not significantly more likely to adopt appliances, or use electricity as the main energy source. One reason may be that acquiring appliances, or using electricity for different services, entails additional costs, and eligible households affected by droughts may not have the resources to make these investments. We saw from the results of Table A5 that droughts may have a negative impact on household assets. Households living in drought-affected areas are likely to be liquidity-constrained, if persistent drought conditions erode their assets, which may hinder their ability to purchase appliances or make auxiliary investments (such as in light bulbs, electric cook-stoves or heating systems).

To test this hypothesis, we estimate a reduced-form model on the sub-sample of drought-affected households, evaluating the effect of program eligibility on household borrowing. This model includes household and year fixed effects, as well as district-specific time trends and province-year fixed effects. The results are presented in column (1) of Table A7 in the appendix. We find that assignment to the program had no significant effect on the likelihood of households acquiring a loan, and thus attempting to augment their liquidity, in drought-affected areas.

Next, we evaluate whether borrowing helped improve outcomes for eligible households in drought-affected areas, by including an interaction term between program eligibility and the dummy variable for taking a loan. The results of columns (2) to (14) of Table A7 show that generally speaking, this was not the case: this suggestive evidence illustrates that for households that took a loan, the impact of program eligibility on the likelihood of drought-affected eligible households adopting appliances such as fridges and electric cook-stoves, or on their use of electricity for heating, cooking or lighting, compared to ineligible households, was generally speaking either weak or significant and negative (in the case of fridge ownership). Most of these results are insignificant at even the 10% level. Furthermore, we do not find any evidence to suggest that drought-affected eligible households who took a loan were more likely to build toilets in their homes, or to participate in subsistence agriculture.

On the other hand, we find that the effect of eligibility on the likelihood of spending on electricity was positive and significant for households that borrowed. While taking loans did not have a significant impact on the likelihood of these households acquiring electricity or piped water access, we find that eligible households in drought-affected areas were more likely to use a borehole as their main water source on taking a loan, an effect that is insignificant for households that did not borrow. This finding resonates with the results of our RDD models, and further sketches out the type of drought-affected households who used a borehole on being eligible for the program, namely households that had taken a loan. In general, this suggestive evidence also shows that there were no significant effects of eligibility for households that had not taken a loan (except on the likelihood of owning an electric stove, in column (3), where we find a negative effect for program eligibility). Lastly, we also observe that eligible households who borrowed were likely to have reduced total monthly consumption expenditure, compared to ineligible households.

Access to credit may enable drought-affected (and eligible) households to build resilience to dry conditions, and to purchase a borehole pump to draw groundwater, and perhaps even spend on electricity, given the results of columns (11) and (13) of Table A7. This also suggests that the 50 KwH electricity allocation was, most likely, not enough for households. Moreover, while asset depletion may be an outcome of droughts, and it may be an important determinant of drought-affected households' limited use of electricity, an increase in liquidity through loans seemed to be ineffective at ameliorating this problem, in this context. This suggests that drought-affected poor households may not be able to afford investments involving the use of electricity or water, and further support may be needed through structural changes, such as stronger labor markets or social security nets to enable them to make these investments.

The empirical findings of this study suggest that the Indigent Program may have offered some benefits to enable households to cope with droughts, for e.g., it increased their probability of using a borehole to draw groundwater, however this effect that was largely driven by household borrowing. We learnt in the previous sub-section that households living in drought-unaffected areas were more likely to grow crops in response to non-zero expenditure on electricity or water, an effect that we do not find for households in drought-affected areas, for whom the only positive finding we obtained was for higher life satisfaction. The findings of this section show that the benefits of the program may have not percolated to drought-affected households, who did not experience any differences in appliance uptake or electricity use, even if they borrowed.

For relatively poor households living in drought-affected areas, the scope for using electricity or water to adapt to climate change may be large, but the findings of this study suggest that structural changes may be needed to increase their capacity to adapt to extreme weather, or to climate change. While easier access to credit, subsidies for purchasing appliances or making complementary investments (such as in heating systems), or more affordable supply of electricity and water may be pivotal measures in the short-run, building resilience requires further economic measures, such as improvements in employment and education opportunities, healthcare as well as education systems.

4.3.3 Impact of Borehole Adoption on Groundwater Levels

Our main finding from the RDD estimations was that eligible households were more likely to use a borehole as their main water source, and that this effect was stronger for drought-affected households. One natural question that arises is, can increased borehole adoption potentially exacerbate groundwater levels, and thus drought conditions as well? If this were the case, one possible implication is that while boreholes may facilitate short-run adaptation by providing households with a direct water source, increased adoption may not be sustainable or viable in the medium or long-run. In this section, we present some results of estimating the effect of average borehole adoption at the district level (calculated for our data sample) on the groundwater level in that district. We use data provided by the Department of Water Statistics (DWS) on the average groundwater level in a region, using the groundwater level status (GWLS) measure, which is measured on a percentage scale, with 0 denoting the shallowest groundwater, and 100 denoting the deepest groundwater level (Fourie, 2022). Thus, dry areas tend to have lower GWLS values.

These results are presented in Table A8 in the Appendix. We find that an increase in average borehole adoption at the district level is associated with a decline in the groundwater status, i.e.., lower groundwater levels. In our main specification in column (5), in which we include district and year fixed effects, as well as province-specific time trends, we find that when the average share of adoption of boreholes as the main water source increases by 0.1, the GWLS measure declines by 7.38. This result is significant at the 1% level, and on including district-level covariates (for the scPDSI, temperature as well as rainfall, and the sum of nighttime lights). Thus, we get some suggestive evidence that districts with higher borehole adoption rates were likely to have lower groundwater levels.

It is not straightforward to compute the impact of Indigent Program eligibility on the GWLS, due to the fact that the decision to use a borehole is an individual household decision, whereas the GWLS is captured at the district level. We learnt in the main RDD results in Table 3 that eligible households were about 4 percentage points more likely to use a borehole as their main water source, compared to ineligible households at the program threshold. However this is a highly local effect, that cannot be easily converted to effect sizes at other values of the running variable, and thus, along the income distribution in general. However, it is likely, based on the previous results, that higher rates of borehole adoption are associated with lower groundwater levels.

4.4 Robustness Checks and Placebo Checks

This section presents the results of the robustness checks and placebo checks of the main results of this paper.

In Appendix B, we present the results of the robustness and placebo checks for the main RDD-based models of this paper. Table B1 and B2 present the results of using an alternative functional form for the parametric RDD model, namely omitting the interaction term between the running variable and the treatment indicator, and using a linear polynomial in the running variable. This ensures that the relationship between the outcome variables and the running variable would be the same, whether or not households were eligible for the Indigent Program. The main RDD results are confirmed on using this alternative functional form as well. However, unlike the main results of the paper, we find that drought-unaffected households were likely to experience an increase in consumption expenditure, on being eligible for the program, and that the effects of eligibility for the program on consumption expenditure of drought-affected and unaffected households were significantly different. However, with the exception of the use of boreholes, the remaining results remain insignificant.

In Tables B3 and B4, we estimate the reduced-form parametric RDD models, using a quadratic polynomial instead of a linear polynomial. The main results of Tables 2 and 3 are confirmed on using this alternative functional form for the models, except we find that the significant results for program eligibility on the use of boreholes at a bandwidth of 1000 Rand no longer holds (in panel A). However, the effect is still significant and positive at the bandwidth of 2000 Rand.

Tables B5 and B6 estimate the main models, using a non-parametric RDD methodology. We estimate these models using the optimal bandwidth for each model (derived using the approach of Calonico et al. (2014)), and double this bandwidth. The overall sample results are presented in Panel A. For doing the heterogeneity analysis in panels B and C, we use the approach proposed by Carill et al. (2018) for subgroup analysis in an RDD setting, using propensity score-based weighting (based on (Abadie, 2005)). Observations are weighted, in this model, by the inverse of their conditional probabilities of belonging to a subgroup, given a set of covariates. This inverse-probability score weighting methodology ensures that the groups are balanced, when performing the subgroup analysis. Columns (7) and (8) of these tables provide the p-values testing the null hypothesis that the two groups (drought-unaffected and drought-affected households) are similar to one another, at the optimal bandwidth and at double this bandwidth. Columns (9) and (10) provide the p-values testing the null hypothesis that the coefficients are the same for both subgroups, again at the optimal and at twice the optimal bandwidths, respectively. The p-values in columns (7) and (8) suggest that in these models, the groups of drought-unaffected and drought-affected households are 'balanced', i.e., similar in terms of observables.

