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DODGING DAY ZERO:
DROUGHT, ADAPTATION, AND INEQUALITY IN CAPE TOWN

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ABSTRACT

A near-catastrophic drought in Cape Town, South Africa illustrates three general implications of climate change for publicly-provided utility services. First, to reduce aggregate water demand, the public utility increased prices, leading to large demand reductions by richer households. Prior to the drought they use twice the public piped water of poorer households. At the peak of the drought, they use less. Second, some of the differential demand reduction comes from richer households substituting away from public water toward privately financed groundwater. This private adaptation both lowers the public utility's total revenue and shifts costs onto poorer households, consequences that persist after the drought abates. Third, policy interventions mitigate some of the fiscal and distributional impacts of private adaptation. These findings highlight how climate adaptation, in the context of publicly provided goods and services, can create pecuniary and environmental externalities with equity consequences.

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1 Introduction

How will climate change affect inequality? The existing literature has emphasized two main channels. The first observes that lower-income households tend to live and work in settings where physical climate damages are large (Graff Zivin and Neidell, 2014; Burke, Hsiang and Miguel, 2015; Hsiang, Oliva and Walker, 2019). The second channel notes that costly private adaptation to climate change favors higher income households (Carleton et al., 2022, 2025). An emerging literature highlights a third channel: private climate adaptation itself can be a source of pecuniary or environmental externalities (Abajian et al., 2023; Hsiao, 2024).

We study the distributional consequences of adaptation in the context of the public provision of rival goods—utility services—that are climate exposed. Droughts and heatwaves lead to rationed water supplies, rolling electricity blackouts, and higher prices (Harmsen, 2017). Changes to the price or quality of the publicly-provided good induce some households to pay the fixed cost of adopting private substitutes. In the short run, this adaptation through substitution reduces demand for the public supply when it is most scarce, as in the case of a climate shock.[1] However, after the shock, adoption of private substitutes can lead to persistent reductions in the utility's revenue base and shifts in the distribution of costs across users. These changes will be regressive if wealthier consumers have disproportionate access to privately financed substitutes, such as groundwater wells or rooftop solar panels.

This previously unstudied link between climate change and inequality is potentially wide reaching. Upward of 7 billion people around the world depend on public utilities for water and/or electricity (World Health Organization et al., 2024), while an estimated 1 billion people live in cities vulnerable to drought (Ahmadi et al., 2020; He et al., 2021). We illustrate its empirical relevance in the context of an historic drought in Cape Town, South Africa, the 21st century's poster child for near-catastrophic water scarcity (Visser, 2018; Booysen, Visser and Burger, 2019; Ziervogel, 2019; Brühl et al., 2020).

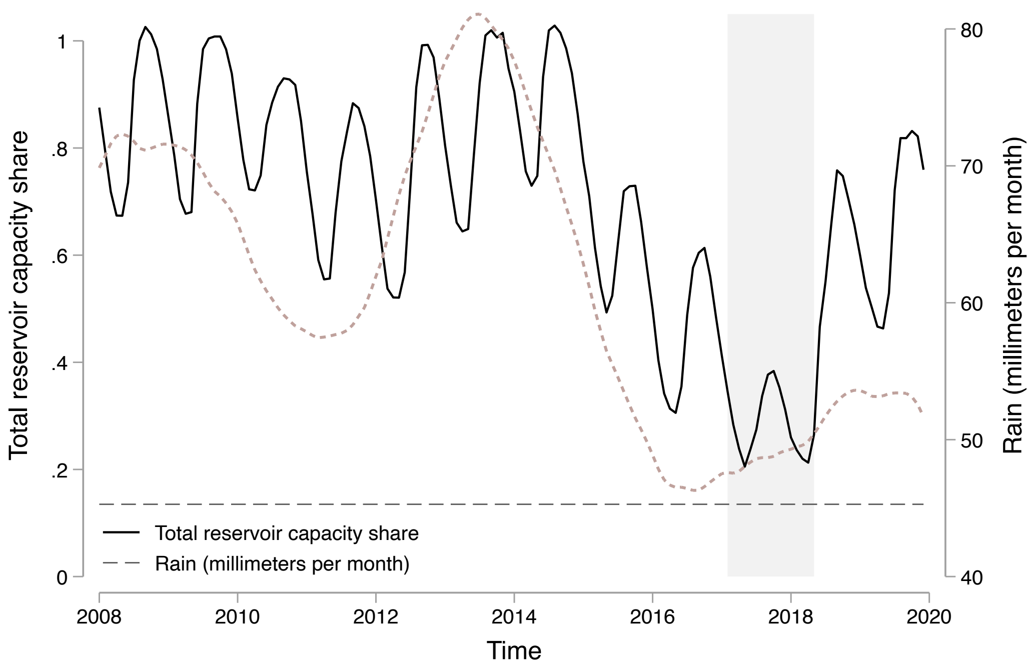
The municipal government in Cape Town is responsible for supplying piped water to over 4 million residents, a rapidly growing and highly unequal population. Like many public utilities around the world, Cape Town recovers the cost of supplying water with volumetric (i.e., per unit) pricing in the form of increasing block tariffs (IBT). This is justified on equity grounds: by charging a higher marginal price at higher quantities, high consumers—who are typically assumed to be wealthier—contribute a larger share of the utility's revenue relative to their consumption (Andres et al., 2021; Foster and Witte, 2020). Pre-drought, the IBT combined with lower consumption by lower-income households meant that the average

[1] We refer to adoption of substitutes as "adaptation." Households adapt to changes in prices or quality of the publicly provided good—driven by the climate shock and policy—by adopting substitutes.

marginal price faced by the poorest households in our sample was 44% lower than the average marginal price faced by the richest households.

A decade of below-average rainfall and a high dependence on surface water culminated in the threat of "Day Zero"—a term for the point when reservoir levels fall so low that the city's pipes run dry. The countdown to Day Zero began in 2017. Steep price increases, usage restrictions and social pressure campaigns were launched to manage demand (Brühl and Visser, 2021). Ultimately, Day Zero was narrowly avoided, as shown in Figure 1.

Figure 1: Cape Town reservoir levels and rainfall around Day Zero



NOTES: Left vertical axis shows monthly capacity share across the six largest dams supplying municipal water to Cape Town between January 2008 and December 2019. Dotted line shows the 13.5% capacity, the threshold below which the city would shut off piped water. Right vertical axis shows monthly rainfall averaged across the six dams. Gray-shaded area marks the February 2017 to May 2018 water crisis.

To develop intuition for how Day Zero was avoided and its long-term consequences, we develop a simple model of a public water utility (PU) that recovers fixed and variable costs through volumetric pricing. The model illustrates several implications for how an aggregate supply shock (e.g., a drought) and access to private substitutes (e.g., groundwater wells) affect public water demand and revenue both during and after a shock. First, regardless of the pricing scheme used by the PU, it must raise prices during the shock to ensure that demand does not exceed (inelastic) supply.[2] Second, higher prices lower aggregate public

[2]The utility may instead choose to adopt other demand-side management strategies such as rationing, a common practice in other low and middle income countries. Predictions from the model also hold when demand is managed through rationing.

water demand and revenue more when private substitutes are available; this lowers the amount by which prices must rise to curtail demand enough to meet the supply constraint during the drought. Third, when adaptation through substitution is optimal only for richer households, a larger share of the utility's costs will be shifted onto poorer consumers. These impacts are path dependent: once richer households overcome the fixed cost of private adaptation and have access to an alternative supply, the pecuniary externality remains even when supply constraints cease to bind after the shock.

Using a combination of the near-universe of household-level water billing data, satellite-based imagery, and numerous other data sources, we provide descriptive evidence of public water use and private substitution patterns across Cape Town's income distribution—which we proxy with property values—before, during, and after the drought. We first document that public water use across Cape Town fell precipitously, by around 50% relative to pre-drought levels.[3] The decline was highly uneven and resulted in a convergence in public water use between high and low property value households. Prior to the drought, households in the top decile of property values consumed roughly double the water of households in the bottom decile, with large seasonal fluctuations in demand among the wealthier households.[4] By the end of the drought, higher property value households were consuming *less* public water than lower property value households.[5] Perhaps even more surprisingly, the convergence persisted for up to two years after PU prices returned to normal and restrictions were lifted.

We next provide descriptive evidence that at least some of this convergence can be explained by substitution toward private groundwater by wealthier households. We do this using three lines of evidence. The first employs a remotely-sensed proxy for the greenness of outdoor vegetation (normalized difference vegetation index or NDVI). Prior to the drought, parcels with higher NDVI values tend to have higher property values and to report more water intensive outdoor land use, consistent with the interpretation that NDVI reflects variation in outdoor water use. However, unlike public water use, NDVI did not exhibit convergence across property value deciles during the drought. This suggests that richer households supplemented outdoor watering using substitutes for public water, such as greywater, stored rainwater or groundwater.

While we do not observe all potential substitutes, we show two additional lines of evidence using data on groundwater drilling and depths. To the extent that other adaptive

[3]Our water use data come from billing records, which cover around three-quarters of residents of Cape Town. Households in informal settlements are not in the billing records.

[4]Seasonal water demand is consistent with differential outdoor irrigation for gardens and lawns during dry and rainy months (Rathnayaka et al., 2015).

[5]This finding echoes the results in Cook, Brühl and Visser (2021), who show that the Gini coefficient for water use in Cape Town declined through mid-2018, around the end of the drought.

technologies like greywater and rainwater storage require costly investments and are therefore more accessible to wealthier households, they should follow similar patterns. Using data on groundwater drilling applications, we document an early-2017 spike in applications, which increase steadily for the remainder of the drought. Higher-value parcels are associated with more drilling applications, with households in the top decile accounting for 29.7% of total drilling applications in our data. Next, data from groundwater monitoring wells indicate a drop in groundwater levels in richer neighborhoods during the drought that is not present in poorer neighborhoods. The decline in groundwater levels in richer neighborhoods is comparable to some of the fastest-depleting aquifers in the world.

The changes in public water consumption impacted the PU's total revenue from residential consumers, and shifted the distribution of costs across property value deciles. After the drought (and after tariffs returned to normal), total volumetric charges were 22% lower than pre-drought levels. This is due in part to disproportionately lower bills for wealthier households who, prior to the drought, paid higher marginal prices on higher consumption blocks due to the IBT. In other words, pre-drought, a large share of the revenue used to cover the costs of municipal water supply came from wealthy, high consumption households. As their consumption fell, so did their marginal price; these effects combined to shift a larger share of the PU's costs onto lower income households.

Post-drought policy innovation served to mitigate both the fiscal and distributional challenges created by the drought. To overcome the revenue shortfall, the municipal government introduced a fixed charge: *total* charges increased by around 4% over this time period. The fixed charge was further differentiated by property value,[6] offsetting some of the regressive cost shift caused by substitution by wealthier households. To further address distributional concerns, low income households also received a larger water subsidy, provided as a free block on the IBT. We show that without these policy changes, the richest deciles would have paid 51.8% less post-drought. Together, policy changes—triggered by a climate-induced shock—moved the municipality onto a more efficient pricing regime with the introduction of fixed charges, while also mitigating potentially regressive distributional outcomes through careful income-based targeting of tariff reform.

Finally, to quantify the effects of private substitution away from public water during the drought, we extend our theoretical framework to a discrete choice model of household water demand. Results show that observed groundwater drilling lowered aggregate demand for public water by 5.3% during the crisis and 4.9% after the crisis relative to a no-drilling counterfactual. Without substitution towards groundwater, the utility would have had to

[6]Specifically, the lowest property value households were exempted from the fixed charge. For everyone else, the fixed charge was a function of pipe size, which is correlated with property value.

raise prices an additional 50.0% during the crisis to achieve the observed reduction in demand. For households at the top of the property value distribution, drilling reduced revenue by around 20% relative to the counterfactual both during and after the crisis. We calculate that had the PU not introduced fixed charges following the crisis period, volumetric charges would have needed to increase by 50% on the margin to recover the same revenue.

This paper joins a long line of theoretical and empirical work that studies the relationship between income inequality and the public provision of goods and services (e.g., Galbraith, 1958; Bergstrom, Blume and Varian, 1986; Besley and Coate, 1991; Epple and Romano, 1996). This literature demonstrates that the availability of private substitutes has the potential to change both the supply of and demand for publicly provided goods, depending on how public provision is financed. In the context of public utilities, this financing depends on the design of tariffs to cover the fixed cost of supply (e.g., Borenstein and Bushnell, 2022; Borenstein, Fowlie and Sallee, 2023). In theory, when demand is sufficiently price elastic, consumption charges may not generate sufficient revenue to cover costs, leading to a fiscal unraveling (or "death spiral") for the utility (Baumol and Bradford, 1970; Henderson, 1986).[7] Higher tariffs create incentives for substitution away from publicly provided water or energy (as shown in the case of rooftop solar adoption by Borenstein, 2017; Gorman, Jarvis and Callaway, 2020). We show that a climate-induced supply shock can create incentives for the adoption of private substitutes that have persistent effects on public provision and redistribution.[8]

In our setting, like in many others, richer households are more likely to adopt substitutes. Related papers on rooftop solar and electric vehicles describe a similar income gradient in technology adoption that redistributes the financing of publicly provided goods (Borenstein, 2017; Feger, Pavanini and Radulescu, 2022; Davis and Hausman, 2022; Glaeser, Gorback and Poterba, 2023; Metcalf, 2023; Bollinger et al., 2023), but do not explicitly link to climate shocks as drivers of adoption.[9] In our case, rather than adapting to the climate shock directly, households adapt to the public water utility's response to the drought. This underscores the importance of understanding not just how policy will adapt to climate change (e.g., Hsiao, Moscona and Sastry, 2024), but also how households and firms will adapt to climate-induced

[7] McRae (2015) describes another potential mechanism for unraveling where a utility becomes unable to recoup its marginal costs due to government restrictions on pricing.

[8] In this sense, our paper echoes the findings in Costa and Gerard (2021), where an energy supply shock led to habit formation and appliance adoption that lowered consumption in the long run.

[9] Hsiao (2024) demonstrates that differential adaptation by income can also impose pecuniary externalities via market prices. More similar to our context, Brown and Muehlenbachs (2024) provide evidence that public safety power shutoffs in California contributed to the adoption of rooftop solar but do not study the distributional implications. Brehm, Johnston and Milton (2025) show that changes in grid reliability affect solar panel adoption, and affect electric utility tariffs. Finally, Hadachek et al. (2024) show that increased groundwater extraction for agriculture during a drought causes residential wells to dry up.

policy change. While unequal adoption of substitutes implies yet another regressive impact of climate change (Dingel, Meng and Hsiang, 2021; Carleton et al., 2022), the mediating role of tariffs highlights the importance of policy interventions aimed at mitigating differential impacts on the poor.

More generally, we contribute to understanding water demand among the world's more than 4 billion urban residents. Water scarcity contributes to conflict (Sekhri, 2014; Almer, Laurent-Lucchetti and Oechslin, 2017; Unfried, Kis-Katos and Poser, 2022) and groundwater depletion leads to subsidence and relative sea level rise (Nicholls et al., 2021; Hsiao, 2022). Prior work has studied the impacts of prices and rationing for managing demand during supply shocks (Fisher et al., 1995; Wichman, Taylor and Von Haefen, 2016; Browne, Gazze and Greenstone, 2021; El-Khattabi et al., 2021). We instead focus on how access to substitutes mediates the impact of policy on demand for public services more generally (Abajian and Pretnar, 2024; Brehm, Johnston and Milton, 2025). Substitution toward groundwater may cause a different environmental challenge since aquifers, in Cape Town and elsewhere, are typically unmanaged and tend to be overextracted under open access conditions. Substitution away from publicly provided services in other settings can introduce new environmental externalities which may be positive (e.g., natural landscaping to save water) or negative (e.g., diesel generators as an alternative to the grid) relative to the status quo.

2 Theoretical framework

This section lays out a general framework for considering how adaptation to climate change may affect the public provision of rival goods. The model centers around the case of a municipal water utility when its ability to supply water is constrained and customers have access to private substitutes.

When a shock—such as a drought in the Cape Town setting—reduces the aggregate water supply available to the PU, it is forced to either raise prices or impose quotas to curtail demand. This increase in prices (or increase in the shadow value of water beyond the quota) induces households to adopt private substitutes for public water, which affect aggregate demand for public water both during *and* after the shock. Anticipating our empirical setting, the model presented here focuses on groundwater wells as households' channel for adaptation through substitution. However, other substitutes with a fixed cost of adoption would produce insights similar to the ones we present here. Section 6 introduces a quantitative version of the household problem laid out here, which we calibrate to observed behavior in Cape Town and use to simulate how the drought would have evolved absent private adaptation.

2.1 Model

Household's problem Our model consists of a PU that serves two households indexed by i, one poor p and one rich r. Each household solves a static utility maximization problem over water consumption each period t. Both households have quasilinear utility $u_i(\cdot)$ over water and outside consumption. The PU sets a price schedule for water Θ_t each period that determines the cost of water consumption. We assume that $u'_r(\cdot) > u'_p(\cdot)$ such that water demand from the rich household, $m_r(\Theta)$, is weakly larger than that for the poor household, $m_p(\Theta)$, for any price schedule.

In addition to deciding how much public water to purchase each period, households decide whether to adopt an alternative private water source. Households may drill up to one groundwater well at a fixed cost c^d, which reflects the market price for drilling along with any application fees or taxes. Drilling a well is an absorbing decision that provides an additional λ kiloliters (kL) of water each period from the time of drilling forward.[10] Each period, households decide first whether to drill a well and then how much water to consume. Writing the costs of water demanded from the PU under price schedule Θ_t in a given period as $c_t(m_i)$, households drill when it maximizes static utility:[11]

$$u_i(m_i^d(\Theta_t) + \lambda) - c^d - c_t(m_i^d(\Theta_t)) \geq u_i(m_i(\Theta_t)) - c_t(m_i(\Theta_t)) \tag{1}$$

where the superscript d denotes optimal demand for public water conditional on having drilled a well. Appendix A.1 shows that it becomes more likely that drilling is optimal for either household as λ and Θ_t increase or as c^d decreases.[12]

Utility's problem The PU meets water demand each period after it sets the price schedule Θ_t by paying a unit cost for water of $\phi_t \geq 0$. In addition to covering its variable costs of meeting demand, the PU also must recover a fixed operating cost F. To match the pre-drought setting in Cape Town, we assume initially that the PU must rely solely on volumetric pricing and that households do not yet consider drilling groundwater wells. Let

[10] We abstract here from any intensive margin decisions on how much groundwater to extract conditional on drilling or whether to drill additional wells. We consider the intensive margin in the quantitative model in Section 6.

[11] This abstracts from any forward-looking behavior by households when drilling wells and by the PU when setting prices. While some results will not translate to a version of this problem characterized by a fully-specified dynamic game where PU and households' behavior responds to beliefs over future actions by other agents, insights resulting from the fact that there is some price at which households adopt wells (and lower aggregate demand in future periods, all else equal) hold quite generally.

[12] These static results hold for a very broad set of cost functions that Θ_t may induce. Appendix A.1 shows the results for λ and c^d require almost no assumptions on the cost function $c(m)$ induced by Θ. The result with regard to the drilling decision being non-decreasing in Θ requires more restrictive conditions and is satisfied when the cost function is twice continuously-differentiable and supermodular in (m, Θ).

$$M(\Theta_t) = m_r(\Theta_t) + m_p(\Theta_t) \tag{2}$$

denote aggregate demand each period and let

$$R(\Theta_t) = c_t(m_r(\Theta_t)) + c_t(m_p(\Theta_t)) \tag{3}$$

denote aggregate revenue. We assume the PU's problem is to set the price schedule to cover both its fixed and variable costs of providing services:

$$\begin{aligned} \Theta_t = \underset{\omega}{\operatorname{argmin}} & \left| R(\omega) - F - \phi_t M(\omega) \right| \\ \text{s.t.} \qquad & M(\Theta_t) \leq \bar{M}_t \end{aligned} \tag{4}$$

subject to the conditions that it cannot sell a total quantity of water greater than the aggregate supply constraint $\bar{M}_t$.[13]

If the PU had full flexibility over prices, the optimal price structure when supply constraints do not bind is a two-part scheme where households face fixed charges that sum to F and marginal prices of ϕ_t. In contrast, when the PU cannot implement a fixed charge and the supply constraint is not binding, the PU chooses a price schedule from those which solve the implicit function $R(\Theta) = \phi_t M(\Theta) + F$ which allows the PU to recover its total cost at the expense of having to price water above its marginal cost.[14] It is well-known that this pricing regime is often inefficient (Feldstein, 1972). However, when supply constraints are binding, revenue and welfare under purely volumetric pricing can coincide with those under the constrained optimal two-part tariff scheme. When the PU faces a binding aggregate supply constraint $\bar{M}_t$ (e.g., due to a drought), it must contract demand so as to bring it in line with lower supply. Unless the PU can impose quotas on consumption, it *must* raise prices above marginal cost to ensure demand does not exceed $\bar{M}_t$. If volumetric revenues can be set so that aggregate demand does not exceed exceed $\bar{M}_t$ and revenue covers both F and $\phi_t \bar{M}_t$, social welfare under volumetric pricing coincides with the first-best outcome.[15]

[13] An additional assumption implicit here is that, all else equal, the PU selects a price schedule from among those that meet its budget constraint—in the case where the solution to equation (4) is not unique—to maximize household welfare. This is a special case of the decision of a PU that maximizes a combination of consumer surplus and profits, an objective function standard to the utilities literature (Timmins, 2002).

[14] We assume throughout that such price schedules exist.

[15] Explicitly, note that when supply is constrained the PU under a two-part tariff will set a cost schedule Θ_t such that $M(\Theta_t) = \bar{M}_t$ and charge fixed costs summing to $F + \phi \bar{M}_t - R(\Theta_t)$ across both households. As long as there exists a volumetric price schedule $\tilde{\Theta}_t$ such that $M(\tilde{\Theta}_t) = \bar{M}_t$ and

$$R(\tilde{\Theta}_t) = F + \phi_t \bar{M}_t$$

Consequences of private adaptation Now consider the case where households have the option to drill groundwater wells. Suppose that to curtail demand during a drought, the PU raises prices to a level where the rich household chooses to adapt to drought pricing by drilling for groundwater according to equation (1) while the poor household does not.[16] Drilling causes the rich household's demand curve to contract from the pre-drilling level m_r to m_r^d. With adaptation, price increases lower demand even more than when adaptation is absent, which helps meet the PU's supply constraint:

Lemma 1. *Price increases contract demand by more when adaptation is available than when it is not.*

Proof. See Appendix A.2. □

All proofs are relegated to Appendix A. Lemma 1 shows that adaptation allows the PU to curtail more demand with a given price increase. In turn, the price increase required to curtail demand to below a given level is lower than when agents have no access to private substitutes.

Adaptation also induces path dependence in demand. A price increase that causes the rich household to drill a well impacts both current and future demand and revenue:

Proposition 1. *Adaptation lowers aggregate demand and revenue for the PU under any price schedule.*

Proof. See Appendix A.3. □

Proposition 1 gives that when households adapt, demand and revenue under all future price schedules Θ are lower than the case where no households adapt. When adaptation decisions differ across households, this has distributional implications:

Proposition 2. *When only the rich household adapts, the cost share borne by the poor household is higher than it would be absent adaptation for any price schedule:*

$$\frac{c_t(m_p)}{c_t(m_p) + c_t(m_r^d)} \geq \frac{c_t(m_p)}{c_t(m_p) + c_t(m_r)} \tag{5}$$

Proof. See Appendix A.4. □

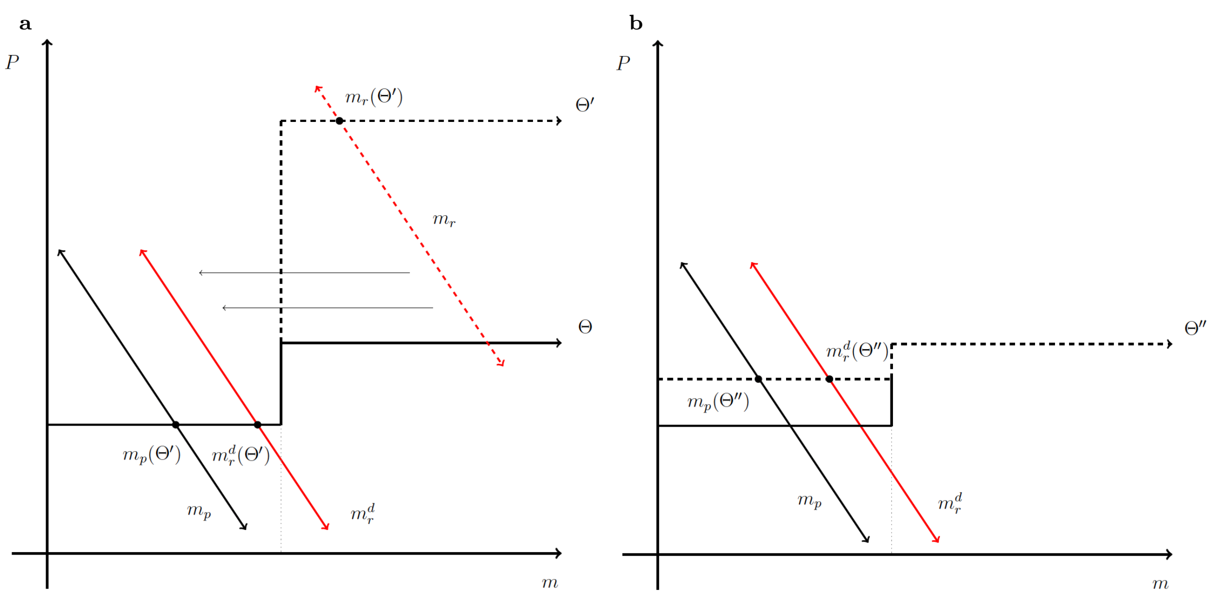
When only the rich household drills, the share of total costs borne by the poor is higher in all future periods.

consumer surplus is no higher under a two-part tariff (although there may be distributional consequences).

[16] Other differences such as access to credit or higher rates of home ownership, which are outside of our model, may also lead the rich household to have a greater propensity to drill.

Application to increasing block tariffs Figure 2 illustrates our predictions in the case of an increasing block tariff (IBT) pricing schedule, a volumetric pricing schedule that is often used by PUs including in our Cape Town setting. The IBT before the drought is Θ, which cross-subsidizes the lower marginal price for the poor household by imposing a higher marginal price for the rich household. To lower aggregate demand during the drought, the PU changes the IBT to Θ' so as to decrease demand from the rich household. This price increase induces the rich household to drill a groundwater well, lowering its demand for public water from the dashed red line m_r in to the solid one m_r^d in Figure 2a. This is beneficial during the drought; private adaptation leads to a larger contraction in demand than would have occurred absent drilling and makes it easier for the regulator to meet its supply constraint (Lemma 1).

Figure 2: Public utility demand before and after a shock under IBT



NOTES: The effects of adaptation on demand and revenue under an IBT price schedule. Panel (a) shows how a price increase from Θ to Θ'—in response to a supply shock—causes the rich to adopt private substitutes. This contracts the rich household's demand for the publicly provided good from m_r to m_r^d. When adaptation leads to permanently lower demand, the PU may have to raise future prices above the original price schedule Θ to meet cost recovery requirements (the shift to Θ'' in panel b).

However, adaptation also leads to lower aggregate demand *after* the drought since demand from the rich household is permanently lower in future periods (Proposition 1). If the PU returns the IBT to the original level Θ, revenue will be lower than the pre-drought level and the poor household will pay a higher share of costs (Proposition 2). Finally, if revenue under the new aggregate demand curve at the pre-drought pricing schedule no longer covers the PU's total costs, the PU may need to raise prices, including on blocks that affect the poor household (e.g., if the blocks are fixed or the rich household's demand falls to the level of the poor household). The potential for adaptation to undermine redistributive goals is illustrated in Figure 2b. To meet revenue constraints under the new aggregate demand curve, the PU must post a new schedule Θ'' which increases both the level and share of costs borne by the poor household.

2.2 Generalizations

The intuition from our framework extends along several dimensions.

Fixed charges How would this scenario change if the PU had access to fixed charges? Absent income effects, there is no effect of fixed charges on household drilling decisions. Because aggregate demand in equation (2) is solely determined by the price schedule Θ, shocks that curtail supply would still force the PU to raise prices above marginal costs (or impose quotas) and potentially lead richer households to drill wells.

However, fixed charges do change the dynamic aspect of the PU's cost recovery problem. First, the PU can always cover its costs; even if aggregate demand fell to zero, the PU could simply charge each household some share of the fixed cost F. Second, fixed charges that can be differentiated across households allow the PU to achieve any level of cost distribution between the poor and rich households while also providing sufficient water services to the poor.[17]

Quotas Public utilities often rely on quotas or rationing rather than prices to curtail demand. A quota-based strategy for demand reduction can also induce households to adopt outside alternatives. In our model, if a quota were imposed on consumption at some level lower than $m_r(\Theta)$ under the original price schedule, the rich household may still find drilling a well optimal. The decision to adapt will still depend on the relative cost of drilling versus the effectiveness of groundwater as a substitute.

Other forms of private adaptation Adaptation to drought is not limited to groundwater drilling. Households can pursue other means of self-supply (e.g., through purchasing rainwater tanks or greywater recycling systems) or conserve water (e.g., through water-saving appliances, drought-resistant vegetation or even water-saving habit formation). Like with

[17]Fixed charges may also influence households' expectation of how the PU sets future marginal prices, since the PU can ensure that it will only ever raise volumetric prices to curtail demand (as opposed to raising volumetric prices in order to collect additional revenue). If drilling decisions are forward looking, this guarantee of weakly lower future prices will in general (weakly) raise the price threshold at which households drill in any given period.

groundwater drilling, high enough prices or quantity restrictions may drive agents to invest in other forms of adaptation that lower their water needs. If these investments are durable, they become other channels by which adaptation permanently lowers demand for public goods after a supply shock.

3 Background: Cape Town's water crisis

The City of Cape Town is home to over 4 million residents and is growing rapidly. Like in many cities, the Cape Town municipal government is responsible for supplying water to households and businesses, managing distribution and working with the national Department of Water and Sanitation to coordinate supply and treatment. Domestic consumers account for around 80% of Cape Town's public water usage (City of Cape Town, 2020). Most households in Cape Town have publicly-provided piped water in their homes, which is metered and billed monthly. Informal settlements are served by standpipes and are omitted from our data and analysis. For most of the time period we study, consumption is priced on an increasing block tariff, set to cover both fixed and variable supply costs (see Figure D.1 and Table E.1). Tariffs are updated annually, on July 1. The block tariff structure is intended to both encourage conservation and cross subsidize water consumption from richer—who are assumed to consume more—to poorer households (Muller, 2008).[18] Until 2015, South African regulations required that utilities recover all costs through volumetric charges; a revision to the regulations in 2015 allowed for the introduction of fixed charges, but these were not adopted by the municipal utility until 2018 (DWS, 2015).[19]

South Africa is the most unequal country in the world by some metrics (World Bank, 2023) and Cape Town is one of the most unequal cities in South Africa (Euromonitor, 2017). The city follows national policy in providing support to what are referred to as indigent households. Qualification for indigent status is applied as a default to households with property values below a threshold (300,000 ZAR up to June 2016; 400,000 ZAR beginning July 2016), but can also be obtained through an application process.[20] Until July 2018, qualified households received a fixed grant amount on their monthly bill, independent of

[18]A large literature discusses whether block tariffs are progressive or not (Whittington, 1992; Borenstein, 2012; Szabo, 2015; Nauges and Whittington, 2017), which depends directly on the correlation between income and consumption. In Cape Town, using imputed income data from the census, Cook, Brühl and Visser (2021) find a strong positive correlation pre-drought; we observe a similar pattern, using property value as a proxy for long-run income.

[19]While general funds (e.g., property taxes or transfers from national government) might allow the municipal water utility to operate at a deficit for a short period, the tariffs are set to cover projected costs each year (Simpson et al., 2019).

[20]Figure D.2 shows the share indigent by property value decile.

consumption levels (see Table E.1). If the grant exceeded billed water charges, the value rolled over to the next bill. In July 2018, the grant was replaced with a 10.5 kL free water allocation each month.[21] Prior to the water crisis, all charges were based on the volume of consumption (i.e., volumetric charges). In July 2018, the city added fixed monthly charges for non-indigent customers, based on the size of the metered connection.

During our study period, six main surface water reservoirs provide 98% of the public water supply, making the city highly dependent on rainfall. Most rain falls in Cape Town during the South African winter (June-August). Beginning in the early 2010s, rainfall began to decline and by 2015, the Western Cape was in a drought (see Figure D.3).[22] For the purposes of our analysis, we define the "drought" as beginning in 2016, when tariffs first deviated from regular adjustments, and the "water crisis" as starting in February 2017, when substantially elevated restrictions were announced. The "post-drought" period begins in June 2018. The term "Day Zero" was first invoked in May 2017 to refer to the minimum viable reservoir level (13.5% of capacity) for piped water supply; below that level, residents would have to queue for water at standpipes around the city. The term spread through the media and became a slogan for the city's water saving effort. In December 2017, the first estimate of Day Zero was set for April 22, 2018. Figure 1 shows reservoir capacity shares over time; during the water crisis, they dropped as low as 20%.

Policy responses to the water crisis drew on a wide range of instruments: tariff increases, water restrictions, pressure management and communication campaigns. Cape Town's annual tariff schedule updates include "normal" tariffs, as well as (higher) tariffs associated with different levels of water restrictions. Level 2 is normal; Level 7 is a shutdown of public water supply, i.e., Day Zero. During the crisis, Cape Town escalated from Level 3 in February 2017 all the way up to Level 6b in February 2018. Among non-indigent customers, the average real price of water increased by 230% between March 2015 and March 2018, in spite of dramatic decreases in consumption; the marginal price on the highest block increased by over 2000%. Tariff increases were communicated through wide-reaching information campaigns that included local community leaders and the media. At the height of the crisis, residents were asked to limit public water use to 50 litres of water per person per day (City of Cape Town, 2018c), and bans were placed on filling swimming pools, washing cars or watering gardens.[23] Water restrictions were difficult to enforce, however.

[21] Up to July 2017, all households received 6 kL of free water each month. From July 2017 to June 2018, the free block was restricted to indigent households, who also continued to receive a water grant. In July 2018, the water grant was eliminated and the free block was increased to 10.5 kL for indigent households.

[22] Changing rainfall patterns in the region have been attributed to climate change (Otto et al., 2018; Pascale et al., 2020).

[23] Other non-price strategies included media, such as public advertising, signboards on highways, behavioral nudges sent to customers (Brick, De Martino and Visser, 2023) and an online city-wide water map that

Households were also given information about the benefits of groundwater access for irrigation purposes, and water from boreholes and wells was not subject to outdoor water use restrictions, though the City did little to monitor access or use prior to 2018 and current information on private use remains limited (Faragher and Carden, 2023). Multiple companies around Cape Town offer drilling services, with prices ranging from 6,500 to 8,500 ZAR for a well and 30,000 to 180,000 ZAR for a borehole. Cape Town overlies three aquifers (primarily the Cape Flats Aquifer, but also the Table Mountain Group and Atlantis Aquifers), with parcel-level drilling potential determined by local geological conditions.[24] Recharge rates are generally high but heavily rainfall dependent (Gintamo, Mengistu and Kanyerere, 2021).

Table E.2 provides a timeline of the events surrounding the countdown to Day Zero. By February 2018, the water situation in Cape Town began improving, with forecasts of Day Zero pushed back to July 9, 2018. By June 2018, forecasts for Day Zero were officially canceled.

4 Income, water use and groundwater substitution

In this section, guided by our theoretical framework, we analyze how households responded to the Cape Town water crisis, allowing for heterogeneity by property value, our proxy for long run income.[25] As discussed in Section 3 and consistent with the premise that tariffs are one strategy for managing demand, average water prices in Cape Town increased dramatically during the crisis, as shown in Figure D.1 and Table E.1. By the end of 2018, tariffs returned to pre-crisis trends.

In what follows, we describe our data and dataset construction alongside each result.[26] While the start date of each analysis varies by data source, we end all our analyses in December 2019 to exclude the COVID-19 lockdowns in Cape Town.

showed compliance with the water restrictions (Sinclair-Smith et al., 2018; Ziervogel, 2019). Water pressure was reduced in some parts of the city (Bischoff-Mattson et al., 2020) and water management devices that limited usage to 350 liters per day were installed in some households.

[24]We note that parcels with very little unbuilt land may not be suitable for drilling. This may be more true in low property value areas, highlighting a set of factors that contribute to the decision to drill that go beyond those reflected in our model.

[25]Figure D.4 uses self-reported monthly income for households in a recent survey conducted by the authors, and shows a correlation of 0.49 ($p < 0.01$) between monthly income and property value. We note that property value is likely correlated with numerous household and property characteristics that determine a household's response to drought and drought policy.

[26]Additional details on data compilation is provided in Appendix C.

4.1 Public water use

Data We start with public water use by property value decile. We use the universe of residential water bills from the City of Cape Town from July 2014 to December 2019, prorating quasi-monthly bills to create a monthly panel of household-level piped water consumption, winsorized at the 95th percentile. We match households' water bills to their property value in 2016 by account number.[27] We restrict attention to 1:1 matches to avoid indeterminacies arising when many properties are matched to a single meter, or vice versa.[28] The remaining sample contains slightly over half a million properties, and excludes multi-unit dwellings and informal settlements. Figure D.5 maps the 2016 property value decile for each of our sample properties.

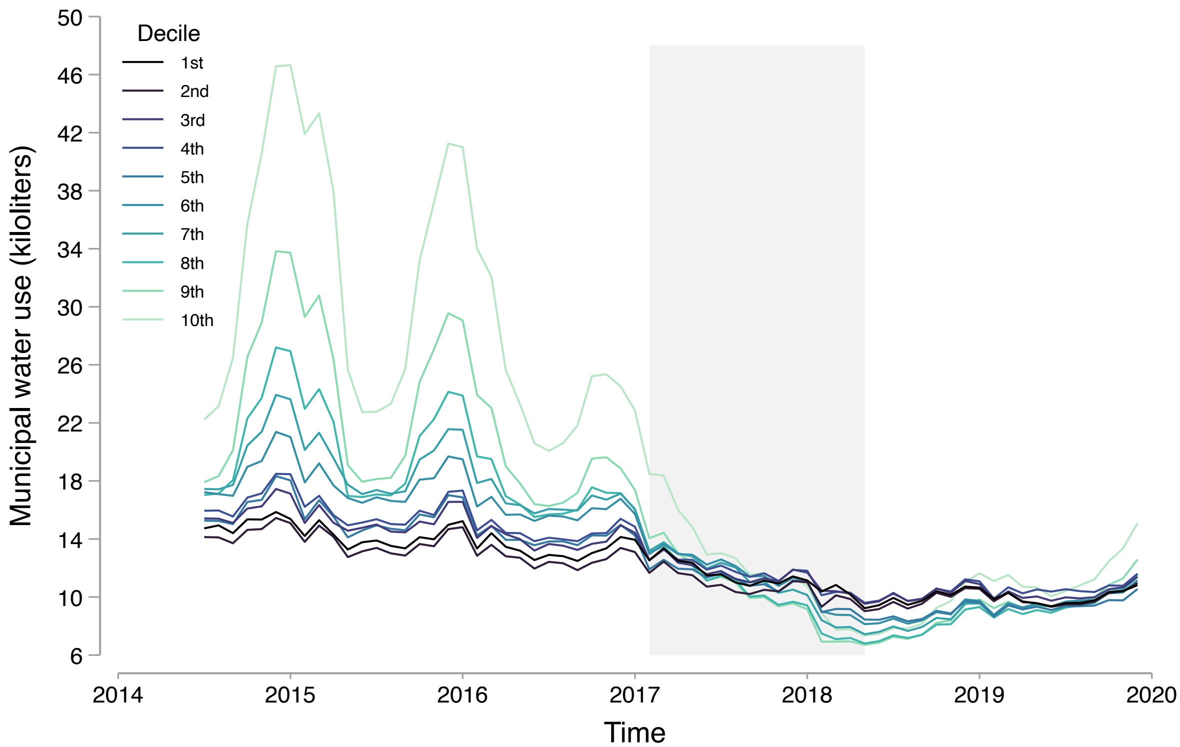
Results Figure 3 plots the means of decile-by-month piped water consumption between July 2014 and December 2019, and reveals three clear patterns. First, there is a pronounced income gradient in piped water use before the drought (2015-16). In particular, the average for households in the top decile (29.7 kiloliters/month) was over twice that of households in the bottom decile (13.8 kiloliters/month) ($t-$stat $= 657.2$). Consumption in high property value deciles also displayed more seasonality than did consumption in lower deciles,[29] consistent with high summer demand for outdoor water use (Rathnayaka et al., 2015). Second, piped water use fell for all deciles during the water crisis (gray-shaded area), but the decrease was larger for higher incomes. Between 2016 and 2018, annual water use fell by 74.5% for households in the top decile and by 28.9% for households in the bottom decile. This asymmetry was sufficiently extreme to temporarily reverse the pre-drought income gradient in consumption: in 2018, upper decile households were consuming *less* public water than lower decile households ($t-$stat $= 111.1$). Third, the convergence in piped water use persisted after the water crisis ended. Well into late 2019, over a year after Day Zero was called off, there was little sign of a return to the pre-crisis divergence in piped water use across incomes even though prices had largely returned to pre-crisis levels (Figure D.1). These findings are consistent with our theoretical framework: richer households lowered their piped water consumption to a larger degree, and this demand reduction persisted even as prices fell.