We use a linear polynomial, uniform kernel, and heteroskedasticity-robust nearest-neighbour standard errors in all these estimations, and we use the same set of covariates that we used for the parametric estimations. On using this methodology as well, we are able to confirm the direction and significance of the main results of the RDD analysis. Indeed, we find that the impact of program eligibility on electricity and piped water access, as well as expenditure, was weak in 2017, even on using the non-parametric approach. Furthermore, program eligibility had similar effects on other outcome variables as well. For instance, we observe that eligible households were more likely to use a borehole as their main source of water, a finding once again driven by the drought-affected households. In these estimations, we also find that at the overall level, households were less likely to use electricity as the main energy source for cooking *and* for heating. On analysing the heterogeneity of these results by subgroup, we find that this is once again driven by the behavior of Indigent Program eligible drought-affected households, who were less likely to use electricity for these purposes.

In Table B7, we present the results of some placebo checks for our RDD models. In these estimations, we are focusing on the result on borehole adoption, given that this was the only finding for which we obtained significant results at the overall level. Firstly, we test the sensitivity of our results to using an alternative income threshold for the Indigent Program. As of 2017, districts were either using a monthly household income threshold of 1601 Rand, or of 3201 Rand, to define indigent households. In row (1), we use a threshold of 1500 Rand, whereas in row (2), we use a threshold of 4000 Rand. We observe that neither the results at the overall level, not for drought-affected households, are significant in these specifications.

Next, in rows (3)-(6) of Table B7, we estimate the same parametric RDD model for the use of boreholes as the main water source, but for different years in our sample. As we argued in the Introduction and in the Methodology sections, 2017 was a particularly drought-intensive year for South Africa. We should not expect to find similar results for the years 2008, 2010, 2012 and 2014, assuming that it was drought exposure which drove eligible households to adopt boreholes as water sources. Indeed, we do not obtain significant results either at the overall level in Panel A, or for drought-affected households in Panel C, in rows (3) to (6). We do obtain a positive effect for eligible drought-unaffected households in 2012, however this result is not consistent at a bandwidth of 2000 Rand. Conversely, in the year 2014 we find that eligible drought-unaffected households were less likely to use a borehole. In general, these results provide support to suggest that drought-affected households in the year 2017 may have benefited from the Indigent Program, in terms of borehole adoption.

In row (7) of Table B7, we test the sensitivity of our results, using an alternative measure of drought. Groundwater levels can also be used as a measure of persistent dry conditions in a region. As mentioned before, we use data provided by the DWS on the average groundwater status of a region which is measured on a percentage scale, with 0 denoting the shallowest groundwater, and 100 denoting the deepest groundwater level (Fourie, 2022). We use a cut-off of GWLS less than the 25^{th} percentile to denote drought conditions. On using this indicator in row (7), we are able to confirm the main direction of results, i.e., the eligible drought-affected households were likely to adopt a borehole, whereas we do not obtain the same result for drought-unaffected households in 2017. Thus, our results are robust to the choice of drought indicator as well.

Lastly, in row (8), we present the result of using an alternative measure of drought, to construct which we take the weighted average of the scPDSI values over the five closest grid points to the centroid of the district, inverse-weighted by distance. For creating the binary drought indicator as before (=1 if the scPDSI is less than the median value for our data), we find that the the mean scPDSI using this measure is about -2.50 (compared to -2.48, in our main results). Thus, the binary drought indicator is very similar in terms of summary statistics to that used in our main results. On using this indicator to check the consistency of the borehole result, we find very similar findings in columns (3) to (6) of Table B7 (note that the results of columns (1) and (2) are exactly identical to those in our main results in Table 3, given that we only changed the definition of the heterogeneity indicator, namely the drought variable). As earlier, eligible households are more likely to use a borehole in drought-affected areas, a result that is insignificant for drought-unaffected areas. Thus, our main results are confirmed on using an alternative drought measure.

5 Conclusion and Policy Implications

The objectives of this paper were to investigate adaptation to extreme weather events (such as droughts) through the lens of the Indigent Program, using household-level panel data from South Africa, and to attempt to provide a more complete picture of how a) social programs could support adaptation behavior, and b) how electricity and piped water access or use can contribute towards adaptation for vulnerable households.

As a first result, we find that the program was largely ineffective in enhancing electricity access as well as piped water access among poor, rural households in South Africa, and it also did not have a significant impact on the likelihood of households spending on electricity or on water in 2017 in drought-affected areas. However, eligible households were more likely to use a borehole as their main source of water, a result that is driven by the behavior of households living in drought-affected areas, and is robust to different specification as well as placebo checks. We do not find a similar effect of program eligibility on other outcomes related to appliance adoption, electricity or water use, or welfare.

While the overall effects of program eligibility were largely insignificant, we also find that both expenditure on electricity or on water, as well as acquiring access to these amenities, have a positive and significant impact on the likelihood of households growing crops, an effect that is largely dominated by the drought-unaffected households. Access to the amenities also has a positive impact on monthly household consumption expenditure, which is likely to be driven more by the drought-affected households (even though the effect was insignificant for them). We do not find any other significant employment or health-related benefits of these acquiring the amenities, or of spending a positive amount on them.

In trying to disentangle the mechanisms for our findings, we learn that drought-affected but Indigent Program-eligible households that had borrowed were more likely to have used boreholes as their main water source. This form of 'mal-adaptation', while useful in mitigating short-run welfare losses, may exacerbate existing climate risks, if pursued on a large scale. Thus, access to credit may have acted as a potential means of adaptation in this setting. However, borrowing did not facilitate adoption of other appliances, or electricity/water use in general for households. We attribute the marginal effects of the program, especially on drought-affected households, to both a lack of significant benefits offered by the Indigent Program, and the impact of droughts on household assets.

We argue that the Indigent household program in South Africa may have partially enabled poor households to adapt to droughts (at least in the short-term, if it facilitated adoption of borehole pumps), but it needs to be accompanied by policies that make it easier for households to purchase durable goods such as appliances. In the absence of further financial assistance (in the form of other social welfare programs, or subsidies for appliances), as well as adaptation policies such as crop insurance, natural disaster insurance, etc., households may not be able to benefit from acquiring electricity, or piped water.

The findings of this study have important repercussions in the debate on rural electrification, especially in countries like South Africa, where emissions reduction is becoming increasingly important. This paper shows that it is critical for policy-makers to keep extreme weather and climate change in mind when designing electrification policies, as it may affect the ability of households to benefit from using grid electricity. Moreover, the findings shed light on sufficient credit as a possible short-run means of adaptation, and thus it may be important to provide households with easy and equitable means of acquiring liquidity. Credit may enable vulnerable households to buffer their losses, acquire new skills, or seek employment elsewhere. Of course, borrowing comes at cost, and these costs are likely to be heterogeneous across households as well. Policy-makers need to ensure that the poorest households are able to borrow easily, without facing difficult repayment conditions.This paper shows that social support schemes such as the Indigent Program may have some place in ensuring the provision of basic services such as electricity to disadvantaged households, however with limited benefits offered, they may end up being ineffective.

Lastly, another policy implication of this study is on electrification policy in low and middle-income countries. For policy-makers, it is important to understand why ensuring access does not always lead to immediate welfare gains. Previous literature has found that households that acquire access only experience gains after some time, or that they need additional investments to benefit from acquiring access. This study also confirms this finding, and points to the important role that these additional investments can play. Decentralized solutions such as pico/micro-grids, or solar home systems are important for enabling rural households living in remote areas to first acquire electricity, but long-term development may require governments to invest more resources in ensuring that households are able to connect to the grid. The findings of this study suggest that in order to understand why there are limited long-term welfare gains from electrification may require evaluating how climate change may effect households economically, socially as well as behaviorally. This remains a future area of research.

This is particularly relevant, in light of South Africa's commitments during COP26 in Glasgow, Scotland, especially its goal of achieving a reduction in emissions from the use of coal in electricity generation, i.e., emphasis on *mitigation*. Given that steps such as greening the electricity sector (through increased deployment of renewables, for example) would reduce greenhouse gas emissions, it may contribute towards reducing the intensity or frequency of extreme weather events in the long-run. It is thus important in this context, for policy-makers to hasten the transition to cleaner sources of energy, through technology transfer agreements with developed countries, for example (as South Africa agreed to do during COP26), which may also reduce the importance of adaptation measures over the long-term. However, as our study shows, given the effects of extreme weather events on socioeconomic outcomes, adaptation is imperative in the short- or medium-term. To this end, well-designed social policies should contribute towards increasing the resilience of poor households in low and middle-income countries.