[27] We use 2016 property values to coincide with the start of the drought. This means that, as households move and are assigned new meters, they drop from our sample. Where we plot aggregate statistics (e.g. total revenue) over time, we scale them up as if the full sample remained.

[28] This eliminates apartment buildings, for example, which are found in both high and low property value areas. The restriction reduces our sample by 15.6%; remaining properties are likely to be inhabited by single households with full control over their water use.

[29] The seasonal swing in consumption is 10.57 kL (s.e. 0.056) larger for households in the 10th decile than for households in the 1st decile.

Figure 3: Average public utility water consumption by property value decile



NOTES: Monthly public piped water consumption (in kiloliters per month), averaged across parcels in the same property value decile. Gray-shaded area marks the February 2017 to May 2018 water crisis.

4.2 Adaptation through adoption of private substitutes

During the crisis, households likely engaged in numerous strategies to reduce piped water use, all of which may contribute to the differential reductions across income deciles in Figure 3. Rather than trying to rule out alternatives or test their relative importance, we focus on one strategy, which is representative of—and not mutually exclusive to—other potential forms of substitution: groundwater has a fixed cost of adoption and permanently alters water use patterns once adopted.

A reduction in piped water consumption may overstate a household's total reduction if some water supply comes from substitutes, including groundwater. In Cape Town, groundwater is not potable without treatment, so a primary use is in outdoor watering. Outdoor water use is increasing in income and is relatively more price sensitive than indoor water use (Mansur and Olmstead, 2012), so if richer households used only piped water, we would expect to see a contraction in outdoor watering as large or larger than what we observe in the billing data. If, however, high-income households were differentially able to substitute towards groundwater for outdoor irrigation, the contraction in outdoor water use might be less pronounced.

4.2.1 Remotely-sensed moisture index

Data As an independent proxy for outdoor water use, we turn to the Normalized Difference Vegetation Index (NDVI), a widely-used remotely-sensed measure for vegetative health (Gao et al., 2015), which we construct using remote imaging from Sentinel-2 satellites available at a 20 meter resolution between January 2016 and December 2019.[30] To isolate residential outdoor water use, we remove pixels identified as natural vegetation (e.g., forests, shrubland, grassland), water (e.g., lakes, ocean), and other non-vegetation classes (e.g., sand dunes, roads, rail, mines) as defined by the South Africa National Landcover Dataset. We further apply geospatial masks to remove tree cover and residential structures. As robustness checks, we also consider two alternative indices, the Normalized Difference Moisture Index 1 (NDMI-1) and Normalized Difference Moisture Index 2 (NDMI-2). Appendix C.2 describes index construction and how they differ in greater detail. For each index, we calculate monthly values both at the parcel level as well as at the decile level aggregated using parcel area weights.

We conduct three tests to validate these proxies for outdoor water use. First, Table E.3 shows NDVI, NDMI-1, and NDMI-2 values across parcels within each property value decile. To avoid the potential influence of Day Zero, these baseline statistics are constructed for the 12 months in 2016. Mean values for all three indices generally increase with property values, possibly reflecting more baseline outdoor irrigation by wealthier households. For example, the difference in average monthly NDVI in 2016 between the 1st and 10th property value decile is 0.2 (t =8.3). For comparison, Figure D.6 shows that the within-year seasonal variation in average NDVI (across deciles) is around 0.15.

Second, Table E.4 shows parcel-level regressions examining how the satellite-based proxies correlate with self-reported outdoor residential land use, categorized as parcels without outdoor space (omitted category), with outdoor space that has low water demand (e.g., uncared-for garden or lawn, pavement, concrete, dirt, artificial turf, drought-tolerant plants), and with outdoor space with high water demand (e.g., grass, plants, flowers).[31] Consistent with the wealth gradient in Table E.3, higher property values in 2016 are correlated with higher NDVI values. Parcels with outdoor space with low water demand do not exhibit statistically significantly higher NDVI values than parcels with no outdoor space. However,

[30] Sentinel-2 data are not available before 2016.

[31] Parcel-level residential land use data come from a household survey of water use in Cape Town (N = 702). While the survey was conducted in 2022, we restrict the sample to respondents who reported no outdoor land use change since 2017. Because the omitted category in Table E.4 consists of parcels without outdoor space, the parcel-level NDVI (and other indices) do not have buildings removed.

parcels with outdoor space with high water demand do have precisely estimated higher NDVI (and other index) values. To interpret coefficients from column 1 of Table E.4, parcels with high water demand outdoor space have 0.035 higher NDVI (s.e. 0.008); this is equivalent to the NDVI effect from a 350K ZAR increase in property value, roughly the difference between the 25th and 75th property value percentiles in the estimating sample.

Third, we show that NDVI and other indices respond to rainfall. Figure D.6 overlays the time series of monthly average NDVI across deciles and rainfall, showing strong co-movement. Table E.5 and Figure D.7 show estimates from regressing monthly NDVI values on contemporaneous and lagged rainfall for each property value decile across 2016-2019. NDVI responds to local rainfall and higher property value deciles are modestly more responsive.[32] Altogether, evidence that NDVI responds to outdoor land use and to rainfall suggest that it meaningfully proxies for residential outdoor water use.

Figure D.7 highlights the influence of rainfall, which we remove by regressing monthly NDVI for each property value decile on local contemporaneous, 1-month lag, and 2-month lag rainfall. We conduct our analyses using the regression residual from this model, which is purged of any baseline decile-specific NDVI-rainfall dependence but retains any potential changes in that dependence due to residential water use.

Results Figure 4a plots the rainfall-residualized NDVI measure by property value decile before, during, and after the water crisis. As with Figure 3, higher decile parcels exhibit higher NDVI values prior to the water crisis, consistent with more outdoor watering; in 2016, properties in the 10th decile have on average 0.2 higher residualized NDVI than households in the first decile (t =16.5). However, in contrast to public piped water use (Figure 3), we see little convergence in NDVI residuals during or after the water crisis.[33] Instead, NDVI differences across deciles remain largely unchanged from 2016 through 2019, consistent with substitution toward other water sources for outdoor use. Figure D.8 shows this pattern holds using raw unresidualized NDVI values and rainfall residualized NDMI-1 and NDMI-2 values. Figure D.9 confirms the absence of differential decile-specific trends using estimated linear trend coefficients for each decile. While these estimated trend coefficients are noisy, they do not indicate convergence across property value deciles for any of the indices.

[32] We can weakly distinguish the contemporaneous and cumulative rainfall effect between the 1st and 10th decile with p-values of 0.092 and 0.093, respectively.

[33] To test for convergence, we perform a difference-in-difference regression comparing residualized NDVI for 1st and 10th decile properties in 2018 compared to 2016; the resulting coefficient for 10th decile properties in 2018 ($\beta = -0.009$) is statistically indistinguishable from zero (s.e. $= 0.011$, $p = 0.438$).

4.2.2 Groundwater drilling applications

Data Next, we turn to applications for groundwater drilling licenses between January 2016 and December 2019. We split the data into two samples. One sample consists of all license applications. A second sample consists of license applications that include the spatial identifier necessary to match the application dataset to the property value dataset. This latter sample has few pre-2017 matches and so primarily shows drilling since 2017.[34]

We highlight two potential concerns with the data. First, while the City of Cape Town mandates that all residents apply for a license before drilling, enforcement is lax. For example, a door to door survey in Newlands (a wealthy suburb) found that roughly one in ten boreholes were licensed (Schachtschneider, 2020).[35] The application data miss unlicensed drilling and may also include some licenses issued but never exercised. A second concern is that application data may also include existing (previously unlicensed) boreholes and wells. Social pressure to reduce water use and restrictions on outdoor watering may have encouraged households with existing groundwater access to apply for licenses. With these caveats in mind, we analyze applications over time and how they vary across property value deciles.

Results Figure 4b shows the cumulative borehole and well licenses by property value decile between January 2017 and December 2019 from the sample of applications merged to property values. Applications increased sharply in February 2017, shortly after a large increase in the marginal price for high consumers (see Table E.1), which we mark as the beginning of the water crisis (see Table E.2), which may have also affected expectations over future price increases. This increase in drilling licenses in 2017 is historically large as shown in Figure D.10 which plots total cumulative licenses since 2012. These applications also follow a clear wealth gradient with more licenses in higher deciles. As a point of reference, average surveyed annual income for households in our first property value decile is 46,000 ZAR, implying that the price of a wellpoint and (deeper) borehole is 14-18% and 65-390% of these households' annual income.[36] By the end of 2019, 29.7% of all drilling applications come from households in the top decile.

We corroborate this aggregate evidence with household-level regressions of the 2016-2019 change in (log) municipal water use on drilling applications, shown in Table E.6 and Figure

[34]The match rate of licenses since 2017 with municipal water bills is 78%.

[35]The same survey found higher coverage of licensed wells in a less wealthy mixed residential and industrial neighborhood. Anecdotally, the spike in demand for licenses during the crisis further increased wait times and the rate of unlicensed drilling. Together, this suggests that the patterns below may understate differences in applications across property value deciles and over time.

[36]It is also possible that poorer households in our sample drill less because they live on parcels with less outdoor space. A number of factors may contribute to the decision to drill that go beyond those which we observe.

D.11. A drilling application is associated with a 14.2% larger reduction in municipal water use on average (s.e. 0.014).[37]

4.2.3 Groundwater depths

Panels (a) and (b) of Figure 4 suggest that higher income households maintain outdoor water use while reducing their municipal water bills by—at least in part—substituting toward groundwater. Ideally, we would be able to directly assess the share of the municipal water use reduction attributable to groundwater substitution. We lack the data necessary for this exercise; instead, we examine a proxy for extraction using aggregate data on groundwater depths from monitoring wells maintained by the South African Department of Water and Sanitation.[38]

Data Panel data from Cape Town's groundwater monitoring wells are unbalanced and noisy. To address this, we restrict our sample to wells with at least six observations per year, trim extreme outlier values, and linearly interpolate missing monthly values. The remaining 11 wells are mapped in Figure D.5. We use the geographical coordinates of monitoring wells and sample parcels to identify the average property value of parcels within a 1 km radius of each well.[39] We then group monitoring wells by whether this average is above ($N = 6$) or below ($N = 5$) the median property value in Cape Town. While these wells technically draw from the same aquifer (i.e., Cape Flats), water does not flow uniformly across the aquifer due to spatial heterogeneity in subsurface geological properties. As such, these monitoring wells likely capture spatial heterogeneity in local groundwater levels, and more so for the set of wells near above median value parcels which are spread across the city, as shown in Figure D.5, than for wells near below median value parcels which are more spatially clustered.

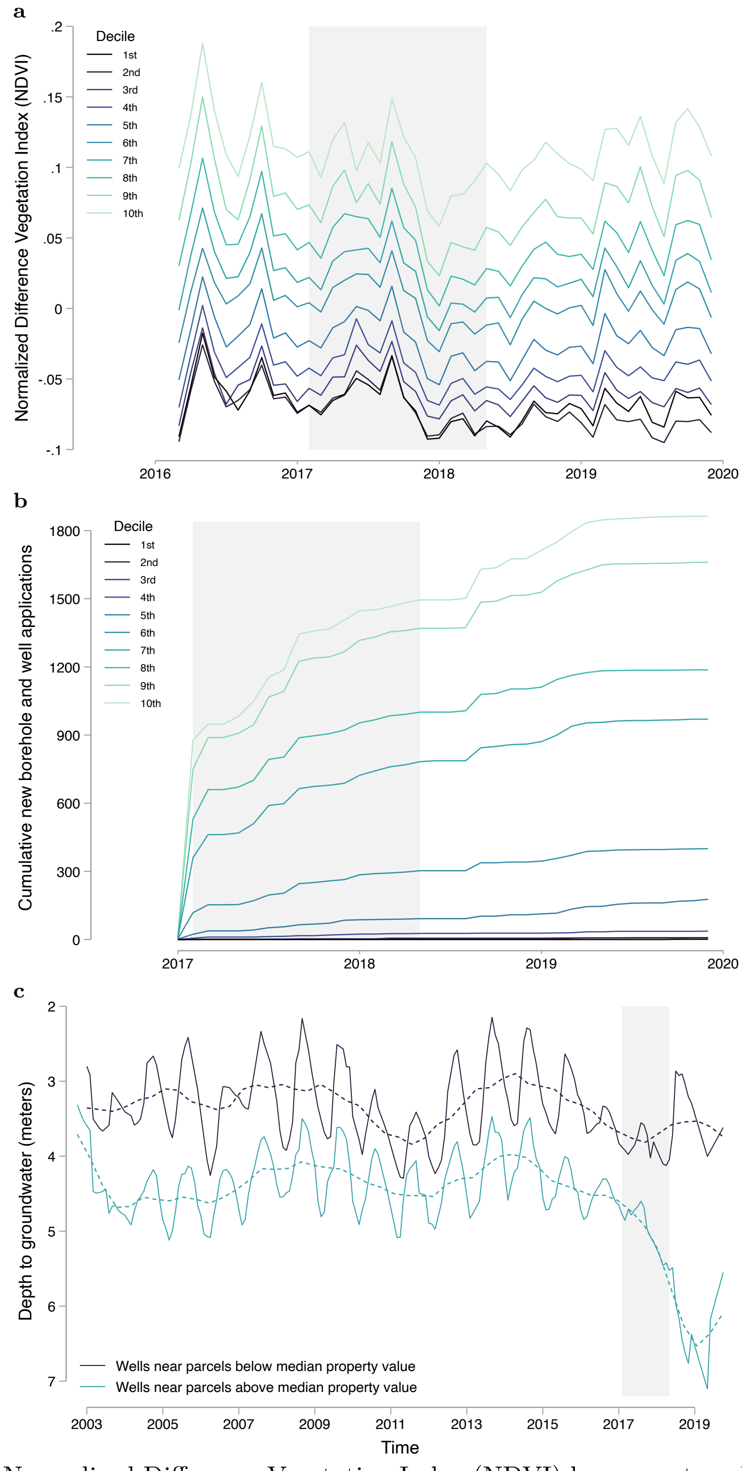
Results Figure 4c shows monthly depth to groundwater separately for monitoring wells near below-median property value parcels (in black) and above-median property value parcels (in green). Both sets of monitoring wells exhibit seasonal variation consistent with rainfed

[37] We caution against a causal interpretation for both endogeneity and measurement error reasons: groundwater drilling may be correlated with other household characteristics or investments, and unlicensed drilling combined with new licenses for existing access biases coefficients toward zero.

[38] Monitoring well data accessed from: https://www.dws.gov.za/NGANet/Security/WebLoginForm.aspx.

[39] A tight radius around each monitoring well enables a comparison of groundwater level trends between richer and poorer households. Wider radii would complicate the comparison by bringing in lower valued parcels in the average for wells located in rich neighborhoods and vice-versa for wells located in poor neighborhoods.

Figure 4: Groundwater substitution by property value decile



Notes: (a) Monthly Normalized Difference Vegetation Index (NDVI) by property value decile with decile-specific rainfall effect removed. (b) Monthly cumulative applications for new boreholes and wells by property value decile since January 2017 from sample merged with parcel-level property values. (c) Monthly groundwater levels for monitoring wells located near below- (black) and above- (green) median property value parcels, based on the average 2016 property value within a 1km radius of the well. Dotted lines show a local polynomial fit with an Epanechnikov kernel and a rule-of-thumb bandwidth following Fan and Gijbels (1996). In all panels, gray-shaded area marks the February 2017 to May 2018 water crisis.

recharge.[40] While groundwater levels for wells near below-median parcels are largely steady from 2003 to 2019, wells near above-median parcels exhibit a sharp decline in levels beginning at the start of the water crisis, at a rate of roughly 1 meter per year.[41] To place this decline into context, it is comparable to rates of decline in Mexico City and Beijing, two cities with prominent groundwater concerns (Werner et al., 2013). Figure D.12 shows an analogous version of Figure 4c using the raw groundwater monitoring well data without dropping outliers and interpolating missing values, with similar overall patterns. Table E.8 further verifies this result showing estimates from a differential trend break model under various alternative data constructions (detailed in Appendix C.4).

5 Distributional, fiscal and policy implications

Together, the data indicate that at least some of the convergence in public water use across property value deciles reflects substitution by richer households away from publicly-provided piped water towards privately-provided groundwater. This form of adaptation may have helped Cape Town avoid Day Zero. However, it also created other challenges, including fiscal and distributional changes, as described in our theoretical framework.

Pre-drought, the revenue model in Cape Town depended on the increasing block structure of the tariff schedule for both revenue and redistribution. High consumers cross-subsidized lower consumers, who were also poorer, on average. As the level of piped water consumption from high income households fell during the drought, the property value gradient in volumetric charges collapsed (Figure 5a).[42] At the peak of the water crisis, the lowest property value deciles faced higher water bills than did customers in the highest deciles, at a time when everyone's water bills increased due to the dramatic price increases (see Figure 5b). Consistent with our theoretical framework and with results from Cook, Brühl and Visser (2021), the cost share borne by low property value households increased during the crisis.

During the water crisis, the utility raised water prices abruptly in early 2018. Following the return to more normal tariffs in late 2018, billed volumetric charges were 22% lower

[40]Table E.7 shows similar rainfall sensitivity for above- and below-median wells, suggesting that our results are not driven by differential sensitivity to the drought.

[41]During the crisis, wells near above-median property value properties experience an increase in depth to groundwater of 0.89 (s.e. 0.18) meters greater on average than wells near below-median property value properties.

[42]We calculate total consumption charges based on winsorized consumption and the tariff; it reflects billed revenue, rather than revenue remitted. Households in Cape Town make payments toward a consolidated bill that reflects charges across multiple household accounts (e.g., water, sewerage, refuse; water is typically largest). We do not observe water-specific payments. Aggregate collection ratios—the share of billed revenue remitted—fell during the drought, from around 80% in 2016 to just below 70% in 2018 (City of Cape Town, 2021). In 2019, they recovered to pre-crisis levels.

than the pre-drought mean (2015 vs 2019), again consistent with our theoretical framework. Together, these results highlight the limitations of volumetric pricing for revenue and redistribution during and following a climate-induced supply shock.