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Appendix

Appendix A

Figure A1: RDD Validity: McCrary Test

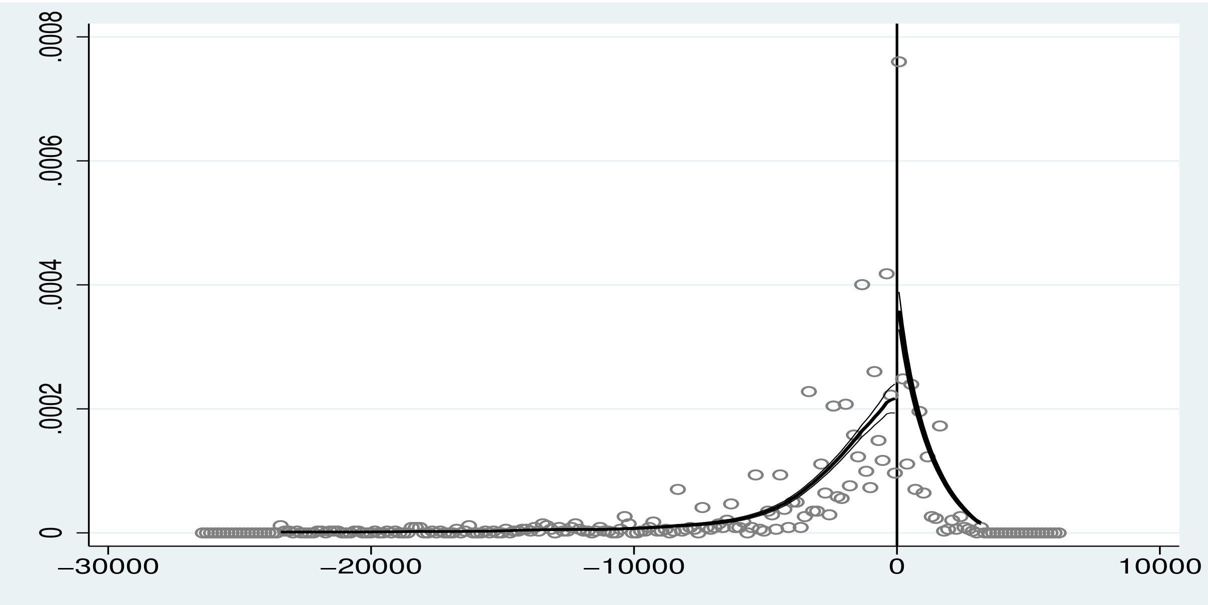
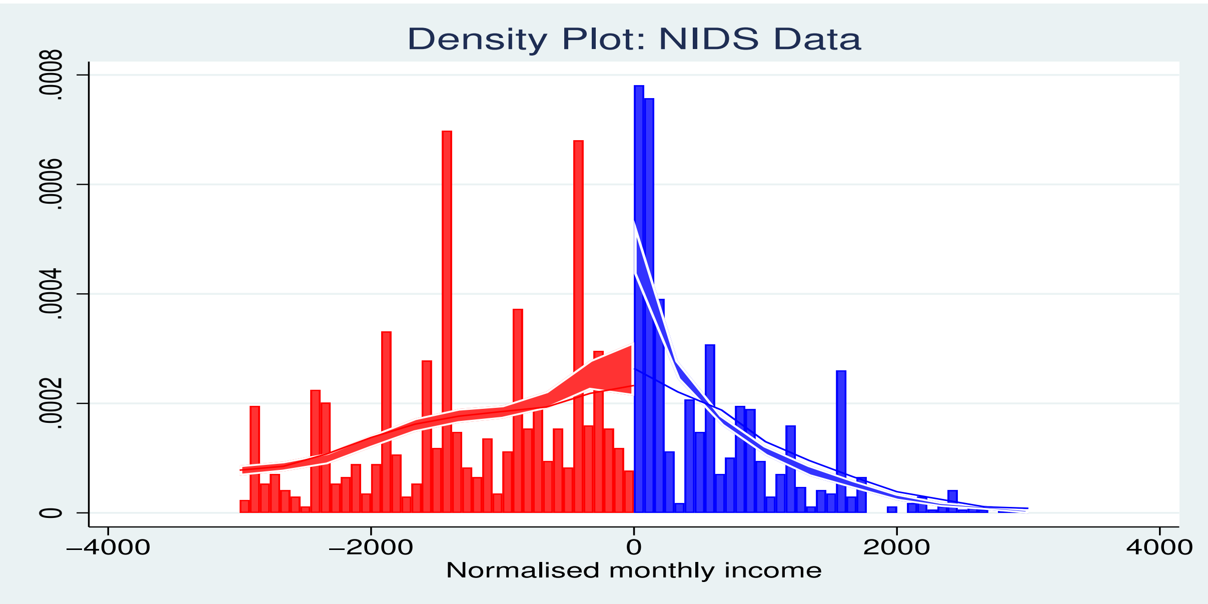
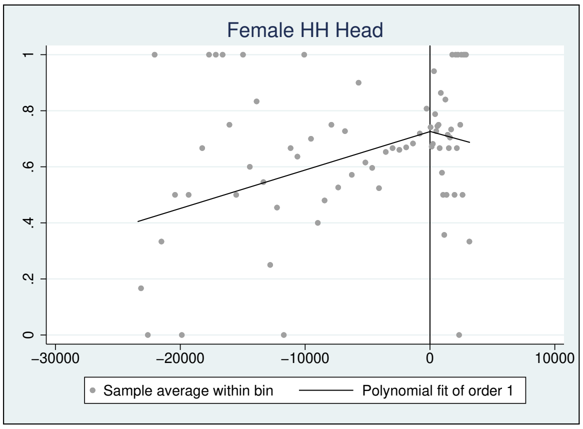
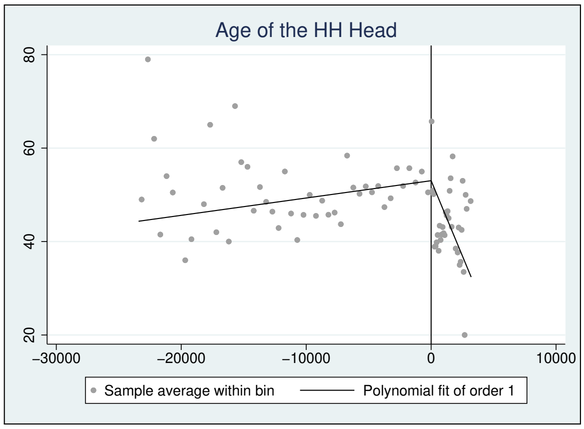


Figure A2: RDD Validity: Manipulation Testing Plot (Cattaneo et al., 2020)

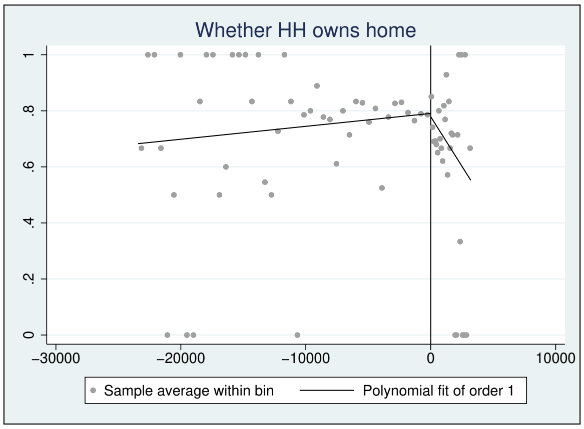




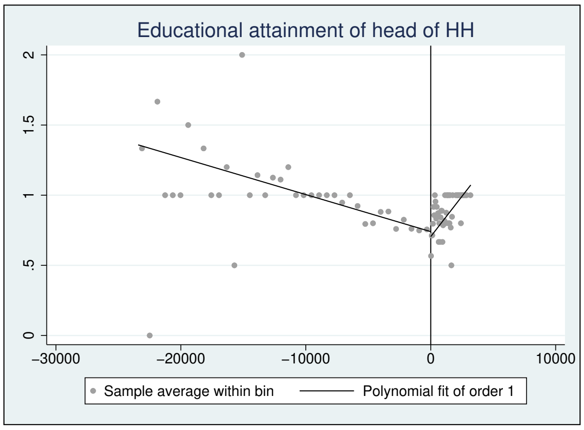
(a) Female HH Head



(b) Age of the HH Head



(c) Whether HH Owns Home



(d) Educational Attainment of HH Head

Figure A3: Covariate balance: RD Plots for Some Socioeconomic Variables

Table A1: Covariate Balance: RDD

Dependent Variable	BW = 1000	BW = 2000
Column	(1)	(2)
Whether HH lives in a modern dwelling	-0.076	-0.075*
	(0.057)	(0.042)
Observations	1020	1516
Whether HH owns a private vehicle	0.012	0.009
(0.023)	(0.017)	
Observations	1018	1513
Whether HH experience a negative event in the last two years (crops or livestock)	-0.004	-0.009
	(0.036)	(0.025)
Observations	1015	1510
Whether HH lives in an area with street lighting	0.027	0.0005
	(0.026)	(0.019)
Observations	1017	1512
Log of number of rooms in the house	-0.082	-0.08
	(0.071)	(0.05)
Observations	1020	1516
Zulu or Xhosa language	-0.031	0.027
	(0.051)	(0.037)
Observations	1010	1501