Two municipal policy responses affected both overall revenue and its distribution across property value deciles: changes to free water provision and the implementation of a fixed charge. As described in Section 3, Cape Town's tariff schedule prior to the drought included a free block for all customers. In July 2017, as water supply fell, policy makers removed the 6 kL free price block for non-indigent households only, while indigent households continued to receive 6 kL of free water and a water grant.[43] These subsidies provided some buffer for indigent households. In spite of this, their average water price (inclusive of 0s) increased in 2018 (Figure 5b).[44] Between February and June 2018, indigent households continued to receive the 6 kL free water and indigent grant, and additionally received a discount on the second tariff block. The magnitude of the indigent grant also grew in real terms between 2016 and mid-2018 (see Table E.1). In July 2018, the indigent water grant was removed and the indigent-only free block was extended to 10.5 kL. This coincided with the introduction of a monthly fixed charge, from which indigent households were exempt.[45]

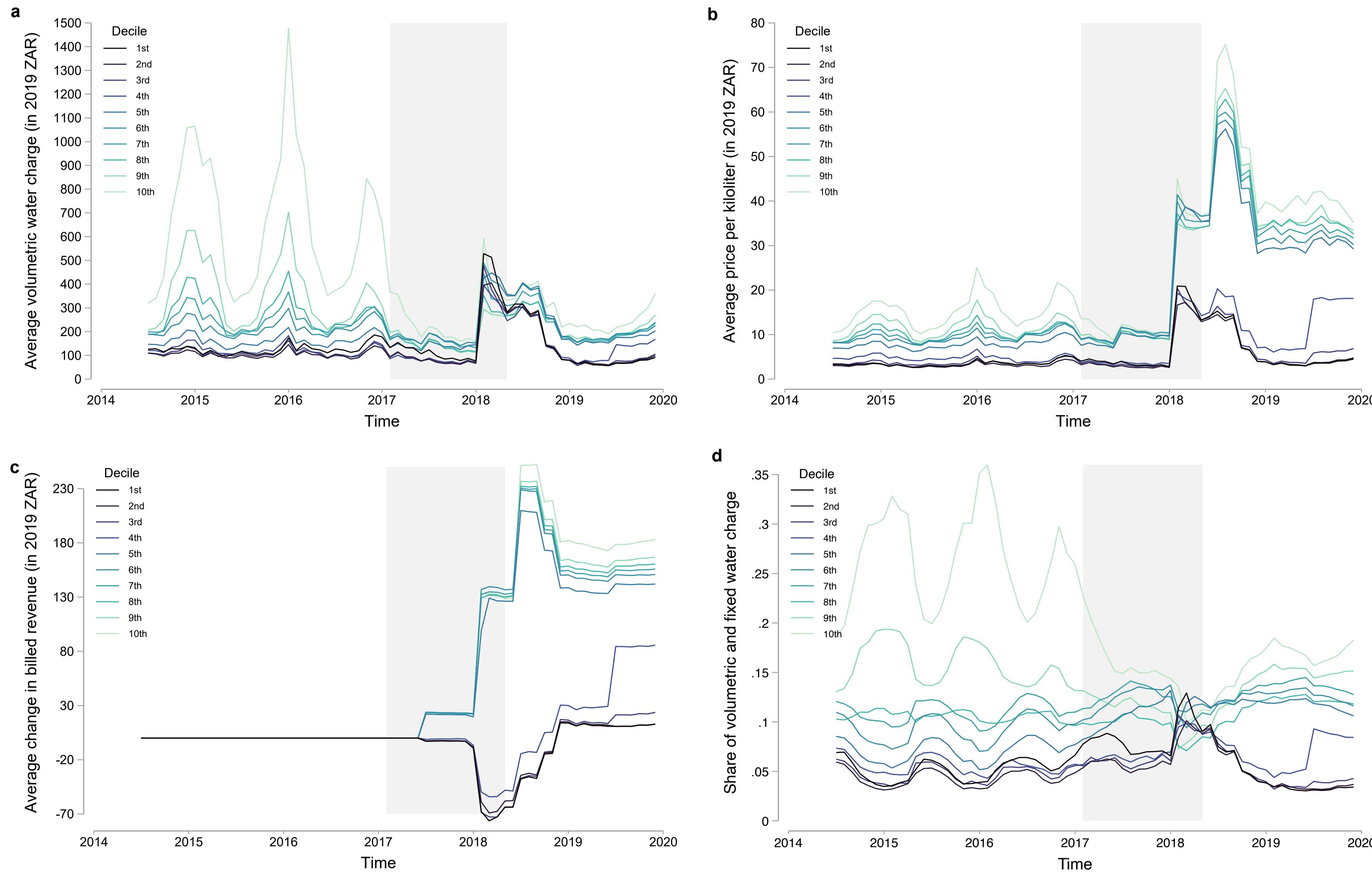
Figure 5c shows the redistributive impacts of these policies taken together; assuming that each of these changes is inframarginal to consumption, we plot the average difference between the observed monthly water bill by decile and a counterfactual that shuts down these policy changes by holding all redistributive policies at their January 2017 levels, immediately before the beginning of the crisis. Specifically, in the counterfactual, we set the price of the first 6 kL of water to 0 for all households and use the time-varying non-indigent 2nd block (6-10.5 kL) price for all households, hold the indigent grant fixed at its early-2017 value (122.99 ZAR) throughout the remaining time period, and remove fixed charges. Relative to this no-policy-change counterfactual, observed total charges are higher for the top 6 property value deciles starting in July 2017 (i.e., removal of free water for non-indigent households), and more so from the beginning of 2018 onward. For the first four deciles of the property value distribution, observed charges are lower than in the no-policy-change counterfactual at the peak of the crisis, but exceed the counterfactual after the drought. This is largely

[43] We provide a conservative calculation of the value of the indigent grant by ignoring the accumulation over time (since we do not observe the starting balance, we cannot calculate this) and set the water bill to zero when consumption charges fall below the grant value.

[44] The spike in prices in the 4th decile in June 2019 corresponds to a city-wide property revaluation that caused many of these households to lose their indigent status; we hold our decile definitions fixed using 2016 property values.

[45] The size of the monthly fixed charge varies based on the width of the household's metered water connection. In our sample, the majority of non-indigent households pay either 56 ZAR or 100 ZAR per month in fixed charges.

Figure 5: Municipal water charges and share by decile



Notes: (a) Monthly average consumption-based water charge by decile. (b) Monthly average water price by property value decile, inclusive of fixed charges. (c) Monthly average change in billed revenue from redistributive policy changes. (d) Monthly share of total residential water charges (consumption and fixed) by property value decile. Gray-shaded area marks the February 2017 to May 2018 water crisis.

because the counterfactual indigent grant was more generous than the fixed quantity of free water once the value of that free water fell as tariffs returned to normal.

Figure 5d shows the observed share of total volumetric and fixed household charges in each decile of the property value distribution. Contrary to the predictions of our theoretical framework in the absence of fixed costs, the cost share in the bottom deciles was slightly lower after the drought than before; this is due to the pricing changes introduced by the PU. However, the large pre-drought spread between top and middle deciles did not re-emerge. As a result, the poorest deciles were protected by policy, while most of the pecuniary externality from reduced consumption by the rich fell on the middle class.

6 Quantifying the role of adaptation

How much of a role did private substitution to groundwater play in the fiscal and distributional outcomes documented in Section 5? To answer this question, we build a discrete choice model based on the theoretical framework in Section 2 that allows us to quantify the effects of groundwater drilling on public water demand.

6.1 Setup and calibration

The modeled economy is populated by a continuum of households, each of whom takes one of ten possible types indexed by $i \in \{1, \dots, 10\}$. Each type comprises a tenth of total households and maps to one of the ten average property value deciles in Section 4. In each month t, households first make a discrete decision over whether to drill a groundwater well and then decide how much public water to purchase from the PU and how much groundwater to extract in the case where they have drilled a well. Each month evolves as follows: first, the PU sets a volumetric price schedule separately for indigent and non-indigent households; second, households make drilling decisions; and third, households make public water and groundwater consumption decisions conditional on prices and drilling.

Type-i households have utility from total water consumption w_t that is parameterized by their type α_i:[46]

$$\nu(w_t|\alpha_i) = \alpha_i \, \frac{w_t^{1-\gamma} - 1}{1 - \gamma}$$

[46]Under quasilinear utility, the model can be reformulated as the problem of many identical agents in each property value decile under arbitrary levels of income heterogeneity within and across deciles. The equivalence of this formation with one where agents within deciles have heterogeneous α parameters hinges on the assumption that the variation in α *within* each decile is small enough such that all households choose a demand level in the same tariff block. We examine the validity of this assumption in Appendix B.

where $w_t = m_t + g_t$ is the sum of public water consumption m_t and groundwater consumption g_t. Households have linear utility over public water charges, the fixed cost of adopting groundwater (if they choose to do so), and the costs of extracting groundwater (conditional on adoption).

Prior to selecting consumption levels each month, households first make a decision over whether to drill a groundwater well after observing the type-specific schedule of charges for public water consumption $c_{i,t}(m_t)$. We assume the cost of drilling a well is c^d for all households and that once they have drilled, they can extract groundwater g_t each month at a cost of ψg_t^2.[47]

For a type-i household without a groundwater well—those with $D_t = N$—utility is

$$u(m_t|\alpha_i, D_t = N) = \nu(m_t|\alpha_i) - c_{i,t}(m_t)$$

which yields the first order condition for public water consumption:

$$m_{i,N,t} \leq \left(\frac{c'_{i,t}(m_{i,N,t})}{\alpha_i}\right)^{-1/\gamma} \tag{6}$$

where $c'_{i,t}(m_{i,N,t})$ is the marginal price of public water for type-i households evaluated at their optimal level of demand conditional on not having drilled a well, $m_{i,N,t}$. This equation will hold with equality when demand does not intersect with the vertical portion of the IBT schedule. For households that choose to drill—those with $D_t = D$—utility is

$$u(m_t, g_t|\alpha_i, D_t = D) = \nu(m_t + g_t|\alpha_i) - c_{i,t}(m_t) - \psi g_t^2$$

with the first order conditions for public and groundwater consumption:

$$m_{i,D,t} + g_{i,D,t} \leq \left(\frac{c'_{i,t}(m_{i,D,t})}{\alpha_i}\right)^{-1/\gamma} \tag{7}$$

$$m_{i,D,t} + g_{i,D,t} = \left(\frac{2\psi g_{i,D,t}}{\alpha_i}\right)^{-1/\gamma} \tag{8}$$

where $m_{i,D,t}$ and $g_{i,D,t}$ are type-i households' optimal demand levels for public water and groundwater conditional on having drilled.

The conditions above are sufficient for informing our static calibration based on cross-sectional data. Each step in the procedure for recovering the model's structural parameters is outlined here; a comprehensive description is relegated to Appendix A.5. We fo-

[47]This cost captures both the costs of physical extraction (i.e., pumping) as well as any additional time or monetary costs households incur to make use of the groundwater they extract.

cus on three two-month snapshots from around Day Zero for calibration and counterfactuals, each of which serves as a vignette of one stage in the drought: a *pre-crisis* period as November-December 2016, a *crisis* period as February-March 2018, and a *post-crisis* period as October-November 2018. Calibration selects structural parameters such that modeled demand coincides with observed demand in the pre-crisis and crisis periods, while we perform counterfactuals for the crisis and post-crisis periods.

Given that we do not observe household-level drilling decisions, we require several additional assumptions for the model to be identified: limited within-decile heterogeneity in α_i parameters; that the bottom four property value deciles in the model are comprised solely of indigent households while the other deciles contain none (see Figure D.2); and that all wells and boreholes were drilled between the end of the pre-crisis period and start of the crisis period. From there, we estimate the model's parameters in three steps, detailed further in Appendix A.5. First, we recover γ—the parameter governing the price elasticity of demand for water—using observed changes in prices and quantities demanded during the crisis (relative to the pre-crisis period) for households in the fifth property value decile.[48] Second, we recover the set of decile-specific demand shifters α_i by inverting the first order condition in eq. (6) and evaluating the expression in the pre-crisis period under the assumption that no households had drilled wells at that point. Finally, we use the first order conditions in eqs. (7) and (8) to recover the groundwater extraction cost parameter ψ.

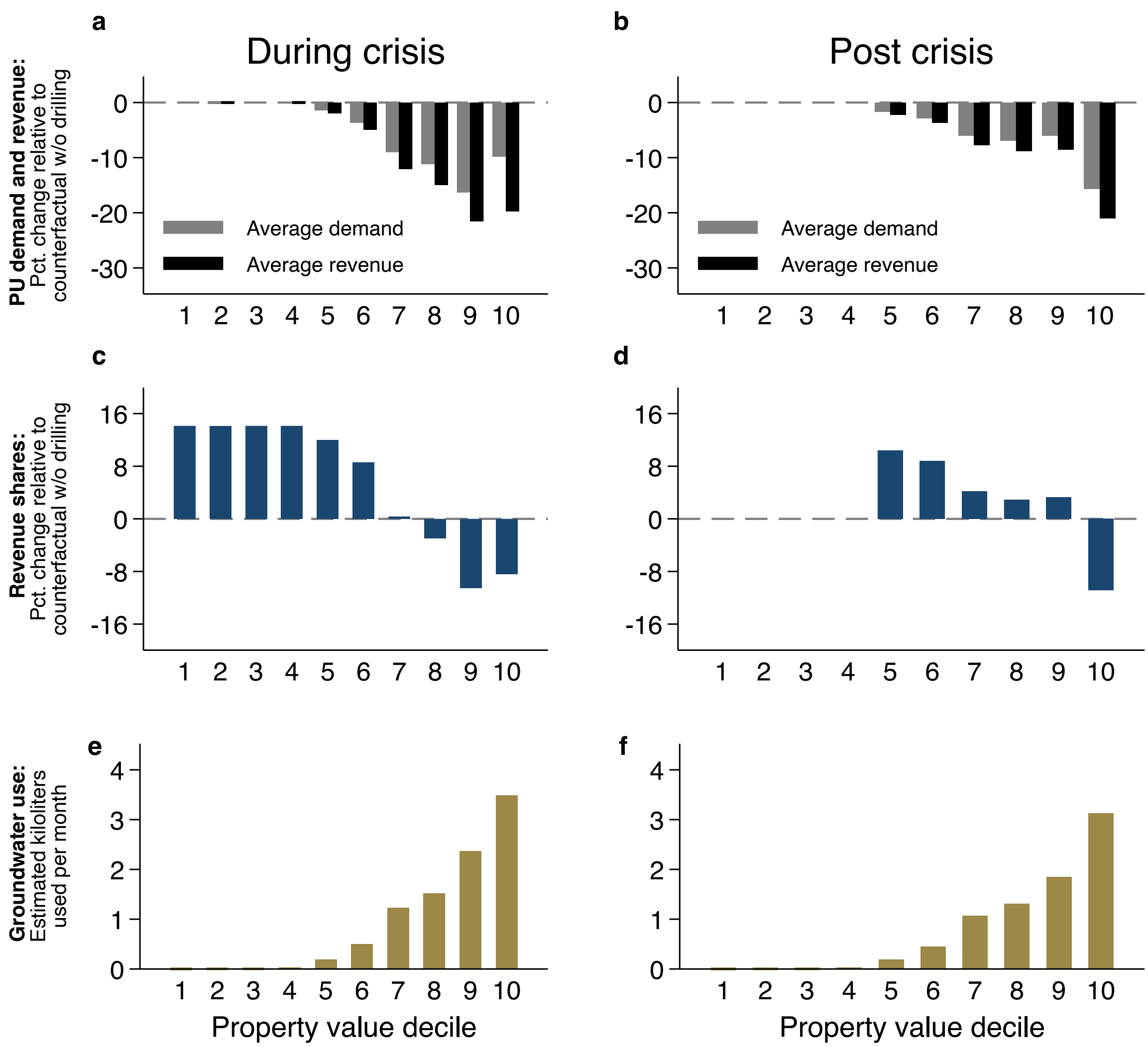
6.2 Counterfactuals

With fitted parameters $\{\hat{\alpha}_i, \hat{\gamma}, \hat{\psi}\}$ in hand, we construct counterfactual decile-specific public water use, revenue, and groundwater consumption in the absence of drilling. We perform this calculation for two periods: the crisis, when PU prices were at historical highs near the end of the drought, and the post-crisis when PU prices returned closer to baseline levels and additional free water was granted to indigent households (see Table E.1). Figure 6 plots the predictions for water demand under observed drilling levels relative to the no-drilling counterfactuals for the crisis (left panels) and post-crisis (right panels) periods. The outcomes we consider are changes in decile-specific public water use and revenue (top row), share of PU revenue (middle row), and groundwater use (bottom row). We evaluate the ability of the model to match observed piped water consumption and revenues in each decile during and after the crisis in Appendix B.

Under the high PU price schedule during the crisis, modeled in the left panels of Figure 6, we find that private substitution to groundwater lowered total demand (summed across

[48]We choose the 5th decile because few households in that decile are indigent or drilled wells.

Figure 6: Modeled outcome differences between groundwater drilling and no drilling



NOTES: Figures show the difference in decile-specific outcomes between the drilling factual and no-drilling counterfactual for PU prices during the crisis period (left panels) and post-crisis period (right panels). Top row shows percent change in public water use and revenue. Middle row shows the percentage changes in the share of PU revenue paid by each decile relative to the no-drilling counterfactual. Bottom row shows modeled groundwater use in kL per month.

deciles) for public water by 5.3%, or roughly 0.2 million kL per month. This came with 12.4% lower total PU revenue over the same period. Figure 6a shows that much of the drop in total public water use and revenue is driven by consumption changes by upper-decile households. The shift to groundwater by richer households (Figure 6e) led to a shift in the share of PU revenue from richer to poorer households (Figure 6c); the cost share for the bottom four property value deciles is 1.49 percentage points higher under the observed level of drilling than it is in the counterfactual had no drilling occurred. The additional decline in demand for piped water due to adaptation also increased the demand curtailment effect of price increases during the crisis. Without private substitutes, prices in the second IBT tier (6-10.5kL) would have needed to increase by an additional 50.0% (from 46 to 69 ZAR) to achieve the reduction in demand under observed levels of drilling.[49]

The consequences of groundwater adoption are more muted in the post-crisis period, as shown in the right-hand panels of Figure 6. That said, drilling induced during the drought had lasting consequences. Demand for (revenue from) public water was 4.9% (11.4%) lower in the post-crisis period due to drilling. Again, much of the drop in total public water use and revenue is driven by higher property value households (Figure 6b) who substitute more to groundwater (Figure 6f). Due to the concurrent introduction of an additional block of free water to indigent households in the post-crisis period, the bottom four deciles' cost shares are unaffected by drilling and the cost shift occurs instead between middle and high property value households (Figure 6d). The model also allows us to investigate the revenue benefits of the fixed charge implemented in July 2018; specifically, by how much would volumetric prices have to increase to match the observed level of revenue? We estimate that absent the fixed charges, the post-crisis IBT would have increased by 50.4% (from 34 to 52 ZAR) in the 6.0-10.5 kL block to make up for the revenue generated by fixed charges.

7 Conclusion

Cape Town's brush with Day Zero offers a cautionary tale for the $67 billion global water utilities market (Zion Market Research, 2023) with an estimated 1 billion people living in drought-vulnerable cities (Ahmadi et al., 2020; He et al., 2021). This case study points to broader lessons. First, customer responses to the utility's policy changes during the supply shock depend on access to private substitutes. Where substitution requires costly

[49] To solve for the required price increase, we use the model to solve for the price level in the second (6-10.5 kL) step of the IBT that, absent adaptation, would cause demand in both the baseline and counterfactual scenarios to be the same in aggregate. We focus on the required change in the second pricing block since it is the one that determines marginal prices (and thus demand) for all non-indigent households during the crisis under a counterfactual where no households could access groundwater.

fixed investment—which is plausible in many cases—differential private adaptation by richer households can create pecuniary and environmental externalities with equity consequences that persist even after the shock. There are analogs for climate mitigation where private efforts to reduce greenhouse gas emissions, such as adoption of residential rooftop solar panels or electric vehicles, undermine the overall financing of publicly-provided goods (such as electricity and highways) and the equitable distribution of costs across users (Borenstein and Bushnell, 2022; Borenstein, Fowlie and Sallee, 2023; Metcalf, 2023; Glaeser, Gorback and Poterba, 2023).

Second, policy interventions can play an outsized role in managing demand, cost recovery, and redistribution. These policies will respond to climate shocks. Had Cape Town's policy response been less aggressive during the water crisis, it might not have avoided Day Zero. On the other hand, it might have seen less substitution away from municipal water and avoided the associated long-run challenges for utility revenue. Economists have long argued for fixed charges to cover the fixed costs of utilities (e.g., Borenstein, 2016). The Cape Town case highlights that fixed charges can address the revenue problem, but will only support redistributive goals if they are targeted to high-income households. In a setting where the utility also observes characteristics like property values, this may be feasible. In others, it will require new data sources for targeting as suggested by Borenstein, Fowlie and Sallee (2023). In this case, the drought appears to have been instrumental in spurring a transition to more efficient pricing by the utility; whether future shocks may also provide impetus for pricing reforms in other settings remains an open question.

A final challenge—and one beyond the scope of our theoretical framework—is environmental. Like much of the world, Cape Town's private groundwater extraction is largely unregulated and likely to approximate open access conditions. This implies that by inducing groundwater drilling, Cape Town's Day Zero efforts may have exacerbated groundwater externalities, creating concerns about the long-term sustainability of this alternative water supply.[50] While a lack of data on groundwater extraction and understanding of the hydrological properties of the Cape Town aquifer prevents us from quantifying this new externality—a knowledge gap that can be addressed with future research—the Day Zero experience places added emphasis on the need for joint management of surface and ground-

[50]There are two externalities associated with unmanaged groundwater pumping (Provencher and Burt, 1993). The stock externality occurs because one user's extraction lowers available future groundwater water for other users. The pumping cost externality occurs because lower groundwater levels raise pumping costs for others. Both externalities are hard to quantify because they depend on how extraction by one user affects groundwater levels for other users. This requires characterizing the flow rates across all locations of an aquifer through a spatially-dense network of groundwater monitoring wells, which is not available for Cape Town. In Appendix C.4, we offer a back-of-the-envelope calculation for the increase in marginal groundwater extraction cost following the water crisis, an ingredient for quantifying the groundwater externality.

water supplies (Faragher and Carden, 2023). Beyond the Cape Town case, substitution away from publicly provided water or energy is likely to change the type and magnitude of the environmental externalities associated with the consumption of these resources (Borenstein, Fowlie and Sallee, 2023).

References

Abajian, Alexander C, and Nick Pretnar. 2024. "Subsidies for close substitutes: Aggregate demand for residential solar electricity." *European Economic Review*, 170: 104848.

Abajian, Alexander C, Tamma Carleton, Kyle C Meng, and Olivier Deschênes. 2023. "Quantifying the global climate feedback from energy-based adaptation." *Working paper*.

Ahmadi, Mohammad Sadeq, Janez Sušnik, William Veerbeek, and Chris Zevenbergen. 2020. "Towards a global day zero? Assessment of current and future water supply and demand in 12 rapidly developing megacities." *Sustainable Cities and Society*, 61: 102295.

Aina, Ifedotun Victor, Djiby Racine Thiam, and Ariel Dinar. 2023. "Substitution of piped water and self-supplied groundwater: The case of residential water in South Africa." *Utilities Policy*, 80: 101480.

Almer, Christian, Jérémy Laurent-Lucchetti, and Manuel Oechslin. 2017. "Water scarcity and rioting: Disaggregated evidence from Sub-Saharan Africa." *Journal of Environmental Economics and Management*, 86: 193–209.

Andres, Luis A, Gustavo Saltiel, Smita Misra, George Joseph, Camilo Lombana Cordoba, Michael Thibert, and Crystal Fenwick. 2021. *Troubled tariffs: Revisiting water pricing for affordable and sustainable water services.* World Bank.

Baumol, William J, and David F Bradford. 1970. "Optimal departures from marginal cost pricing." *The American Economic Review*, 60(3): 265–283.

Bergstrom, Theodore, Lawrence Blume, and Hal Varian. 1986. "On the private provision of public goods." *Journal of Public Economics*, 29(1): 25–49.

Besley, Timothy, and Stephen Coate. 1991. "Public provision of private goods and the redistribution of income." *The American Economic Review*, 81(4): 979–984.

Bischoff-Mattson, Zachary, Gillian Maree, Coleen Vogel, Amanda Lynch, David Olivier, and Deon Terblanche. 2020. "Shape of a water crisis: Practitioner perspectives on urban water scarcity and 'Day Zero' in South Africa." *Water Policy*, 22(2): 193–210.

Bollinger, Bryan, Naim Darghouth, Andres Gonzalez-Lira, and Kenneth Gillingham. 2023. "Valuing technology complementarities: Rooftop solar and energy storage." *Working paper*.

Booysen, Marthinus Johannes, Martine Visser, and Ronelle Burger. 2019. "Temporal case study of household behavioural response to Cape Town's "Day Zero" using smart meter data." *Water research*, 149: 414–420.

Borenstein, Severin. 2012. "The redistributional impact of nonlinear electricity pricing." *American Economic Journal: Economic Policy*, 4(3): 56–90.

Borenstein, Severin. 2016. "The economics of fixed cost recovery by utilities." *The Electricity Journal*, 29(7): 5–12.

Borenstein, Severin. 2017. "Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates." *Journal of the Association of Environmental and Resource Economists*, 4(S1): S85–S122.

Borenstein, Severin, and James B Bushnell. 2022. "Do two electricity pricing wrongs make a right? Cost recovery, externalities, and efficiency." *American Economic Journal: Economic Policy*, 14(4): 80–110.

Borenstein, Severin, Meredith Fowlie, and James Sallee. 2023. "Who will pay for the energy transition? Affordability, efficiency and electricity price regulation." *Working Paper*.

Brehm, Paul A, Sarah Johnston, and Ross Milton. 2025. "Backup Power: Public Implications of Private Substitutes for Electric Grid Reliability." *Journal of the Association of Environmental and Resource Economists*, forthcoming.

Brick, Kerri, Samantha De Martino, and Martine Visser. 2023. "Behavioural nudges for water conservation in unequal settings: Experimental evidence from Cape Town." *Journal of Environmental Economics and Management*, 121: 102852.

Brown, David P, and Lucija Muehlenbachs. 2024. "The value of electricity reliability: Evidence from battery adoption." *Journal of Public Economics*, 239: 105216.

Browne, Oliver R, Ludovica Gazze, and Michael Greenstone. 2021. "Do conservation policies work? Evidence from residential water use." *Environmental and Energy Policy and the Economy*, 2(1): 190–225.

Brühl, Johanna, and Martine Visser. 2021. "The Cape Town drought: A study of the combined effectiveness of measures implemented to prevent "Day Zero"." *Water Resources and Economics*, 34: 100177.

Brühl, Johanna, Leonard le Roux, Martine Visser, and Gunnar Köhlin. 2020. "Decision-Making in a Water Crisis: Lessons from the Cape Town Drought for Urban Water Policy." In *Oxford Research Encyclopedia of Environmental Science*.

Bruno, Ellen M, and Katrina Jessoe. 2021. "Using price elasticities of water demand to inform policy." *Annual Review of Resource Economics*, 13(1): 427–441.

Burke, Marshall, Solomon M Hsiang, and Edward Miguel. 2015. "Global non-linear effect of temperature on economic production." *Nature*, 527(7577): 235–239.

Burlig, Fiona, Louis Preonas, and Matt Woerman. 2024. "Groundwater and Crop Choice in the Short and Long Run." *Working Paper*.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, et al. 2022. "Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits." *The Quarterly Journal of Economics*, 137(4): 2037–2105.

Carleton, Tamma, Esther Duflo, B. Kelsey Jack, and Guglielmo Zappala. 2025. "Climate adaptation." In *Handbook on the Economics of Climate Change*. Elsevier.

City of Cape Town. 2020. "Our shared water future: Cape Town's water strategy."

City of Cape Town. 2021. "Integrated Annual Report, 2020/21." Cape Town Municipal Government.

Cook, Joseph, Johanna Brühl, and Martine Visser. 2021. "Distributional statistics of municipal water use during Cape Town's drought: implications for affordability, conservation, and tariffs." *Water Resources Research*, 57(6): e2020WR028219.

Costa, Francisco, and François Gerard. 2021. "Hysteresis and the welfare effect of corrective policies: Theory and evidence from an energy-saving program." *Journal of Political Economy*, 129(6): 1705–1743.

Davis, Lucas W, and Catherine Hausman. 2022. "Who Will Pay for Legacy Utility Costs?" *Journal of the Association of Environmental and Resource Economists*, 9(6): 1047–1085.

Dingel, Jonathan I, Kyle C Meng, and Solomon M Hsiang. 2021. "Spatial Correlation, Trade, and Inequality: Evidence from the Global Climate." National Bureau of Economic Research Working Paper 25447.

Driscoll, John C., and Aart C. Kraay. 1998. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *The Review of Economics and Statistics*, 80(4): 549–560.

DWS. 2015. "Norms and standards in respect of tariffs for water service authorities and bulk water servce providers." Department: Water and Sanitation, Republic of South Africa Notice 1123.

El-Khattabi, Ahmed Rachid, Shadi Eskaf, Julien P Isnard, Laurence Lin, Brian McManus, and Andrew J Yates. 2021. "Heterogeneous responses to price: Evidence from residential water consumers." *Journal of Environmental Economics and Management*, 107: 102430.

Epple, Dennis, and Richard E Romano. 1996. "Public provision of private goods." *Journal of Political Economy*, 104(1): 57–84.

Euromonitor. 2017. "Income Inequality Ranking of the World's Major Cities."

Fan, Jianqing, and Irene Gijbels. 1996. *Local polynomial modelling and its applications: monographs on statistics and applied probability 66.* Vol. 66, CRC Press.

Faragher, Tamsin PT, and Kirsty Carden. 2023. "Groundwater governance for improving city water resilience in Cape Town, South Africa." *Frontiers in Sustainable Cities*, 5: 1062661.

Feger, Fabian, Nicola Pavanini, and Doina Radulescu. 2022. "Welfare and redistribution in residential electricity markets with solar power." *The Review of Economic Studies*, 89(6): 3267–3302.

Feldstein, Martin S. 1972. "Equity and efficiency in public sector pricing: the optimal two-part tariff." *The Quarterly Journal of Economics*, 86(2): 175–187.

Fisher, Anthony, David Fullerton, Nile Hatch, and Peter Reinelt. 1995. "Alternatives for managing drought: a comparative cost analysis." *Journal of Environmental Economics and Management*, 29(3): 304–320.

Foster, Vivien, and Samantha Helen Witte. 2020. "Falling short: A global survey of electricity tariff design." *World Bank Policy Research Working Paper*, , (9174).

Galbraith, John Kenneth. 1958. *The affluent society.* Houghton Mifflin Harcourt.

Gao, Ying, Jeffrey P Walker, Mahdi Allahmoradi, Alessandra Monerris, Dongryeol Ryu, and Thomas J Jackson. 2015. "Optical sensing of vegetation water content: A synthesis study." *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(4): 1456–1464.

Gintamo, Tesfaye Tessema, Haile Mengistu, and Thokozani Kanyerere. 2021. "GIS-based modelling of climate variability impacts on groundwater quality: Cape Flats aquifer, Cape Town, South Africa." *Groundwater for Sustainable Development*, 15: 100663.

Glaeser, Edward L., Caitlin S. Gorback, and James M. Poterba. 2023. "How Regressive Are Mobility-Related User Fees and Gasoline Taxes?" *Tax Policy and the Economy*, 37(1): 1–56.

Gorman, Will, Stephen Jarvis, and Duncan Callaway. 2020. "Should I Stay Or Should I Go? The importance of electricity rate design for household defection from the power grid." *Applied Energy*, 262: 114494.

Graff Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics*, 32(1): 1–26.

Hadachek, Jeffrey, Ellen M Bruno, Nick Hagerty, and Katrina Jessoe. 2024. "External Costs of Climate Adaptation: Groundwater Depletion and Drinking Water." *Working paper.*

Harmsen, Nick. 2017. "Load shedding in SA heatwave three times amount ordered." *Australian Broadcasting Corporation (ABC News).*

He, Chunyang, Zhifeng Liu, Jianguo Wu, Xinhao Pan, Zihang Fang, Jingwei Li, and Brett A Bryan. 2021. "Future global urban water scarcity and potential solutions." *Nature Communications*, 12(1): 4667.

Henderson, J Stephen. 1986. "Price discrimination limits in relation to the death spiral." *The Energy Journal*, 7(3).

Hsiang, Solomon, Paulina Oliva, and Reed Walker. 2019. "The distribution of environmental damages." *Review of Environmental Economics and Policy.*

Hsiao, Allan. 2022. "Sea Level Rise and Urban Adaptation in Jakarta." *Working paper.*

Hsiao, Allan. 2024. "Sea level rise and urban inequality." *AEA Papers and Proceedings*, 114: 47–51.

Hsiao, Allan, Jacob Moscona, and Karthik Sastry. 2024. "Food Policy in a Warming World." National Bureau of Economic Research, Inc.

Ito, Koichiro. 2014. "Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing." *American Economic Review*, 104(2): 537–563.

Mansur, Erin T, and Sheila M Olmstead. 2012. "The value of scarce water: Measuring the inefficiency of municipal regulations." *Journal of Urban Economics*, 71(3): 332–346.

McRae, Shaun. 2015. "Infrastructure quality and the subsidy trap." *American Economic Review*, 105(1): 35–66.

Metcalf, Gilbert E. 2023. "The Distributional Impacts of a VMT-Gas Tax Swap." *Environmental and energy policy and the economy*, 4(1): 4–42.

Muller, Mike. 2008. "Free basic water - a sustainable instrument for a sustainable future in South Africa." *Environment and Urbanization*, 20(1): 67–87.

Nauges, Celine, and Dale Whittington. 2017. "Evaluating the performance of alternative municipal water tariff designs: Quantifying the tradeoffs between equity, economic efficiency, and cost recovery." *World Development*, 91: 125–143.

Nicholls, Robert J, Daniel Lincke, Jochen Hinkel, Sally Brown, Athanasios T Vafeidis, Benoit Meyssignac, Susan E Hanson, Jan-Ludolf Merkens, and Jiayi Fang. 2021. "A global analysis of subsidence, relative sea-level change and coastal flood exposure." *Nature Climate Change*, 11(4): 338–342.

Otto, Friederike EL, Piotr Wolski, Flavio Lehner, Claudia Tebaldi, Geert Jan Van Oldenborgh, Sanne Hogesteeger, Roop Singh, Petra Holden, Neven S Fučkar, Romaric C Odoulami, et al. 2018. "Anthropogenic influence on the drivers of the Western Cape drought 2015–2017." *Environmental Research Letters*, 13(12): 124010.

Pascale, Salvatore, Sarah B. Kapnick, Thomas L. Delworth, and William F. Cooke. 2020. "Increasing risk of another Cape Town "Day Zero" drought in the 21st century." *Proceedings of the National Academy of Sciences*, 117(47): 29495–29503.

Provencher, Bill, and Oscar Burt. 1993. "The externalities associated with the common property exploitation of groundwater." *Journal of Environmental Economics and Management*, 24(2): 139–158.

Rathnayaka, Kumudu, Hector Malano, Shiroma Maheepala, Biju George, Bandara Nawarathna, Meenakshi Arora, and Peter Roberts. 2015. "Seasonal demand dynamics of residential water end-uses." *Water*, 7(1): 202–216.

Schachtschneider, Klaudia. 2020. "Blog: Water beneath our feet." World Wildlife Fund.

Sekhri, Sheetal. 2014. "Wells, water, and welfare: the impact of access to groundwater on rural poverty and conflict." *American Economic Journal: Applied Economics*, 6(3): 76–102.

Simpson, Nicholas Philip, Kayleen Jeanne Simpson, Clifford D Shearing, and Liza Rose Cirolia. 2019. “Municipal finance and resilience lessons for urban infrastructure management: a case study from the Cape Town drought.” *International Journal of Urban Sustainable Development*, 11(3): 257–276.

Sinclair-Smith, Ken, Susan Mosdell, Gisela Kaiser, Ziyaad Lalla, Leandre September, Collin Mubadiro, Sarah Rushmere, Katherine Roderick, Johanna Brühl, Megan McLaren, and Martine Visser. 2018. “City of Cape Town’s Water Map.” *Journal: American Water Works Association*, 110(9).

Szabo, Andrea. 2015. “The value of free water: analyzing South Africa’s free basic water policy.” *Econometrica*, 83(5): 1913–1961.

Timmins, Christopher. 2002. “Measuring the dynamic efficiency costs of regulators’ preferences: Municipal water utilities in the arid west.” *Econometrica*, 70(2): 603–629.

Unfried, Kerstin, Krisztina Kis-Katos, and Tilman Poser. 2022. “Water scarcity and social conflict.” *Journal of Environmental Economics and Management*, 113: 102633.

Visser, Willem. 2018. “A perfect storm: The ramifications of Cape Town’s drought crisis.” *The Journal for Transdisciplinary Research in Southern Africa*, 14(1): 1–10.

Werner, Adrian D, Qi Zhang, Lijuan Xue, Brian D Smerdon, Xianghu Li, Xinjun Zhu, Lei Yu, and Ling Li. 2013. “An initial inventory and indexation of groundwater mega-depletion cases.” *Water Resources Management*, 27: 507–533.

Whittington, Dale. 1992. “Possible adverse effects of increasing block water tariffs in developing countries.” *Economic Development and Cultural Change*, 41(1): 75–87.

Wichman, Casey J, Laura O Taylor, and Roger H Von Haefen. 2016. “Conservation policies: Who responds to price and who responds to prescription?” *Journal of Environmental Economics and Management*, 79: 114–134.

World Bank. 2023. “Poverty and Inequality Platform, Gini Index.” World Bank.

World Health Organization, et al. 2024. “Tracking SDG 7.”

Ziervogel, Gina. 2019. “Unpacking the Cape Town drought: lessons learned.” Cape Town.

Zion Market Research. 2023. “Water Utility Services Market Size, Share, Growth Report 2032.”

Appendix to:

Dodging Day Zero: Drought, Adaptation, and Inequality in Cape Town

A Appendix theory

Throughout the proofs associated with the simple model in Section 2, we assume the following:

1. $u_i(\cdot)$ is increasing and strictly concave.

2. The functional $\mathcal{C}(m, \Theta)$ mapping price schedules $\Theta \in \Omega$ and consumption m into costs

$$\mathcal{C}(m, \Theta) : \Big(\{0 \,\cup\, \mathbb{R}_+\} \times \Omega\Big) \longrightarrow \mathbb{R}_+$$

   is strictly positive for all $m > 0$ and nondecreasing in m. Here, Ω is defined as a non-empty subset of the set of all bounded, strictly positive functions on $\{0 \,\cup\, \mathbb{R}_+\}$.

The cost function induced by Θ in the main text, $c(m)$, is the mapping $c : (\{0 \cup \mathbb{R}_+\}) \longrightarrow \mathbb{R}_+$ generated by evaluating $\mathcal{C}(m, \Theta)$ at different values of m holding Θ constant. To make assumptions 1 and 2 more concrete, a common example for a class of price schedule that would fit the criteria above are those described by right-continuous marginal cost curves $\Theta(m)$. This includes the case of constant marginal pricing, upward sloping supply curves, or block tariffs. The cost functional in this case is simply the Riemann integral:

$$\mathcal{C}(m, \Theta) = \int_0^m \Theta(n)\, dn$$

Note finally that the main text is written under the assumption that the demand correspondence for each household

$$m_i(\Theta) = \arg\max_m \Big\{ u_i(m) - \mathcal{C}(m, \Theta) \;:\; m \in [0, \infty) \Big\} \tag{A.1}$$

is non-empty and unique, ignoring the case where $m_i(\Theta)$ may be a set with multiple elements. However, the proof of Lemma 1 holds even when the demand correspondence in equation (A.1) is not single-valued. In the case of set-valued optimal demand levels $m_i(\Theta)$, the result in Lemma 1 becomes that $m_i^d(\Theta) \leq_s m_i(\Theta)$, or that demand is nondecreasing in the strong set order under drilling versus when it is absent (i.e., both the minimal and maximal elements of the demand correspondence $m_i(\Theta)$ are nonincreasing in the drilling decision). Analogues for Corollaries 1 and 2 when the demand correspondence in equation (A.1) is not single-valued are that revenue (cost shares for the poor household) is nonincreasing (nondecreasing) in the strong set order.