Notes: This table includes the reduced-form parametric results estimating the effect of eligibility for the Indigent Program on different covariates to check for covariate balance. These models are estimated without any covariates. The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial, and heteroscedasticity-robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Figure A4: Average scPDSI from 2008-2017 Across Districts in the Diff-in-Diff Sample

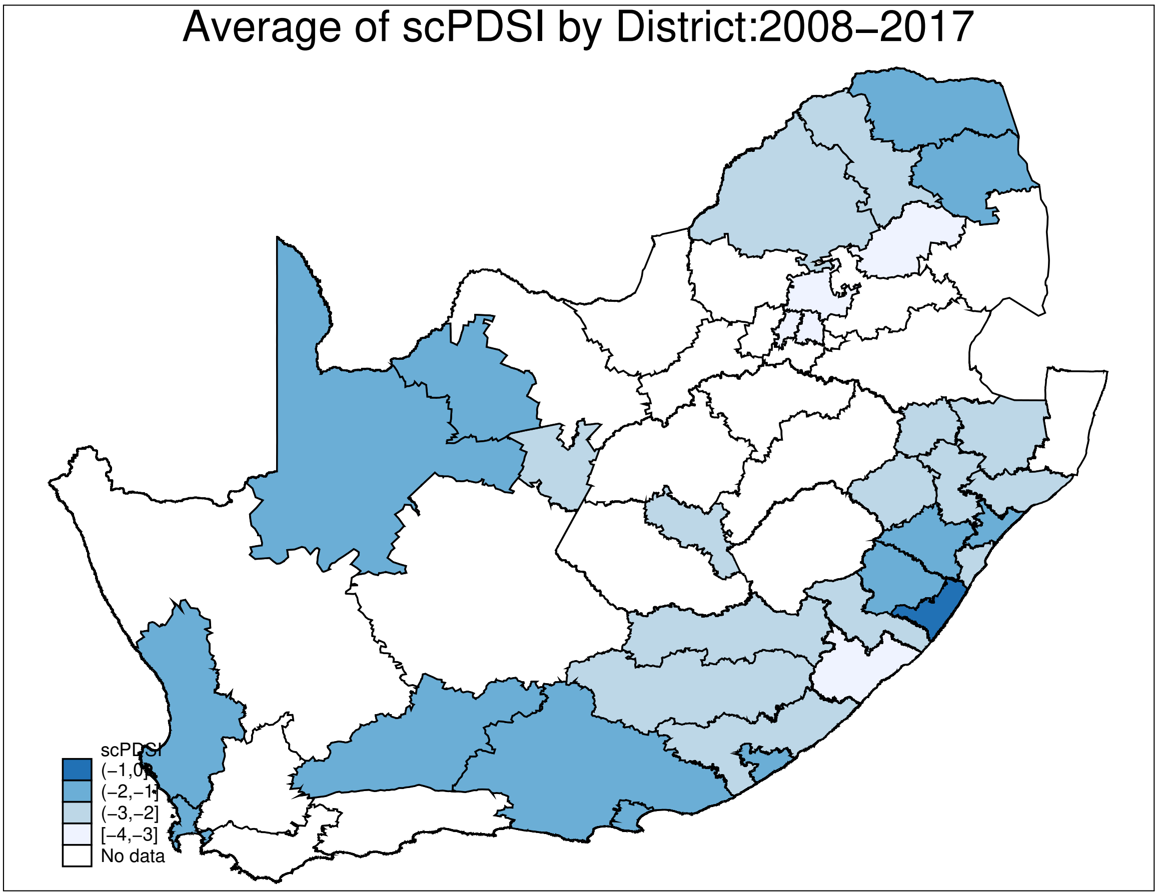


Table A2: Descriptive Statistics of Covariates

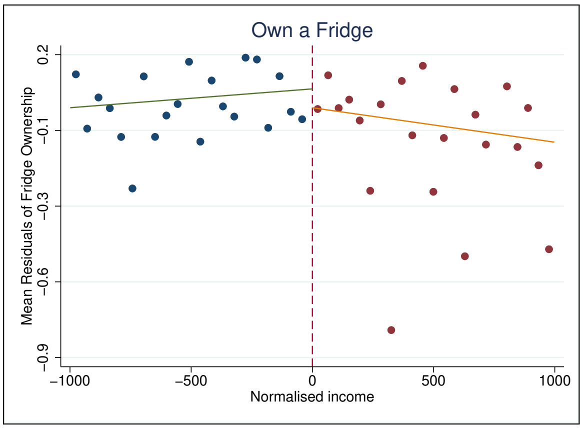
	RDD Sample					Diff-in-Diff Sample				
Variables	Mean	Standard Deviation	Minimum	Maximum	Obs.	Mean	Standard Deviation	Minimum	Maximum	Obs
Monthly household income (Rand, deflated)	3,718.53	3,629.12	0	25019.59	2,197	3,418.196	3,389.437	0	26194.87	8,036
Value of household assets (Rand, deflated)	218,697.2	656,882.7	578.189	20000000	2,132	183,524.8	686,117.6	1.436	23800000	4,995
Household size	4.56	3.079	1	30	2,197	4.77	3.128	1	39	8,036
Household lives in an area with street lighting	0.071	0.257	0	1	2,192	0.074	0.262	0	1	8,022
Any household member owns the dwelling	0.763	0.425	0	1	2,196	0.803	0.398	0	1	8,032
Household lives in a modern dwelling	0.671	0.470	0	1	2,197	0.611	0.488	0	1	8,021
Whether household experienced negative event in last two years	0.088	0.284	0	1	2,186	0.052	0.222	0	1	8,016
Household owns a private motor vehicle in running condition	0.087	0.282	0	1	2,194	0.074	0.261	0	1	8,024
Whether household received rental income in the last month	0.028	0.164	0	1	2,195	0.018	0.134	0	1	8,022
Whether household owns any agricultural land	0.428	0.495	0	1	2,164	0.377	0.485	0	1	7,052
Whether household owns livestock	0.192	0.394	0	1	2,197	0.180	0.384	0	1	8,036
Whether household has taken a loan	0.105	0.306	0	1	2,101	0.091	0.287	0	1	7,512
Head of household: gender is female	0.695	0.461	0	1	2,197	0.652	0.476	0	1	7,983
Head of household: age	50.99	17.03	17	99	2,197	51.086	16.99	12	99	7,966
Head of household: has a bank account	0.453	0.498	0	1	2,101	0.389	0.488	0	1	7,505
Head of household: spoke in Zulu or Xhosa languages (ethnicity)	0.744	0.437	0	1	2,171	0.733	0.442	0	1	8,001
Head of household: educational attainment (in %)										
Uneducated	20.63					26.01				7951
High-school or below	78.09					73.10				7951
Tertiary education	1.28					0.9				7951
Sum of nighttime lights (district-level)	15.546	19.529	0	63	2,197	12.628	19.572	0	63	8,036
Self-calibrated Palmer Drought Severity Index	-2.777	0.739	-4.064	-1.466	2,197	-2.306	1.178	-4.064	2.26	8,036
Weighted average of the cooling degree days above 30 degrees	0.255	0.606	0	3.632	2,197	0.321	1.380	0	21.066	8,036
Weighted average of the heating degree days below 5 degrees	3.099	6.790	0	23.716	2,197	4.113	9.763	0	486.507	8,036
Total annual precipitation (in mm)	778.542	228.857	163.406	1,295.048	2,197	723.935	240.57	163.406	1541.74	8,036

Notes: The summary statistics reported are calculated for the regression sample of households that lived in rural areas in 2017, whose normalised monthly income is within the 99^{th} percentile of the distribution (RDD Sample), and for rural households whose monthly income was within the 99^{th} percentile of the distribution (Diff-in-Diff Sample).

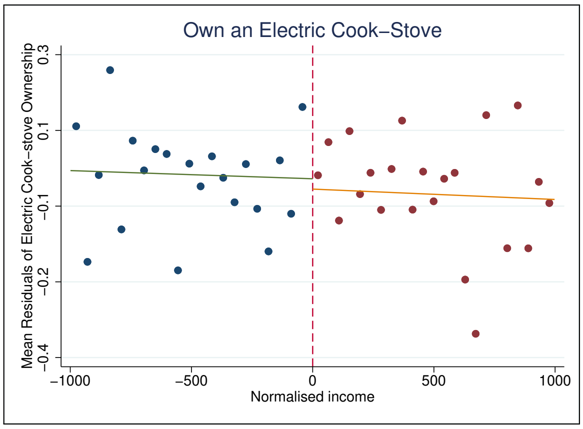
Table A3: Reduced-Form Parametric RDD: Additional Results

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Use of wood for cooking	0.126**	0.057	0.100	-0.006	0.140**	0.088**	0.754	0.272
	(0.051)	(0.037)	(0.115)	(0.074)	(0.056)	(0.043)		
Observations	1016	1508	292	486	724	1022		
Log of monthly net consumption expenditure	0.008	-0.03	-0.023	0.069	0.021	-0.030	0.745	0.334
	(0.055)	(0.042)	(0.127)	(0.091)	(0.061)	(0.047)		
Observations	1015	1503	291	485	724	1018		

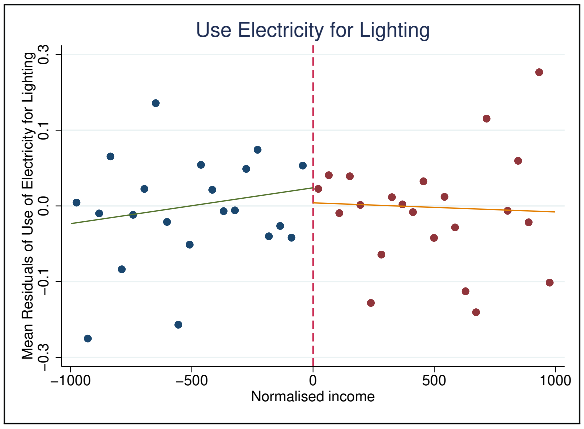
Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on the use of wood as the main energy source for cooking, and on the log of monthly consumption expenditure net of electricity spending, using the flexible parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.



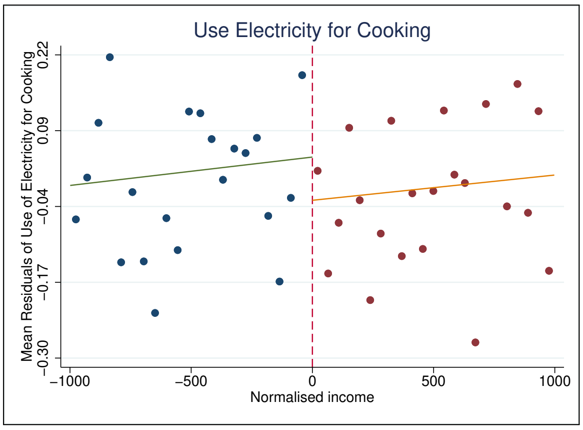
(a) Own a fridge



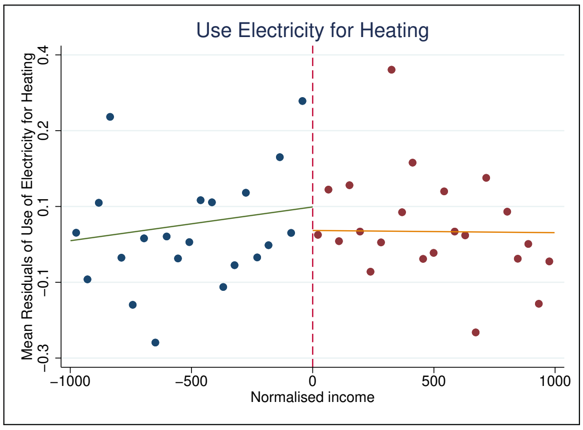
(b) Own an electric cook-stove



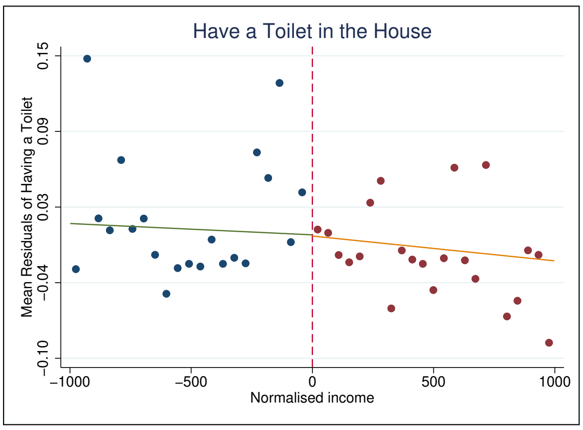
(c) Use electricity for lighting



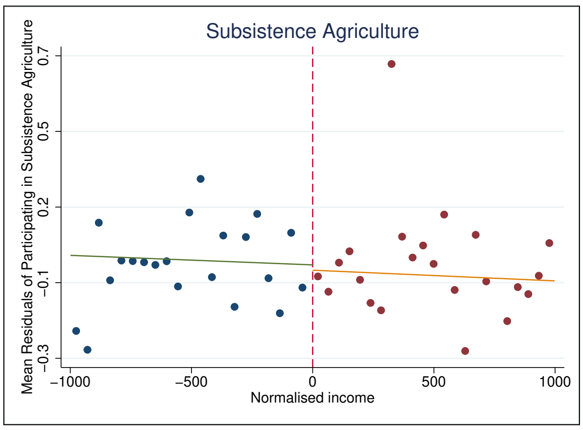
(d) Use electricity for cooking



(e) Use electricity for heating



(f) Have a toilet in the house



(g) Participated in subsistence agriculture

Figure A5: RD Plots: Additional Results

Table A4: Staggered Diff-in-Diff Results

Treatment variable	Spent on elec or water		Access to elec or to piped water	
Dependent variable	Overall	Switchers into treatment	Overall	Switchers into treatment
Column	(1)	(2)	(3)	(4)
Panel A: Overall Sample				
Anyone in household employed in last month	0.000	0.006	-0.023	-0.030
	(0.028)	(0.034)	(0.029)	(0.041)
Observations	3405	1182	3576	876
Household head self-employed in last month	0.010	0.001	0.012	0.014
	(0.013)	(0.019)	(0.019)	(0.023)
Observations	3077	1072	3230	789
Anyone in household grew crops in last year	0.061***	0.060*	0.085***	0.089**
	(0.025)	(0.034)	(0.033)	(0.046)
Observations	3406	1183	3577	876
Household head satisfied with their life	0.083**	0.081*	-0.001	0.029
	(0.038)	(0.048)	(0.038)	(0.063)
Observations	3033	1053	3184	775
Log of monthly consumption expenditure	0.033	0.043	0.082**	0.086**
	(0 .037)	(0.050)	(0.039)	(0.043)
Observations	3406	1183	3577	876
Household head has asthma	0.005	0.015	-0.016	-0.013
	(0.012)	(0.011)	(0.010)	(0.015)
Observations	2954	1025	3108	760
Household head has tuberculosis	-0.004	0.0002	0.024	0.025
	(0.015)	(0.022)	(0.019)	(0.029)
Observations	2870	996	3022	739
Panel B: Drought-unaffected households				
Anyone in household employed in last month	0.015	0.010	0.049	0.049
	(0.064)	(0.096)	(0.067)	(0.084)
Observations	1272	399	1366	327
Household head self-employed in last month	0.026	0.007	0.013	0.006
	(0.028)	(0.036)	(0.038)	(0.044)
Observations	1133	362	1221	293
Anyone in household grew crops in last year	0.097**	0.078	0.120**	0.133**
	(0.047)	(0.078)	(0.057)	(0.074)
Observations	1273	400	1367	327
Household head satisfied with their life	0.055	0.030	0.003	0.085
	(0.063)	(0.084)	(0.087)	(0.097)
Observations	1126	359	1212	291
Log of monthly consumption expenditure	0.116	0.110	0.056	0.036
	(0.110)	(0.130)	(0.099)	(0.134)
Observations	1273	400	1367	327
Household head has asthma	0.006	0.017	-0.044**	-0.035
	(0.025)	(0.035)	(0.024)	(0.032)
Observations	1086	348	1174	281
Household head has tuberculosis	-0.045	-0.042	0.027	0.060
	(0.028)	(0.041)	(0.040)	(0.047)
Observations	1081	340	1168	278
Panel C: Drought-affected households				
Anyone in household employed in last month	-0.004	-0.010	-0.034	-0.037
	(0.042)	(0.056)	(0.051)	(0.068)
Observations	1526	508	1556	360
Household head self-employed in last month	0.010	-0.002	-0.008	-0.008
	(0.018)	(0.017)	(0.023)	(0.030)
Observations	1388	464	1415	330
Anyone in household grew crops in last year	-0.036	-0.030	0.019	0.014
	(0.050)^a	(0.053)	(0.057)	(0.073)
Observations	1526	508	1556	360
Household head satisfied with their life	0.081	0.129**	0.036	0.072
	(0.059)	(0.065)	(0.075)	(0.085)
Observations	1376	463	1403	329
Log of monthly consumption expenditure	0.034	0.046	0.077	0.092
	(0.054)	(0.068)	(0.065)	(0.069)
Observations	1526	508	1556	360
Household head has asthma	0.014	0.018	-0.020	-0.019
	(0.011)	(0.014)	(0.020)	(0.019)
Observations	1327	438	1354	317
Household head has tuberculosis	0.020	0.029	0.024	0.017
	(0.025)^b	(0.032)	(0.038)	(0.057)
Observations	1261	424	1288	302