A.1 Comparative statics over the drilling decision

Several comparative statics results are useful to establish initially. Consider a household's drilling decision, which solves

$$\begin{aligned}\text{drill}_i = \arg\max_{d\in\{0,1\}} \Big\{ & d\Big(u_i(m_i^d(\Theta)+\lambda) - c^d - \mathcal{C}(m_i^d(\Theta),\Theta)\Big) \\ & + (1-d)\Big(u_i(m_i(\Theta)) - \mathcal{C}(m_i(\Theta),\Theta)\Big)\Big\}\end{aligned} \tag{A.2}$$

Call the function in brackets $g(d, \Theta, \lambda, c^d)$. Note that the difference between the value of drilling and not drilling,

$$\begin{aligned}g(1,\Theta,\lambda,c^d) - g(0,\Theta,\lambda,c^d) = \; & u_i(m_i^d(\Theta)+\lambda) - c^d - \mathcal{C}(m_i^d(\Theta),\Theta) \\ & - \; u_i(m_i(\Theta)) + \mathcal{C}(m_i(\Theta),\Theta)\end{aligned} \tag{A.3}$$

is strictly decreasing in c^d and increasing in λ. Then $g(d, \Theta, \lambda, c^d)$ is supermodular in (d, λ) and submodular in (d, c^d) and Topkis' Monotonicity Theorem gives that the drilling decision drill_i is nondecreasing in λ and nonincreasing in c^d.

Finally, when Θ induces a cost function that is twice continuously-differentiable in m and Θ, the envelope theorem lets us write

$$\frac{d[g(1,\Theta,\lambda,c^d) - g(0,\Theta,\lambda,c^d)]}{d\Theta} = \frac{d\mathcal{C}(m_i^d(\Theta),\Theta)}{d\Theta} - \frac{d\mathcal{C}(m_i(\Theta),\Theta)}{d\Theta} \tag{A.4}$$

When $\mathcal{C}(m, \Theta)$ has a weakly positive cross-partial in (m, Θ), the right hand-side above is weakly negative which implies that $g(d, \Theta, \lambda, c^d)$ is nondecreasing in Θ as well.

A.2 Proof of Lemma 1

Proof. Dropping time subscripts, utility for a household that chooses to drill a well—$\text{drill}_i = 1$—and purchase a quantity m_i of public water is

$$U_i(\text{drill}_i = 1, m_i) = u_i(m_i + \lambda) - c^d - \mathcal{C}(m_i, \Theta)$$

while for a household that does not—$\text{drill}_i = 0$—it is

$$U_i(\text{drill}_i = 0, m_i) = u_i(m_i) - \mathcal{C}(m_i, \Theta)$$

Differencing the two holding m_i constant leaves

$$U_i(\text{drill}_i = 1, m_i) - U_i(\text{drill}_i = 0, m_i) = u_i(m_i + \lambda) - c^d - u_i(m_i)$$

When $u_i(\cdot)$ is strictly concave for both households we have

$$\frac{d[U_i(\text{drill}_i = 1, m_i) - U_i(\text{drill}_i = 0, m_i)]}{dm_i} = u_i'(m_i + \lambda) - u_i'(m_i) < 0$$

Households' utility over water demand and their drilling decision is submodular in drill_i and public water demand m_i. By Topkis' Monotonicity Theorem, we must have $m_i^d(\Theta_t) \leq m_i(\Theta_t)$ for any cost schedule Θ_t for both households. This yields the result in Lemma 1, as $m_i(\Theta) - m_i^d(\Theta')$ is then (weakly) larger than $m_i(\Theta) - m_i(\Theta')$ for all $\Theta' \geq \Theta$.

□

A.3 Proof of Proposition 1

Proof. The aggregate demand result follows immediately from Lemma 1. Recall aggregate revenue is given by

$$R(\Theta) = \mathcal{C}(m_p^{d_p}(\Theta), \Theta) + \mathcal{C}(m_r^{d_r}(\Theta), \Theta)$$

where d_p and d_r denote whether the rich and poor households have drilled wells. From Lemma 1, we have $m_i^d(\Theta) \leq m_i(\Theta)$ for any cost schedule Θ. Under the assumption that the cost functional $\mathcal{C}(m, \Theta)$ is nondecreasing, aggregate revenue (holding price schedules fixed) is always nonincreasing in drilling decisions.

□

A.4 Proof of Proposition 2

Proof. We seek to show

$$C(\Theta) = \frac{\mathcal{C}(m_p(\Theta), \Theta)}{\mathcal{C}(m_p(\Theta), \Theta) + \mathcal{C}(m_r(\Theta), \Theta)}$$

is strictly smaller than

$$C^d(\Theta) = \frac{\mathcal{C}(m_p(\Theta), \Theta)}{\mathcal{C}(m_p(\Theta), \Theta) + \mathcal{C}(m_r^{d_r}(\Theta), \Theta)}$$

From Lemma 1, under any schedule Θ we have $\mathcal{C}(m_r(\Theta), \Theta) \geq \mathcal{C}(m_r^d(\Theta), \Theta)$ as demand is weakly lower after adaptation and we assume the cost function is nondecreasing in m.

This in turn implies that $C^d(\Theta) \geq C(\Theta)$. This completes the proof as the choice of Θ was arbitrary.

$\square$

A.5 Calibrating the quantitative model

The goal of the calibration exercise is to solve for the set of α_i values governing water consumption across the ten property value deciles, the parameter γ governing the price elasticity of demand for water, and the groundwater cost parameter ψ. Calibrated parameters are those that minimize the distance between outputs from the model of Section 6.1 when evaluated at historical prices and observed levels of consumption. As we do not observe household-level drilling decisions or groundwater usage, we make several simplifying assumptions that allow the model to be identified from available data. First, we assume any unobservable within-decile heterogeneity in α_i parameters is limited such that aggregate demand across individuals aligns with that of a set of representative agents within in each decile. Second, we assume that the bottom four property value deciles in the model are comprised solely of indigent households while the highest six contain none.[A.2] Finally, we assume that the cumulative applications for boreholes and wells we observe through the end of 2019 in Figure 4b were all drilled in 2017, and that it is a sufficient statistic for the amount of drilling (both registered and unregistered) that occurred during the drought.

We use the assumptions above to calibrate the model using two periods of observed public water demand under different price regimes: a *pre-crisis* period from November to December 2016 (before large tariff increases) governed by costs $c_{i,pre}(\cdot)$, and a *crisis* period from February-March 2018 (when prices were at their peak) governed by costs $c_{i,crisis}(\cdot)$.[A.3] For each of these periods, we calculate average monthly demand for public water in each property decile from Figure 3a, $\bar{m}_{i,pre}$ and $\bar{m}_{i,crisis}$. These observed averages identify $m_{i,pre}$ and $m_{i,crisis}$, expected piped water demand within a decile across households both with and without wells. Under the simplifying assumption that drilling only occurs in 2017, we can use observed pre-crisis demand to write

$$\hat{m}_{i,N,pre} = \bar{m}_{i,pre} \tag{A.5}$$

and demand during the crisis to write

$$\pi_i \hat{m}_{i,D,crisis} + (1 - \pi_i)\hat{m}_{i,N,crisis} = \bar{m}_{i,crisis} \tag{A.6}$$

[A.2] See Figure D.2 for a time series of the observed share of indigent agents in each decile.

[A.3] Both cost schedules are set to exactly match the posted IBTs during that period shown in Table E.1.

where hat notation indicates estimated objects. We estimate the decile-specific share of households that drill, π_i, using the observed decile-specific cumulative number of applications for boreholes and wells in Figure 4b and scaling by a factor that reflects that most new wells drilled during the crisis were not licensed.[A.4] Equation (A.5) states that observed demand before the crisis is representative of average demand from households when no wells are drilled. Equation (A.6) states that observed average demand for piped water is a weighted average of optimal demand from households with and without wells in each decile.

Recovering γ: We recover γ based on observed demand for agents in the fifth property value decile ($i = 5$) by rearranging equation (6) and evaluating it for both pre-crisis and crisis periods

$$\hat{\gamma} = \frac{\ln\left(\frac{c'_{5,crisis}(\bar{m}_{5,crisis})}{c'_{5,pre}(\bar{m}_{5,pre})}\right)}{\ln\left(\frac{\bar{m}_{5,crisis}}{\bar{m}_{5,pre}}\right)} \tag{A.7}$$

We fit the parameter on agents in the fifth decile for three reasons: (1) very few households are indigent; (2) very few households drilled wells (less than 5% of households); and (3) the observed average consumption of public water for these households in the pre-crisis and crisis periods was not at a kink in the marginal cost curve induced by the IBT. Point (1) allows us to avoid issues that could be generated by the simultaneous change in the level of free water allocated to indigent households during the crisis (i.e., any large income effects induced by the new free allotment). Point (2) leads to observed demand for public water from households in the fifth property value decile during the crisis $\bar{m}_{5,crisis}$ to be approximately equal to $m_{5,N,crisis}$. Point (3) ensures that equations (6) and (7) hold with equality for these households in the pre-crisis and crisis periods when evaluated at the observed levels of consumption we see in the data. Evaluating equation (A.7) at the observed values of consumption in the fifth decile for the pre-crisis and crisis periods gives a value of $\hat{\gamma} = 1.68$ or an own-price elasticity of demand for public water of -0.59, roughly in line with existing estimates in the water utilities literature.[A.5,A.6]

[A.4] It is estimated that only one-tenth of all new groundwater wells during the drought had licenses (Schachtschneider, 2020).

[A.5] Aina, Thiam and Dinar (2023) find an elasticity of -0.27 for municipal water demand across several South African provinces. Szabo (2015) finds a larger elasticity of slightly below unity using a structural model of water demand in the South African municipality of Tshwane. Recent meta analysis by Bruno and Jessoe (2021) finds point estimates for price elasticities of residential water demand well below unity across thirteen studies conducted after 2000.

[A.6] To ensure the simple approach above is internally robust, we also estimate this elasticity using household-level panel data and a simulated instrument approach for identification following Ito (2014). This alternative procedure, when estimated on the fifth decile between 2014 and July of 2018, yields a point estimate of -0.43 for the price elasticity of demand.

Recovering α_is: With $\hat{\gamma}$ in hand we can solve for each α_i parameter by inverting equation (6)

$$\hat{\alpha}_i = c'_{i,pre}(\hat{m}_{i,N,pre})\hat{m}_{i,N,pre}^{\hat{\gamma}} \tag{A.8}$$

and using equation (A.5) to substitute observed $\bar{m}_{i,pre}$ for $\hat{m}_{i,N,pre}$ in each decile.

Recovering ψ: Rewriting equation (A.6) for households in deciles nine and ten, we have that PU demand satisfies

$$\hat{m}_{i,D,crisis} = \frac{m_{i,crisis} - (1-\pi_i)\left(\frac{c'_{i,crisis}(\hat{m}_{i,N,crisis})}{\hat{\alpha}_i}\right)^{-1/\hat{\gamma}}}{\pi_i} \tag{A.9}$$

where, unlike in decile five, we are not bound by the imposition that $\hat{m}_{5,N,crisis} = \bar{m}_{5,crisis}$ used to estimate γ above. Instead, we solve the system of equations in (A.9), (7), and (8) to obtain

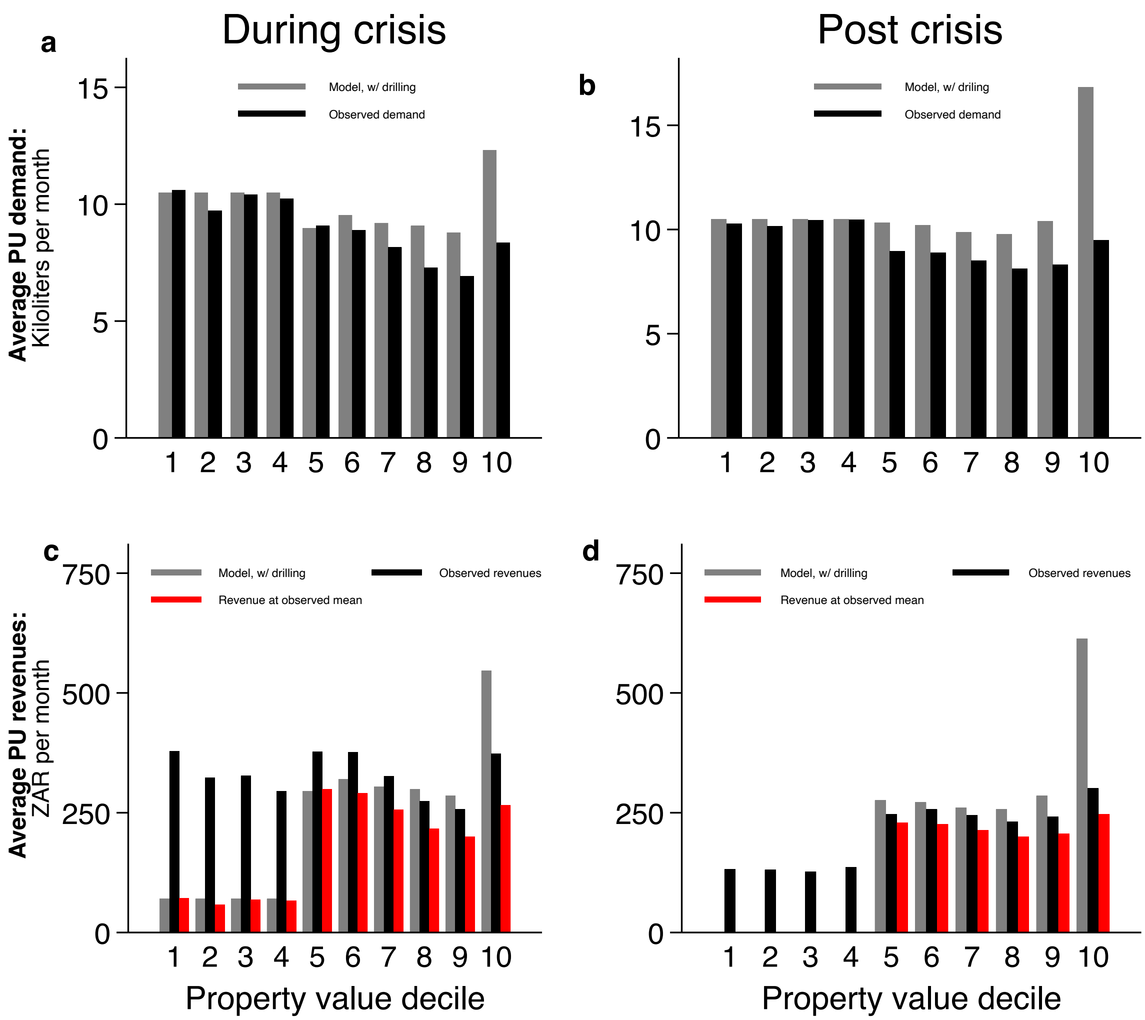
$$\hat{\psi} = \frac{1}{2}\left(\sum_{i=9}^{10} \frac{\hat{\alpha}_i (w_{i,D,crisis})^{-\hat{\gamma}}}{2g_{i,D,crisis}}\right)$$

using the 9th and 10th property value deciles. We recover a cost parameter of $\hat{\psi} = 3.56$.

B Counterfactual model fit

Figure B.1 shows how the calibrated model in Section 6 fares in fitting average household level demand and revenue during the crisis and post-crisis periods. Averages of observed values (black bars) of consumption and revenue during the crisis are constructed using the within-decile means of monthly consumption and revenue for the two month period of February-March 2018; the post period is analog for the months of October-November 2018. The modeled values (gray bars) denote model predictions for average demand and revenue given observed levels of drilling π_i in each decile for the IBTs posted in the crisis and post-crisis periods.

Figure B.1: Modeled and observed demand and revenue in the crisis and post-crisis periods

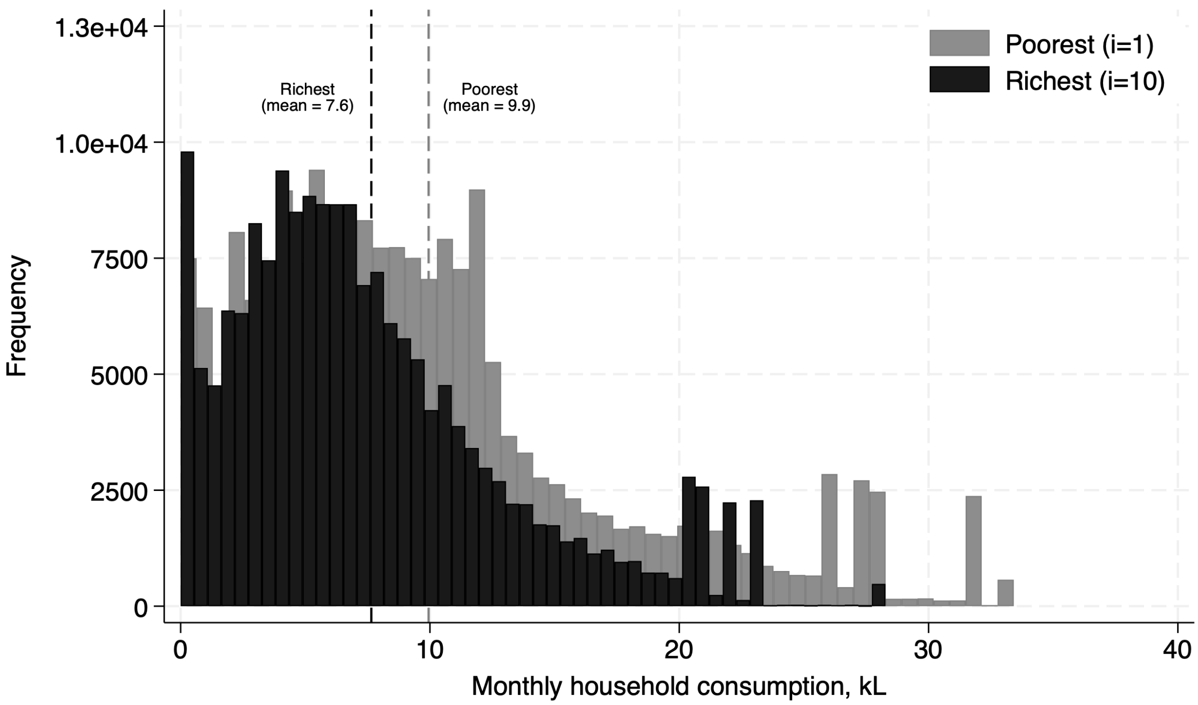


NOTES: This figure compares predicted demand and revenue from the calibrated model in Section 6 evaluated at observed levels of drilling in each decile and observed average demand and revenue during these periods from the data. Panels (a) and (b) in the first row compare modeled and observed demand in each period in gray and black bars respectively. Panels (c) and (d) in the second row compares modeled and observed revenue, but also adds a third series (red bars) that shows what observed revenue would have been if they were generated by the observed mean level of demand (i.e., the black bars in the first row of figures) rather than as an average of observed revenue across agents in each decile.

While the model does fairly well in matching observed average consumption levels in both periods (panels B.1a and B.1b) outside of those for the highest property value decile, it struggles considerably matching observed average revenue (panels B.1c and B.1d). This is because in the data, we see a large degree of heterogeneity in *within-decile* consumption. To illustrate this, Figure B.2 shows monthly consumption at the household level for all households in either the poorest ($i = 1$) or richest ($i = 10$) property value deciles between

February and June 2018. While the mean consumption for the lowest households (9.9 kL) lies below the the 10.5 kL threshold, quite a few households consume over this amount at a marginal price of 100 ZAR/kL or higher. This violates the conditions necessary for aggregation in the model of Section 6, which required that the heterogeneity of α parameters *within* deciles was limited enough such that all households' equilibrium demand levels lay in the same IBT block.

Figure B.2: Histogram of household-level monthly water demand during February to June of 2018 for the top and bottom deciles



Notes: This figure shows a histogram of monthly water usage at the household level for all households in either the poorest or richest decile between February and June of 2018. Dashed vertical lines denote the means values for each decile during that period.

The heterogeneity in observed demand combined with the sharp convexity of the IBT schedule causes modeled revenue—which is generated by the cost of buying an amount of water fitted to average observed demand—to be much lower than average observed revenue due to Jensen's inequality. This leads modeled average costs to be an especially poor fit for households in the lower property value deciles who almost exclusively face the indigent price schedule. However, if we instead allow observed average revenue to be determined by the average demand in each decile (i.e., generate revenue as a function of observed means of demand), the model fit is much closer. The red bars in panels B.1c and B.1d show the results of this exercise where we calculate what revenue would have been in each property value decile if all households consumed water at the observed mean level. These bars track the values produced by the calibrated model evaluated at observed drilling shares much more closely for households not in the tenth decile.

C Data appendix

C.1 Municipal billing data

To assemble the meter-by-month panel of household water consumption and charges, we begin with the text of municipal bills posted in Cape Town from 2014 to 2019. We restrict to billing accounts classified as "domestic" (as opposed to commercial, industrial, state, etc.). Note that informal households (primarily located in informal settlements) do not receive monthly bills and so are not included in our dataset. Within this period, bills posted in May and June 2015, September 2017, and February, March and May 2018 are missing.

Bills are posted quasi-monthly. The median billing period is 29 days and the modal billing period is 28 days but bills can start and end on any day of the month, and some bills cover longer periods; we drop the 1% of bills covering periods longer than 3 months as we cannot reliably attribute their consumption across months. To convert quasi-monthly bills to a monthly panel, we split consumption within a billing period into months by assuming that water consumption occurs uniformly across the days covered by the bill. For example, in the case of a bill that covers the period June 21st to July 20th, we attribute one third of consumption to June and two thirds to July. Wherever missing bills result in partial coverage of a month, we assume that the daily rate of consumption in the missing period is equal to the average daily consumption in the covered period. For example, in a case where a billing account has bills covering February 1st to 5th and 24th to 28th but not 6th to 23rd, we calculate the average rate of daily water use over the 10 covered days and multiply it by 28 to estimate monthly usage. Household-months are treated as missing only when no bill for a given household covers any part of that month; this is most frequently the case when two consecutive months of posted bills are missing, as in May and June 2015, in which case we have access to few household bills covering any part of May. The resulting monthly consumption measure is winsorized at the 95th percentile to address what appear to be errors in the bills, and/or water leaks.

Billed charges calculated by applying the city's tariff schedule to our prorated panel of monthly water consumption. Standard or indigent tariff schedules are applied depending on whether the household receives any kind of indigent support on their bills; specifically, we classify as "indigent support" any indigent grant and any free or discounted water that non-indigent households would not have qualified for (free water in the second tariff block at any time, a second block priced at R15.57 when the first block is free, or free water in the first tariff block any time in or after July 2017). We treat households as indigent in any month between their first instance of receiving indigent support and their last.

We link households by account number with a record of property values in 2016, which serves as our proxy for long-run or permanent income. We use property values from 2016 to coincide with the onset of the drought, and hold these values fixed throughout our analysis. These property values are municipal valuations used for assessing property taxes and applying indigent support, not market values for homes. We restrict our sample to billing accounts for which a single water meter matches with a single property value, eliminating indeterminacies where one account may receive bills for multiple households and water meters. This eliminates apartment buildings, for example, which are found in both high and low property value areas. The restriction reduces our ultimate sample of households by 15.6%; the properties that remain are those most likely to be inhabited by single households with full control over their water use.

Our sample contains slightly more than half a million properties. Because we use 2016 property values and track households based on their municipal account number, households drop from our sample as they move and acquire new municipal accounts. Wherever we plot aggregate statistics (e.g. total revenue) over time, we scale them up as if the full sample remained. We do not adjust for population growth. Monetary outcomes are always converted to December 2019 Rand by applying South African urban CPI.

C.2 Remotely-sensed outdoor water indices

We proxy for residential outdoor irrigation using the Normalized Difference Vegetation Index (NDVI), a measure of the biomass and health of green vegetation. NDVI is constructed using the near infrared (NIR) spectral band and the red spectral band. Values fall between -1 and 1, with higher values indicating greener vegetation. NDVI is calculated as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

To construct NDVI values for Cape Town, we use the NIR and red bands from the Sentinel-2 satellites during the period between January 2016 and December 2019. NIR data is available at a 20 meter-by-20 meter spatial resolution, and red at 10-by-10. From 2017 to 2021 we acquire surface reflectance data directly from the Microsoft Planetary Computer. For 2016-2017, we acquire top-of-atmosphere reflectance and apply atmospheric correction using sen2cor.[A.7]

We further clean the data by applying cloud masking and a Bidirectional Reflectance Distribution Function normalization to account for differences in pixels' surface reflectance due to differences in illumination. To account for the fact that only certain types of land cover will respond to irrigation differences, use the land cover classes defined by the South Africa National Landcover Dataset[A.8] from 2014, 2018, and 2020 to remove pixels identified as natural vegetation (e.g. forests, shrubland, grassland), water (e.g. lakes, ocean), and other non-vegetation classes (e.g. sand dunes, roads & rail, mines). We preserve any pixels classified as cultivated vegetation (planted forest, crops, recreational fields) and residential, commercial, or industrial. We remove any pixels that change between masked and unmasked land cover classes between any two of the three years in the data, as land cover change can result in different measured NDVI even if water use does not change. We abstract away from the fact that even transitions between unmasked land cover classes may also change NDVI even if water use is held constant. We further apply geospatial masks to remove tree cover[A.9] and residential structures.[A.10]

Using a shapefile of 2015 Cape Town parcels, we construct both parcel-level monthly NDVI values and an average monthly NDVI value across parcels within a property value decile using parcel-area weights. Because our sample contains only residential parcels, our NDVI value does not reflect irrigation in public parks or farms, even if their land cover classes are not masked. NDVI also does not reflect outdoor water use outside of vegetation, such as water used in swimming pools or car-washing, and therefore provides only a partial measure of outdoor water use by Cape Town households.

As a robustness check, we follow the same procedure to calculate values for two alternative proxies for outdoor water use. The Normalized Difference Moisture Index (NDMI) measures the water content of vegetation[A.11] and is calculated as $\frac{NIR-SWIR}{NIR+SWIR}$. Our two NDMI measures, NDMI-1 and NDMI-2 differ in which shortwave infrared bandwidth is used, SWIR1 or SWIR2.[A.12]

[A.7] https://step.esa.int/main/snap-supported-plugins/sen2cor/.

[A.8] https://egis.environment.gov.za/sa_national_land_cover_datasets

[A.9] Available here: https://odp-cctegis.opendata.arcgis.com/datasets/43f15d12017145d99533ad0da50620e4_158/about

[A.10] Available here: https://github.com/microsoft/GlobalMLBuildingFootprints

[A.11] https://www.usgs.gov/landsat-missions/normalized-difference-moisture-index

[A.12] https://www.usgs.gov/faqs/what-are-best-landsat-spectral-bands-use-my-research

C.3 Groundwater drilling applications

We acquire data on registrations of boreholes and wellpoints between January 2016 and December 2019 from the Department of Water and Sanitation. As highlighted in the main text, these registrations may overcount new wells and boreholes especially at the beginning of the drought, as residents may have registered pre-existing boreholes as enforcement increased. At the same time, these counts are likely to underestimate the total number boreholes and wellpoints drilled by the end of the drought, consistent with a door to door survey in Newlands (a wealthy suburb) which found that roughly one in nine boreholes were licensed (Schachtschneider, 2020).

Our linking of each application with its 2016 property value decile by parcel identifiers achieves a match rate of 78%, with unmatched applications likely representing both missing or incorrect parcel identifiers and properties which fall outside of our sample (i.e. non-residential or multi-family properties).

C.4 Groundwater depths

We obtain data on groundwater depths from monitoring wells collected by the South African Department of Water and Sanitation, focusing on wells that have observations in 2019, the last year of our sample. Panel data from Cape Town's groundwater monitoring wells are unbalanced and noisy. To address this, we employ four cleaning procedures. First, we keep monitoring wells with at least 6 observations per year. This reduces our sample size from 22 to 11. Second, we remove outlier values that are below the 0.1% and above the 99.9% percentile of depth observations for that well. Third, to ensure that the composition of wells is not changing each period due to missing records, we linearly interpolate any missing monthly values for each well.

We group the remaining 11 monitoring wells by averaging the property value of residential parcels belonging to our sample within 1 km of the well and categorizing the resulting value as above or below the median. Figure D.12 plots the raw time series of average depth to groundwater for the 11 wells in our final sample, split into above- and below-median property value wells, prior to removing outlier values or linearly interpolating.

To further verify the visual evidence from Figures 4c and D.12, we estimate the following differential trend break model for depth to groundwater in monitoring well i and month t:

$$d_{it} = \beta_1[P_i \times t] + \beta_2[P_i \times \mathbf{1}(t \geq \text{Feb. 2017})] + \beta_3[P_i \times \mathbf{1}(t \geq \text{Feb. 2017}) \times t] + \phi_i + \gamma_t + \epsilon_{it} \quad \text{(C.1)}$$

where P_i is a dummy that equals one when the parcels within a 1 km radius of well i has average 2016 property value above the median, ϕ_i are well fixed effects, and γ_t are month fixed effects. Standard errors ϵ_{it} are clustered at the month-level and allows for common serial correlation across wells within a 12 month rolling window following Driscoll and Kraay (1998). Our coefficient of interest is β_3, the break in the differential groundwater depth trend after water crisis for wells near above median property value parcels relative to wells near below median property value parcels.

Table E.8 shows estimates of β_3 for radii distances of 0.5, 1, and 1.5 km to a well when constructing P_i and with and without dropping outliers and interpolating missing values in groundwater depth data. Estimates consistently detect roughly a 1 meter per year drop in groundwater levels for wells near wealthier parcels after the water crisis.

Is a 2 meter (6 ft) drop in groundwater levels in 2017 and 2018 economically significant? While we cannot fully quantify the externality because we do not have a full characterization of the flow rates across all locations of an aquifer needed to understand how extraction by one user affects groundwater levels for other users, we can conduct a back-of-the-envelope calculation for the increase in marginal groundwater extract cost following the water crisis, an ingredient for quantifying the groundwater externality. To do so for the two years since the water crisis, we follow Burlig, Preonas and Woerman (2024) and employ the following relationship between groundwater pumped and electricity used:

$$kiloliter = \frac{(\text{Pump efficiency})(1204.5)}{\text{Depth to gw}} \times kWh$$

With a pump efficiency of 0.57 (obtained from Burlig, Preonas and Woerman (2024)), a marginal price of retail electricity of 66 ZAR/kWh (assumed for the highest IBT block for non-indigent households as shown in Table E.1), the change in pumping cost associated with the two year drop of 2 meters (6 feet) in the groundwater table is:

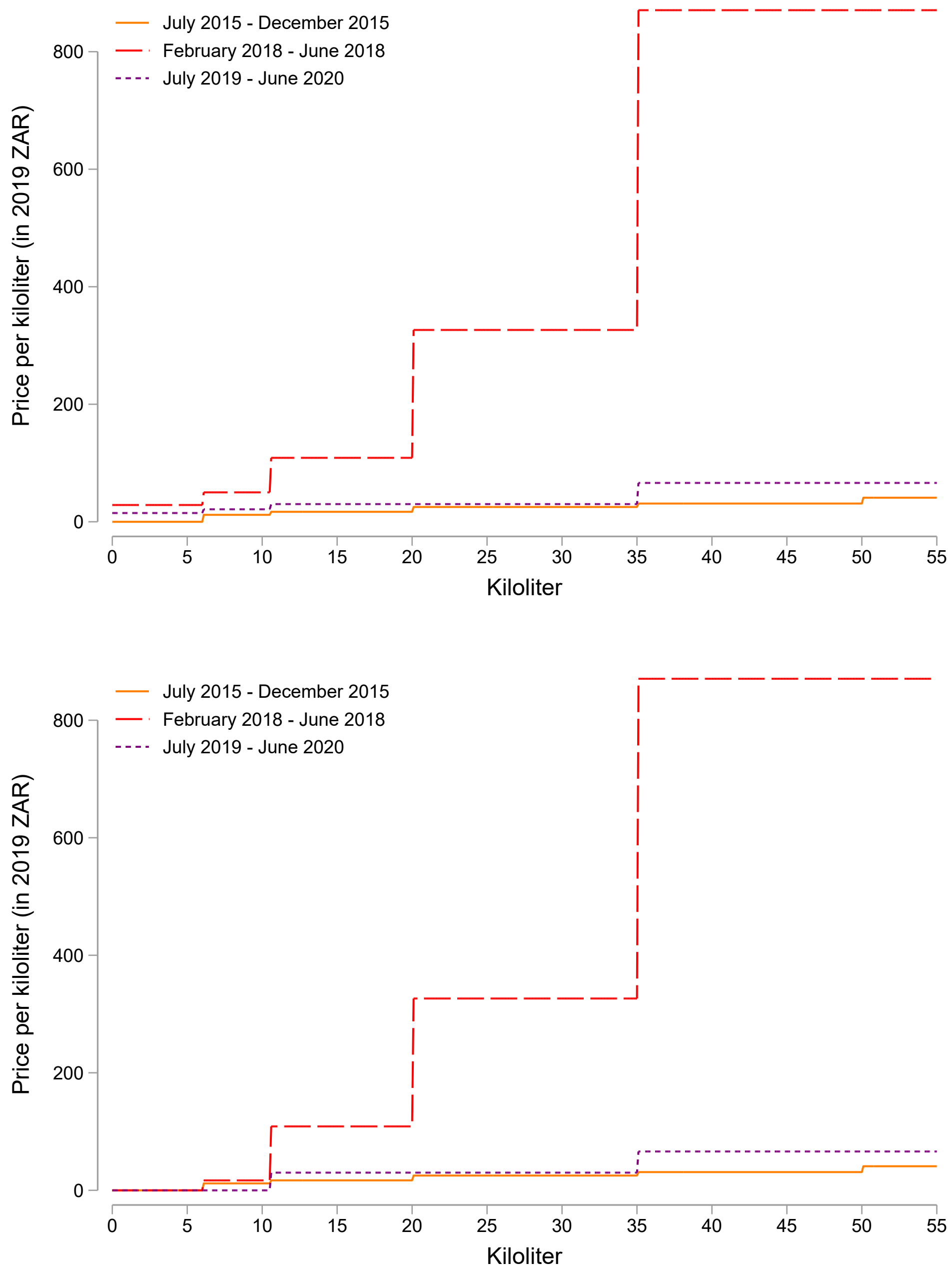
$$\Delta \frac{\text{gw cost}}{kiloliter} = \frac{6 \text{ ft} \times 66}{0.57 \times 1204.5} = 0.58$$

By comparison, the average price of municipal water for 6th-10th decile households in 2019 from Figure 5b is 35 ZAR/kWh, a significantly higher value.

Finally, above- and below-median property value wells may be located in places with different subsurface hydrological features. For example, if the subsurface geology is such that groundwater levels are more sensitive to rainfall in above median property value locations, a common drought across all locations may induce faster groundwater depletion in above median property value locations, even if there is no differential groundwater extraction. Table E.7 shows estimates from separate time series regressions of monthly groundwater depth and rainfall for below and above median property value monitoring wells in the nine year period before the water crisis. While groundwater depths for above median wells are systematically lower, as indicated by the coefficient on the constant term, rainfall sensitivity is nearly identical to that of below median wells prior to the water crisis. We cannot, of course, attribute changes in groundwater depth to particular types of users; changes in extraction by industrial or agricultural users, located disproportionately in high property value areas, could contribute to the patterns we observe. Nevertheless, the similar pre-water crisis relationships between groundwater levels and rainfall across wealthier and poorer households shown in Table E.7 do not contradict the lower pre-water crisis NDVI correlation with wealthier households shown in Table E.3. If outdoor irrigation by wealthier households before the water crisis primarily used municipal water and not groundwater, groundwater response to rainfall may be similar across neighborhoods even as surface water use responds differently to rainfall.

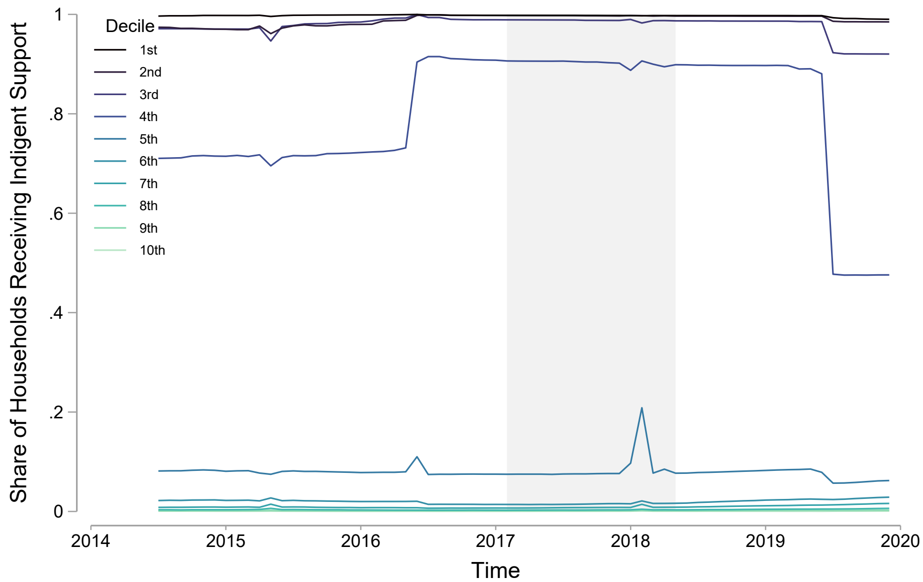
D Appendix Figures

Figure D.1: Water tariff schedules



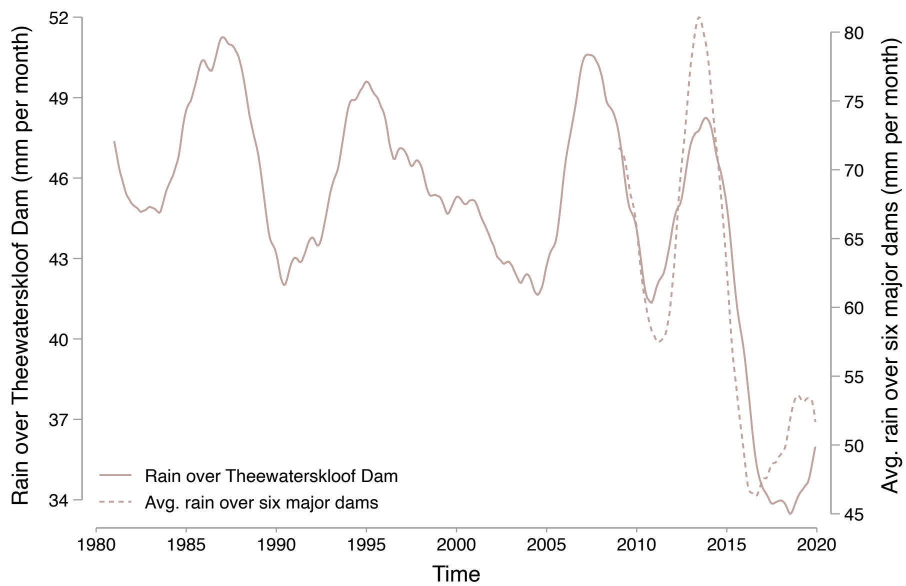
NOTES: Municipal water tariff schedules for non-indigent (top) and indigent (bottom) households. Schedules apply for the period July 2015-December 2015 (solid orange), February 2018 - June 2018 (dashed red), and July 2019 - June 2020 (dotted purple).