Notes: This table presents the results of the staggered diff-in-diff estimations evaluating the effect of electricity access on various socioeconomic outcomes, using the approach of Chaisemartin and D'Haultfœuille (2020). The regression sample in Panel A includes households that live in rural areas. The models include household fixed effects, year fixed effects, district-specific time trends, and controls for log of monthly deflated income, educational attainment, household size, whether the household owned their home, whether they live in a modern dwelling, and whether they were eligible for the Indigent Program. *,** and *** respectively denote significance at 10%, 5% and 1% levels. ^{a} and ^{b} denote coefficients that are similar to different to one another at the 5% level, and at the 10% level respectively. Boot-strapped clustered standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table A5: Effect of Droughts on Socioeconomic Outcomes

Dependent Variable Column	Log of net monthly cons. exp. (1)	Log of income (2)	Employed (3)	Engaged in subsistence agri (4)	Log of assets (5)	Own livestock (6)
Palmer Drought Severity Index	0.031** (0.014)	-0.007 (0.013)	0.024*** (0.009)	-0.018** (0.009)	0.236*** (0.079)	-0.003 (0.008)
Observations	7706	7748	7807	7805	4884	7810

Dependent Variable Column	Own a private vehicle (7)	Own land (8)	Electricity access (9)	Piped water access (10)	Spent on electricity (11)	Spent on water (12)
Palmer Drought Severity Index	-0.0006 (0.005)	-0.060*** (0.014)	0.016** (0.008)	-0.018*** (0.007)	0.031*** (0.008)	0.003 (0.004)
Observations	7800	6899	7796	7808	7714	7661

Notes: The regression sample includes households that live in rural areas, and whose normalised monthly income is within the 99^{th} percentile of the distribution. All estimations include household and year fixed effects, and province-specific time trends, and control for hot and cold temperature extremes, as well as annual rainfall and rainfall squared. Covariates include household size, age of the household head, whether the household own their home, whether the household experienced a negative crop or livestock event in the last two years, whether the household lives in an area with street lighting, and whether the household belongs to Zulu or Xhosa ethnicities. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the household level, and are reported in parentheses. The coefficient on the constant has not been reported.

Table A6: Access and Expenditure Shares By Subgroup: Descriptive Statistics

Panel A		
Access to electricity	Eligibility for the Indigent Program	
	Yes	No
Drought-affected	70% (1486 obs)	79% (2616 obs)
Drought-unaffected	65% (1707 obs)	80% (2121 obs)
Panel B		
Piped water	Eligibility for the Indigent Program	
	Yes	No
Drought-affected	30% (1486 obs)	45% (2618 obs)
Drought-unaffected	31% (1715 obs)	42% (2125 obs)
Panel C		
Expenditure on electricity (conditional on having access)	Eligibility for the Indigent Program	
	Yes	No
Drought-affected	86% (1034 obs)	90% (2042 obs)
Drought-unaffected	84% (1092 obs)	90% (1685 obs)
Panel D		
Expenditure on water (conditional on having access to piped water)	Eligibility for the Indigent Program	
	Yes	No
Drought-affected	4% (441 obs)	8% (1168 obs)
Drought-unaffected	9% (526 obs)	12% (861 obs)

Notes: The summary statistics reported are calculated for sample of rural households over all years. This sample includes households that live in rural areas, whose normalised monthly income is within the 99^{th} percentile of the distribution.

Table A7: Effect of Borrowing on Socioeconomic Outcomes for Drought-Affected Households

Dependent Variable	Took a loan	Fridge	Electric stove	Lighting	Cooking	Heating	Toilet
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eligibility for the Program	0.029						
	(0.021)						
Observations	3850						
Took a loan: eligibility		-0.110*	-0.033	0.082	-0.097	0.078	-0.006
		(0.063)	(0.071)	(0.060)	(0.075)	(0.084)	(0.015)
Observations		363	363	363	363	363	363
Didn't take a loan: eligibility		-0.012	-0.051*	-0.006	0.018	0.035	0.015
		(0.030)	(0.029)	(0.025)	(0.032)	(0.036)	(0.014)
Observations		3487	3486	3487	3487	3485	3486
P-value		0.16	0.814	0.176	0.159	0.638	0.306
Dependent Variable	**Subs. agri.**	**Elec access**	**Piped water access**	**Spent elec**	**Spent water**	**Borehole**	**Log of cons exp.**
Column	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Took a loan: eligibility	-0.117*	0.09	0.032	0.118**	0.009	0.070**	-0.225**
	(0.069)	(0.065)	(0.047)	(0.060)	(0.012)	(0.039)	(0.101)
Observations	363	363	363	362	361	363	363
Didn't take a loan: eligibility	-0.045	0.021	0.023	-0.009	-0.002	0.011	-0.024
	(0.032)	(0.026)	(0.023)	(0.027)	(0.020)	(0.015)	(0.044)
Observations	3485	3482	3486	3449	3445	3486	3487
P-value	0.344	0.324	0.863	0.054	0.637	0.158	0.068

Notes: The regression sample includes drought-affected households that live in rural areas, and whose normalised monthly income is within the 99^{th} percentile of the distribution. All estimations include household and year fixed effects, district-specific time trends, and province-year fixed effects. Covariates include log of household size, age of the household head, whether the household own their home, whether the household lived in a modern dwelling, whether the household lives in an area with street lighting, whether the household has a bank account, whether the household has a private vehicle, educational attainment of the head of the household, and the log of monthly income. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are clustered at the household level, and are reported in parentheses. The coefficient on the constant has not been reported.

Table A8: Effect of Borehole Adoption on Groundwater Levels

Dependent Variable	GWLS	GWLS	GWLS	GWLS	GWLS
Column	(1)	(2)	(3)	(4)	(5)
Average Adoption Rate of Boreholes (District-level)	-61.140***	-98.688***	-50.406***	-72.544***	-73.812***
	(2.209)	(1.886)	(2.178)	(2.197)	(2.416)
District Fixed effects	No	Yes	No	Yes	Yes
Year fixed effects	No	No	Yes	Yes	Yes
Province-specific time trend	No	No	No	No	Yes
Covariates	Yes	Yes	Yes	Yes	Yes
Observations	12523	12523	12523	12523	12523

Notes: The regression sample includes households that live in rural areas. Covariates include average scPDSI, the sum of nighttime lights, the weighted average of the number of cooling-degree days above 30 degrees, the weighted average of the number of heating-degree days below 5 degrees, annual rainfall and annual rainfall squared. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Robust standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Appendix B

Drought Measure

Since this study uses the publicly accessible version of the NIDS data (which does not provide GPS coordinates for the addresses of the households), it is important to ensure that the NIDS as well as the climate data sets speak to one another. The first step is to ensure spatial equivalence between both datasets; we thus need to aggregate the grid-level scPDSI data up to the level of each district (since the district is the smallest identifiable geographic unit in the NIDS dataset). To do this, we identify the coordinates of the centroid of each district included in the NIDS sample using Google Earth. Next, we identify the grid cell from the CRU dataset that is closest to this centroid in terms of distance (using the STATA command 'geonear'), and then use this value as the district-specific scPDSI measure. This exercise yields a value of the scPDSI for each district in our data, for each year.[12] Figure A4 in the Appendix shows the average values of the scPDSI over the five years in our sample, for the districts included in the diff-in-diff analysis. We find considerable heterogeneity in the intensity of drought conditions over different districts. In many districts in our sample we find that the average scPDSI values were quite low, suggesting either severe or extreme drought conditions drought conditions.

Temperature and Precipitation Data

The data on temperature and on precipitation is drawn from the CPC (Climate Prediction Center) Global Daily Temperature and Global Precipitation databases. These databases contain global temperature and rainfall data at a 0.5x0.5° granularity, and from 1979 to present (NOAA Physical Sciences Laboratory, 2021). The relevant variables from this database are the

[12] As a robustness check, we also use an alternative methodology to calculate the average scPDSI at the district level. We take the scPDSI values of the five closest grid cells from the CRU dataset, and then create a district-specific scPDSI measure which is a weighted average of these five grid-level values, using inverse-distance weighting. Our main result is confirmed on using this weighted average drought measure as well. These results are provided in Table B7 in Appendix B.

maximum and minimum daily temperatures for each 0.5 degree grid cell, as well as the annual rainfall in each grid cell. These can be used to compute the mean daily temperature for each grid cell (the sum of both temperatures divided by two), as well as the total annual rainfall. We use the same approach described above for the scPDSI to create a weighted average of the temperature and rainfall variables at a district-level, using information from the five nearest grid-cells to each district centroid and inverse-probability weighting.

In order to capture well-documented non-linearities in the effect of temperature, and to ensure temporal equivalence with the NIDS data (which is at an annual frequency), we use this daily temperature measure to construct two types of annual temperature variables, one which counts the number of cooling-degree days when the mean daily temperature is greater than 30 degrees Celsius in each district, and the other the number of heating-degree days when the mean daily temperature is less than 5 degrees Celsius in each district. In the regression models evaluating the effect of droughts on different socioeconomic indicators (presented in Table A5), we convert these two variables to indicator variables, denoting whether the number of cooling-degree days was higher than 30 degrees Celsius in a district, and whether the number of heating-degree days was lower than 5 degree Celsius.[13] We introduce the total annual rainfall, as well as its square, to capture potential non-linearities in the precipitation effects.

[13] The main results are confirmed on considering the weighted average of different number of grid cells other than 5 for constructing the temperature or rainfall variables, or on using different temperature thresholds, results provided on request.

Table B1: Reduced-Form Inflexible Parametric RDD Results: Electricity and Water

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access to grid electricity	0.011	0.002	0.068	0.025	-0.009	-0.005	0.273	0.589
	(0.042)	(0.033)	(0.053)	(0.043)	(0.046)	(0.035)		
Observations	1016	1508	292	486	724	1022		
Access to piped water	-0.008	-0.006	0.021	-0.002	-0.018	-0.008	0.646	0.883
	(0.049)	(0.038)	(0.067)	(0.055)	(0.052)	(0.040)		
Observations	1016	1508	292	486	724	1022		
Spent on electricity	0.018	0.021	0.093*	0.072*	-0.009	0.004	0.16	0.226
	(0.043)	(0.033)	(0.056)	(0.043)	(0.046)	(0.036)		
Observations	1016	1504	292	486	724	1018		
Spent on water	0.004	0.014	0.100	0.012	0.022	0.014	0.237	0.927
	(0.013)	(0.011)	(0.064)	(0.018)	(0.016)	(0.012)		
Observations	1016	1508	292	486	724	1022		

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on electricity access, piped water access, expenditure on electricity (dummy variable) and expenditure on water (dummy variable) using the parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B2: Reduced-Form Inflexible Parametric RDD Results: Other Socioeconomic Outcomes

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Use a borehole as main water source	0.037**	0.027**	0.004	0.008	0.049***	0.034**	0.26	0.373
	(0.021)	(0.015)	(0.034)	(0.025)	(0.021)	(0.015)		
Observations	1016	1508	292	486	724	1022		
Own a fridge	-0.028	-0.048	0.082	0.053	-0.066	-0.081**	0.093	0.05
	(0.053)	(0.040)	(0.068)	(0.053)	(0.056)	(0.043)		
Observations	1016	1508	292	486	724	1022		
Own an electric cook-stove	-0.023	-0.027	0.044	0.044	-0.047	-0.050	0.283	0.152
	(0.050)	(0.038)	(0.066)	(0.052)	(0.053)	(0.040)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for lighting	-0.012	-0.002	0.055	0.043	-0.036	-0.017	0.145	0.214
	(0.037)	(0.029)	(0.048)	(0.037)	(0.040)	(0.031)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for cooking	-0.080	-0.031	-0.013	0.042	-0.103**	-0.055	0.2	0.174
	(0.053)	(0.041)	(0.071)	(0.057)	(0.056)	(0.043)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for heating	-0.040	0.003	0.014	0.0004	-0.059	0.003	0.431	0.971
	(0.054)	(0.041)	(0.073)	(0.059)	(0.057)	(0.043)		
Observations	1014	1506	292	486	724	1020		
Having a toilet	0.002	0.003	-0.011	0.011	0.007	0.0005	0.643	0.742
	(0.024)	(0.019)	(0.028)	(0.024)	(0.027)	(0.021)		
Observations	1016	1508	292	486	724	1022		
Subsistence Agriculture	-0.017	-0.019	0.03	0.021	-0.033	-0.032	0.473	0.44
	(0.051)	(0.039)	(0.070)	(0.055)	(0.053)	(0.041)		
Observations	1015	1507	292	486	724	1021		
Log of monthly consumption expenditure	0.040	-0.012	0.192***	0.135**	-0.013	-0.061	0.031	0.012
	(0.053)	(0.039)	(0.077)	(0.067)	(0.055)	(0.040)		
Observations	1016	1508	292	486	724	1022		

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on various socioeconomic outcomes using the parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B3: Reduced-Form Parametric RDD Results Using a Quadratic Polynomial: Electricity and Water

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Access to grid electricity	0.002	0.018	-0.111	0.101	0.025	-0.007	0.461	0.302
	(0.074)	(0.049)	(0.165)	(0.087)	(0.082)	(0.058)		
Observations	1016	1508	292	486	724	1022		
Access to piped water	-0.087	-0.020	-0.154	-0.035	-0.087	-0.021	0.78	0.916
	(0.098)	(0.058)	(0.214)	(0.113)	(0.108)	(0.068)		
Observations	1016	1508	292	486	724	1022		
Spent on electricity	0.056	-0.006	0.307	0.152	0.008	-0.049	0.203	0.073
	(0.078)	(0.050)	(0.220)	(0.096)	(0.081)	(0.058)		
Observations	1016	1504	292	486	724	1018		
Spent on water	0.027	-0.007	0.159**	-0.033	0.002	0.003	0.029	0.469
	(0.020)	(0.017)	(0.069)	(0.047)	(0.020)	(0.016)		
Observations	1016	1508	292	486	724	1022		

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on electricity access, piped water access, expenditure on electricity (dummy variable) and expenditure on water (dummy variable) using the parametric RDD methodology with a quadratic polynomial. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B4: Reduced-Form Parametric RDD Results: Other Socioeconomic Outcomes

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values:BW = 1000	P-values: BW = 2000
Dependent variables	BW = 1000	BW = 2000	BW = 1000	BW = 2000	BW = 1000	BW = 2000	H0: Coefficients same	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Use a borehole as main water source	-0.010	0.042*	-0.132	0.027	0.019	0.047**	0.436	0.778
	(0.041)	(0.024)	(0.191)	(0.067)	(0.031)	(0.023)		
Observations	1016	1508	292	486	724	1022		
Own a fridge	-0.033	-0.067	0.063	-0.005	-0.055	-0.095	0.667	0.513
	(0.104)	(0.062)	(0.249)	(0.116)	(0.115)	(0.074)		
Observations	1016	1508	292	486	724	1022		
Own an electric cook-stove	-0.006	-0.033	0.372	0.083	-0.081	-0.077	0.104	0.233
	(0.088)	(0.056)	(0.263)	(0.118)	(0.092)	(0.064)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for lighting	0.024	-0.011	0.008	0.065	0.027	-0.035	0.913	0.273
	(0.064)	(0.042)	(0.160)	(0.077)	(0.070)	(0.049)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for cooking	-0.134	-0.045	0.156	-0.005	-0.185*	-0.068	0.909	0.656
	(0.096)	(0.061)	(0.233)	(0.122)	(0.101)	(0.071)		
Observations	1016	1508	292	486	724	1022		
Use of electricity for heating	-0.211**	-0.052	0.214	0.074	-0.303***	-0.108	0.053	0.207
	(0.098)	(0.063)	(0.246)	(0.125)	(0.104)	(0.072)		
Observations	1014	1506	292	486	722	1020		
Having a toilet	-0.066	-0.003	-0.015	0.017	-0.073	-0.009	0.509	0.633
	(0.054)	(0.032)	(0.059)	(0.036)	(0.065)	(0.041)		
Observations	1016	1508	292	486	724	1022		
Subsistence Agriculture	-0.002	-0.052	0.331	0.085	-0.082	-0.099	0.11	0.18
	(0.094)	(0.059)	(0.236)	(0.119)	(0.104)	(0.068)		
Observations	1015	1507	292	486	724	1021		
Log of monthly consumption expenditure	0.040	0.027	0.291	0.063	-0.108	0.031	0.131	0.824
	(0.053)	(0.056)	(0.251)	(0.131)	(0.085)	(0.060)		
Observations	1016	1508	292	486	724	1022		

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on various socioeconomic outcomes using the flexible parametric RDD methodology, with a quadratic polynomial. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B5: Reduced-Form Non-parametric RDD Results: Electricity and Water

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values: Optimal BW		P-values: Double optimal	
Dependent variables	Optimal	Double optimal	Optimal	Double optimal	Optimal	Double optimal	H0: Groups similar	H0: Coefficients same	H0: Groups similar	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Access to grid electricity	-0.010	-0.001	0.031	0.119*	0.009	-0.010	0.994	0.867	0.999	0.092
	(0.057)	(0.052)	(0.108)	(0.068)	(0.061)	(0.050)				
Observations	2183	2183	246	414	613	910				
Bandwidth	855.39	1710.794	855.39	1710.79	855.39	1710.79				
Access to piped water	0.002	-0.013	0.023	-0.024	-0.005	-0.038	0.964	0.899	0.999	0.896
	(0.085)	(0.078)	(0.206)	(0.095)	(0.082)	(0.052)				
Observations	2183	2183	200	320	540	762				
Bandwidth	674.75	1349.50	674.75	1349.50	674.75	1349.50				
Spent on electricity	0.048	-0.013	0.367**	0.183**	0.003	-0.017	0.996	0.029	1.000	0.031
	(0.061)	(0.058)	(0.167)	(0.083)	(0.068)	(0.043)				
Observations	2177	2177	218	271	582	689				
Bandwidth	783.05	1566.09	783.05	1566.09	783.05	1566.09				
Spent on water	0.025	0.026	0.100	0.044	0.022	0.006	0.924	0.247	0.998	0.392
	(0.021)	(0.018)	(0.064)	(0.042)	(0.016)	(0.011)				
Observations	2180	2180	163	377	451	868				
Bandwidth	491.19	982.38	491.19	982.38	491.19	982.38				

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on electricity access, piped water access, expenditure on electricity (dummy variable) and expenditure on water (dummy variable) using the non-parametric RDD methodology. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial, uniform kernel structure, and heteroscedasticity-robust nearest neighbour standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B6: Reduced-Form Non-parametric RDD Results

Sample	A: Overall Sample		B: Drought-unaffected Sub-sample		C: Drought-affected Sub-sample		P-values: Optimal BW		P-values: Double optimal	
Dependent variables	Optimal	Double optimal	Optimal	Double optimal	Optimal	Double optimal	H0: Groups similar	H0: Coefficients same	H0: Groups similar	H0: Coefficients same
Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Use a borehole as main water source	0.047**	0.042**	0.005	-0.012	0.045**	0.043***	0.985	0.688	1.000	0.265
	(0.026)	(0.023)	(0.097)	(0.048)	(0.020)	(0.016)				
Observations	2183	2183	276	442	707	973				
Bandwidth	1,015.67	2,031.33	1,015.67	2,031.33	1,015.67	2,031.33				
Own a fridge	-0.007	-0.087	0.224	0.062	-0.038	-0.077	0.967	0.401	0.997	0.308
	(0.100)	(0.091)	(0.295)	(0.116)	(0.087)	(0.063)				
Observations	2181	2181	185	304	511	739				
Bandwidth	596.985	1,193.97	596.985	1,193.97	596.985	1,193.97				
Own an electric cook-stove	-0.042	-0.031	0.123	.043	-0.090	-0.043	0.993	0.240	1.000	0.397
	(0.071)	(0.062)	(0.175)	(0.091)	(0.071)	(0.047)				
Observations	2183	2183	232	400	595	891				
Bandwidth	799.363	1,598.73	799.363	1,598.73	799.363	1,598.73				
Use of electricity for lighting	0.006	-0.044	0.136	0.093	-0.012	-0.039	0.973	0.368	0.999	0.079
	(0.061)	(0.055)	(0.160)	(0.067)	(0.060)	(0.039)				
Observations	2183	2183	198	319	539	760				
Bandwidth	662.833	1,325.67	662.833	1,325.67	662.833	1,325.67				
Use of electricity for cooking	-0.185***	-0.139**	0.055	0.093	-0.198**	-0.042	0.997	0.233	1.000	0.213
	(0.076)	(0.071)	(0.196)	(0.096)	(0.088)	(0.055)				
Observations	2183	2183	211	367	574	844				
Bandwidth	714.953	1,429.91	714.953	1,429.91	714.953	1,429.91				
Use of electricity for heating	-0.164*	-0.171*	0.382	0.061	-0.229***	-0.173***	0.914	0.03	0.991	0.201
	(0.098)	(0.099)	(0.268)	(0.171)	(0.094)	(0.067)				
Observations	2179	2179	160	247	432	614				
Bandwidth	439.061	878.122	439.061	878.122	439.061	878.122				
Having a toilet	-0.012	-0.002	0.019	0.005	0.032	0.026	0.997	0.795	1.000	0.566
	(0.037)	(0.036)	(0.039)	(0.031)	(0.037)	(0.021)				
Observations	2183	2183	239	404	602	905				
Bandwidth	831.468	1,662.94	831.468	1,662.94	831.468	1,662.94				
Subsistence Agriculture	-0.009	-0.089	0.188	0.024	-0.133	-0.053	0.997	0.045	1.000	0.488
	(0.073)	(0.064)	(0.132)	(0.086)	(0.086)	(0.052)				
Observations	2181	2181	239	404	602	905				
Bandwidth	830.861	1,661.72	830.861	1,661.72	830.861	1,661.72				
Log of monthly consumption expenditure	-0.022	0.020	0.179	0.041	-0.059	-0.111***	0.996	0.142	0.999	0.668
	(0.064)	(0.068)	(0.161)	(0.110)	(0.064)	(0.055)				
Observations	2183	2183	217	320	582	762				
Bandwidth	756.854	1,368.21	756.854	1,368.21	756.854	1,368.21				

Notes: This table includes the reduced-form results estimating the effect of eligibility for the Indigent Program on several outcome variables, mentioned in the first column. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial, uniform kernel structure, and heteroscedasticity-robust nearest neighbour standard errors. In Panels B and C, the observations are weighted by the inverse propensity score. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

Table B7: RDD Placebo Checks

	Sample Dependent Variables	A: Overall Sample BW = 1000	 BW = 2000	B: Drought-unaffected Sub-sample BW = 1000	 BW = 2000	C: Drought-affected Sub-sample BW = 1000	 BW = 2000	P-values:BW = 1000 H0: Coefficients same	P-values: BW = 2000 H0: Coefficients same
Row	Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	Income threshold of 1500 Rand	0.014	0.017	0.042	0.014	0.004	0.016	0.509	0.965
		(0.019)	(0.016)	(0.055)	(0.043)	(0.017)	(0.015)		
	Observations	986	1460	294	458	692	1002		
(2)	Income threshold of 4000 Rand	-0.037	-0.019	-0.113	-0.052	0.019	0.009	0.193	0.387
		(0.046)	(0.016)	(0.087)	(0.058)	(0.052)	(0.040)		
	Observations	557	1460	196	384	361	675		
(3)	Year: 2008	-0.037	-0.024	-0.056	-0.069	-0.047	0.037	0.937	0.218
		(0.053)	(0.040)	(0.065)	(0.042)	(0.093)	(0.075)		
	Observations	342	671	247	472	95	199		
(4)	Year: 2010	-0.034	-0.026	-0.047	-0.001	-0.0002	-0.077	0.601	0.401
		(0.034)	(0.028)	(0.038)	(0.028)	(0.081)	(0.086)		
	Observations	462	684	338	472	124	212		
(5)	Year: 2012	0.049	0.006	0.106**	0.045	-0.013	-0.043	0.119	0.073
		(0.040)	(0.025)	(0.047)	(0.031)	(0.060)	(0.038)		
	Observations	497	904	297	528	200	376		
(6)	Year: 2014	0.012	-0.015	-0.015	-0.032**	0.036	0.002	0.267	0.258
		(0.023)	(0.015)	(0.027)	(0.015)	(0.037)	(0.026)		
	Observations	963	1522	438	708	525	814		
(7)	GWLS indicator for drought			0.01	0.013	0.102*	0.064	0.151	0.21
				(0.025)	(0.017)	(0.059)	(0.037)		
	Observations			508	774	343	514		
(8)	Weighted average scPDSI measure	0.040*	0.026*	0.040	-0.006	0.049**	0.054***	0.863	0.072
		(0.023)	(0.015)	(0.046)	(0.028)	(0.025)	(0.018)		
	Observations	1016	1508	391	628	625	880		

Notes: This table includes placebo checks for the reduced-form parametric RDD models estimating the effect of eligibility for the Indigent Program on the use of borehole as the main water source. All models include basic covariates (whether the household owned their home, log of household size, gender of the head of the household, age of the household head, educational attainment of household head, whether the household received any rental income, and district dummies). The regression sample includes households that live in rural areas in the year 2017. All models are estimated using a linear polynomial in the running variable, and robust standard errors. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Standard errors are reported in parentheses. The coefficient on the constant has not been reported.

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