Figure D.2: Share indigent by decile



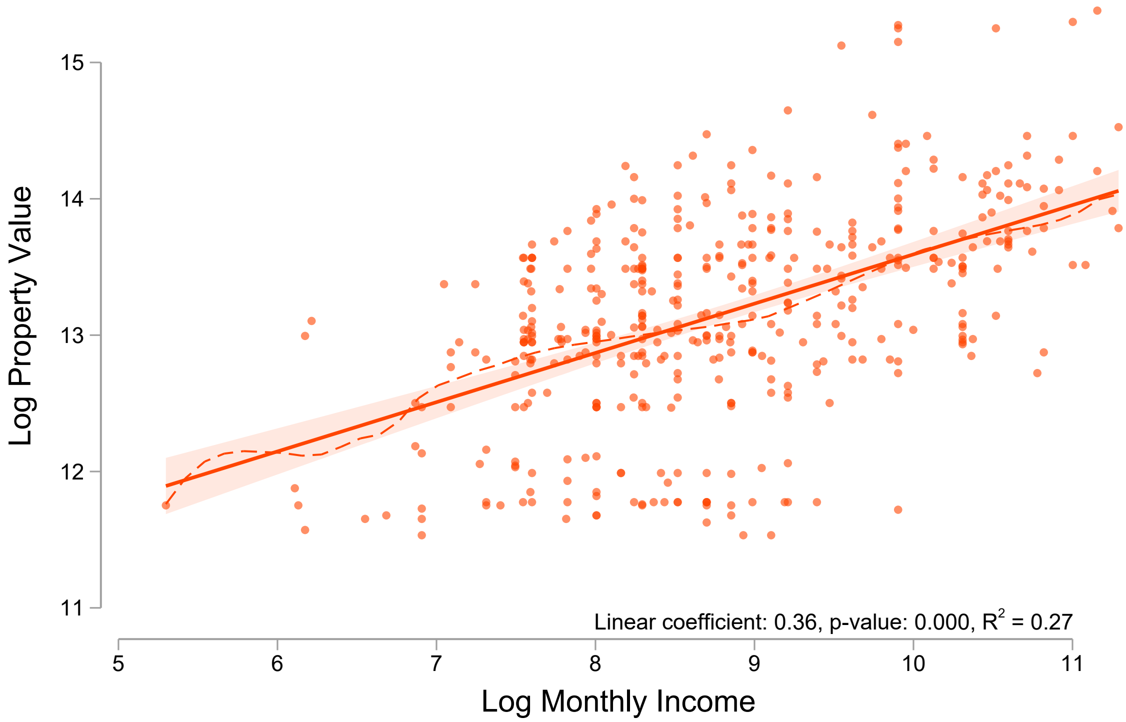
Notes: Monthly share of total indigent households by property value decile. Property value deciles are held fixed based on 2016 property values. Gray-shaded area marks the February 2017 to May 2018 water crisis period.

Figure D.3: Cape Town rainfall



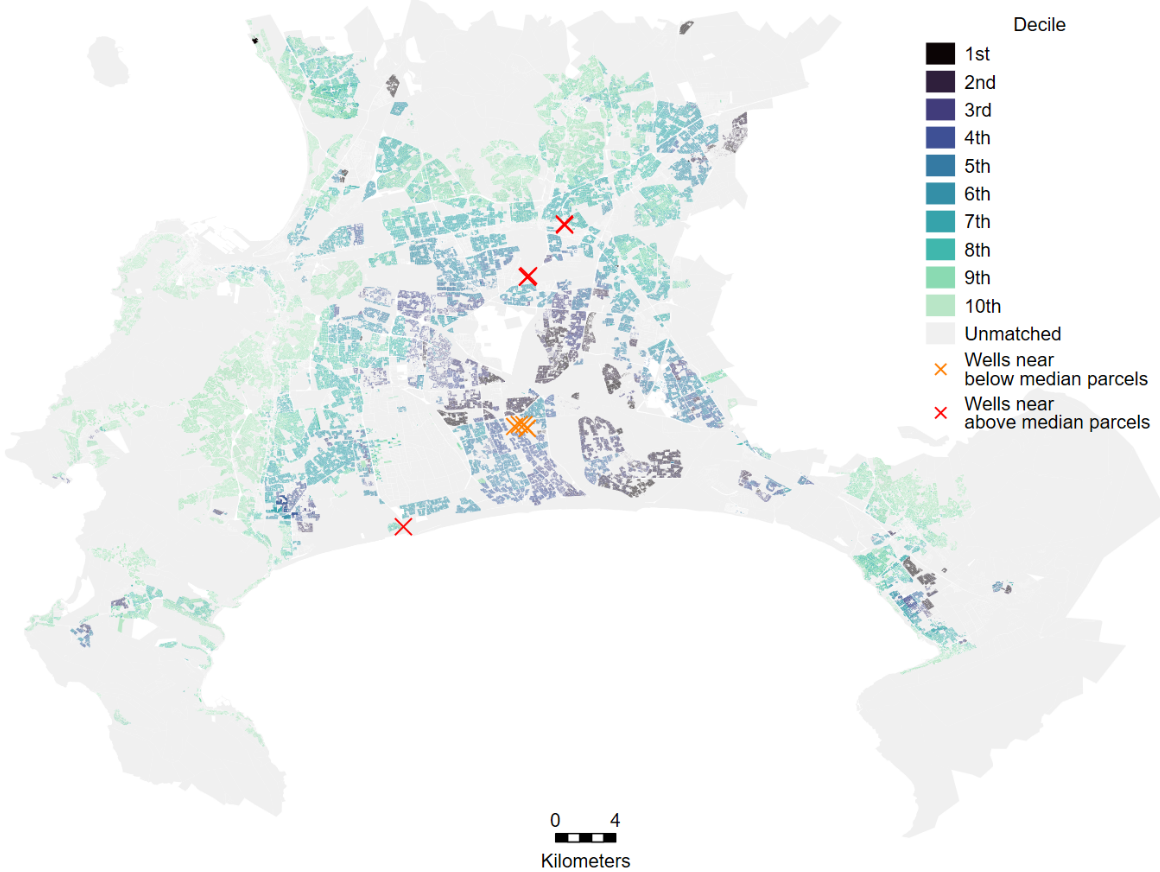
Notes: Time series shows smoothed monthly rainfall from January 1981-December 2019 measured at the Theewaterskloof Dam, the largest reservoir supplying municipal water to Cape Town (left y-axis) and averaged across the six largest dams supplying municipal water to Cape Town (right y-axis, Theewaterskloof, Wemmershoek, Volvlei, Berg River and the two Steenbras dams). Smoothing uses a local polynomial fit with an Epanechnikov kernel and a rule-of-thumb bandwidth following Fan and Gijbels (1996). Data obtained from the City of Cape Town's Department of Water and Sanitation.

Figure D.4: Property value and income



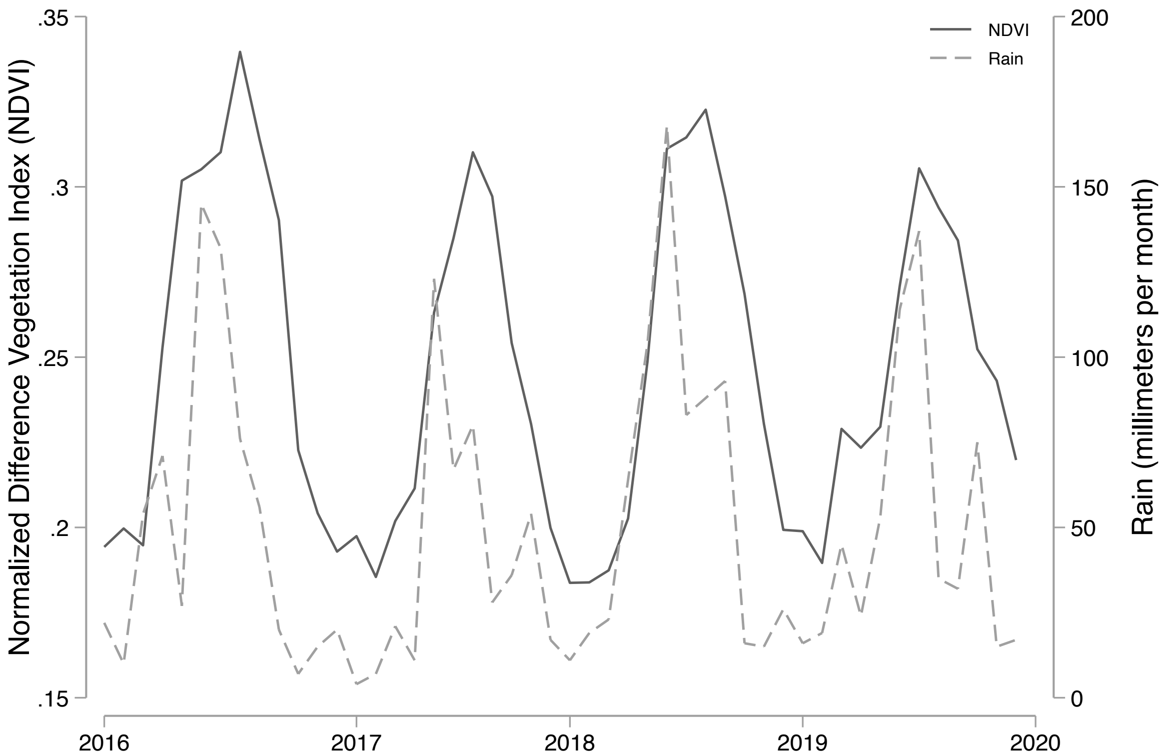
NOTES: Survey data on 2022 total monthly household income correlated with administrative records of 2021 property values. N = 433.

Figure D.5: Cape Town parcels by property value decile and well locations



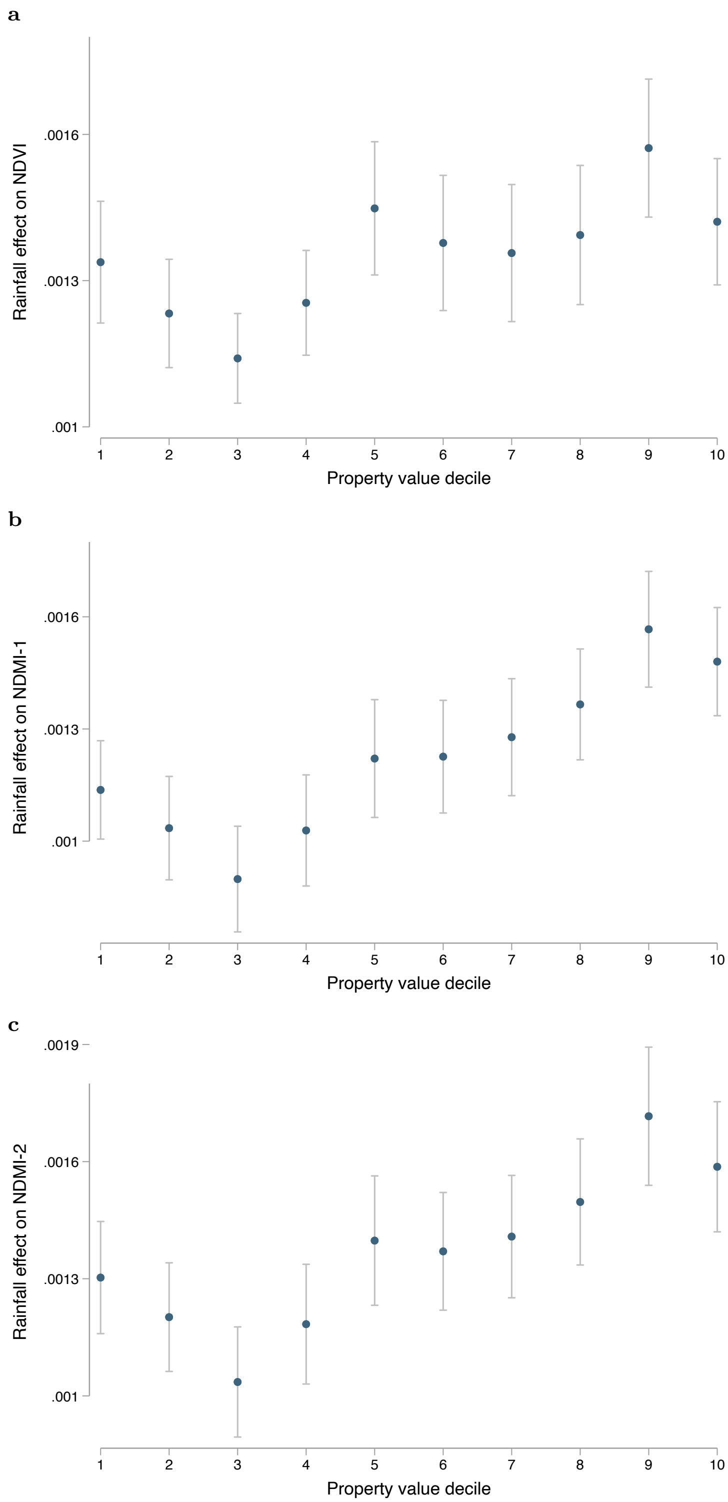
NOTES: Map of parcels by property value decile in 2016. Groundwater monitoring wells near above-median property value parcels are marked in red (N=6), and monitoring wells near below-median property value parcels are marked in orange (N=5). All fall within the Cape Flats Aquifer.

Figure D.6: Sample average NDVI



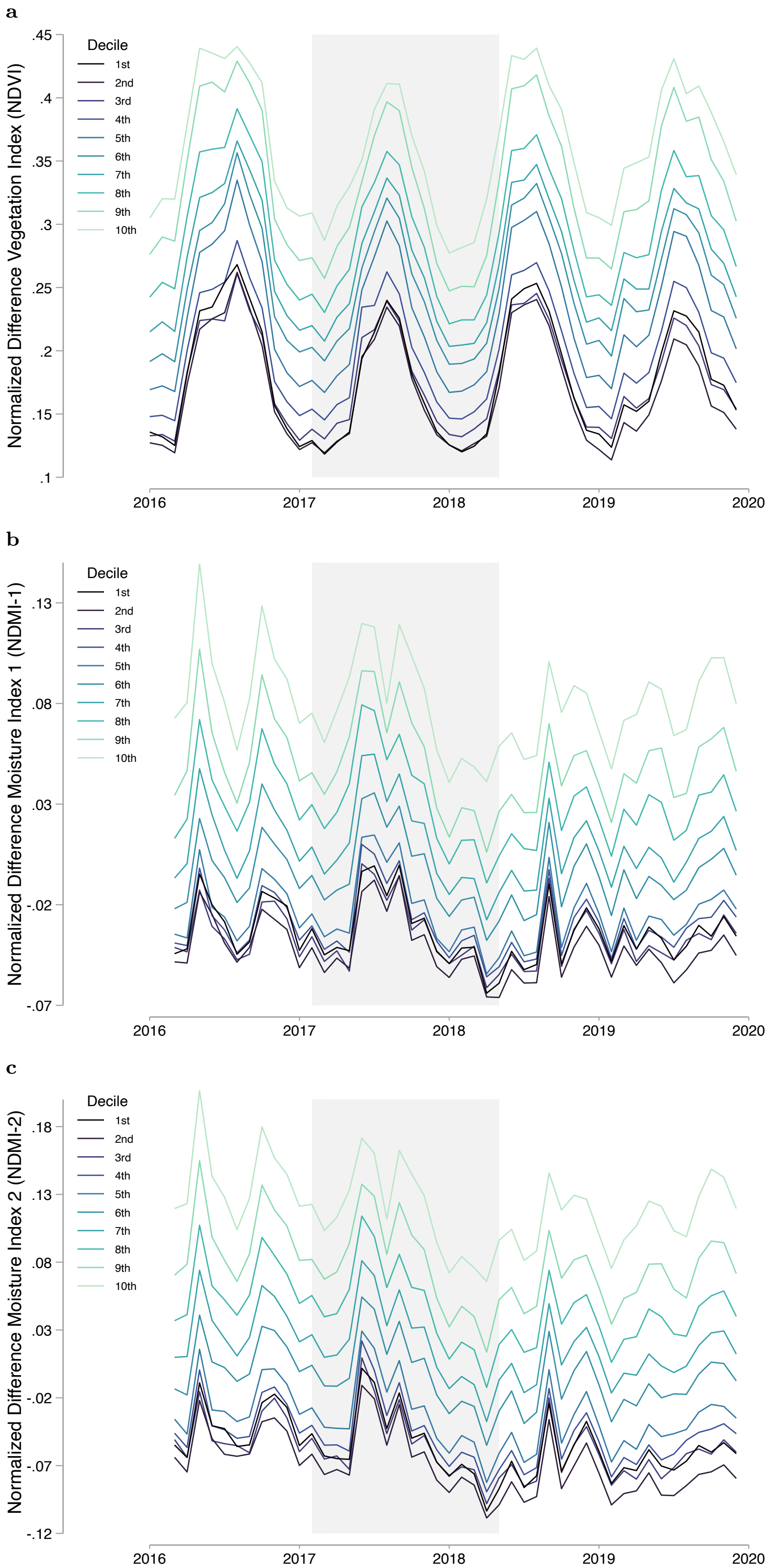
Notes: Monthly average NDVI across deciles and rainfall.

Figure D.7: Rainfall effects on remotely-sensed water indices



NOTES: Panels show the cumulative effect of contemporaneous, 1-month lag, and 2-month lag rainfall on monthly remotely-sensed moisture index for each property value decile. Coefficients, shown in Table E.5, jointly estimated using decile-by-month data from January 2016 to December 2019 in a model that includes decile fixed effects. Standard errors are clustered at the monthly level and allows for common serial correlation across deciles within a 12 month rolling window following Driscoll and Kraay (1998). Outcome is NDVI in panel (a), NDMI-1 in panel (b) and NDMI-2 in panel (c).

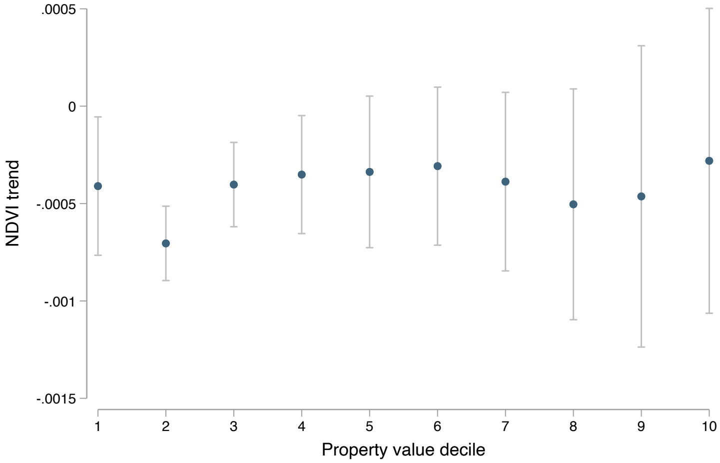
Figure D.8: Additional remotely-sensed water indices by property value decile



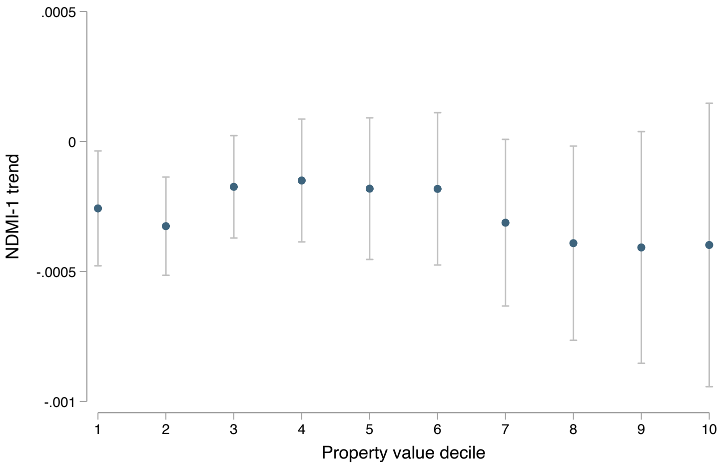
NOTES: (a) Raw monthly average NDVI values by property value decile. (b-d) Rainfall-residualized NDMI-1, and NDMI-2 values by property value decile.

Figure D.9: Estimated trend in remotely-sensed water indices by property value decile

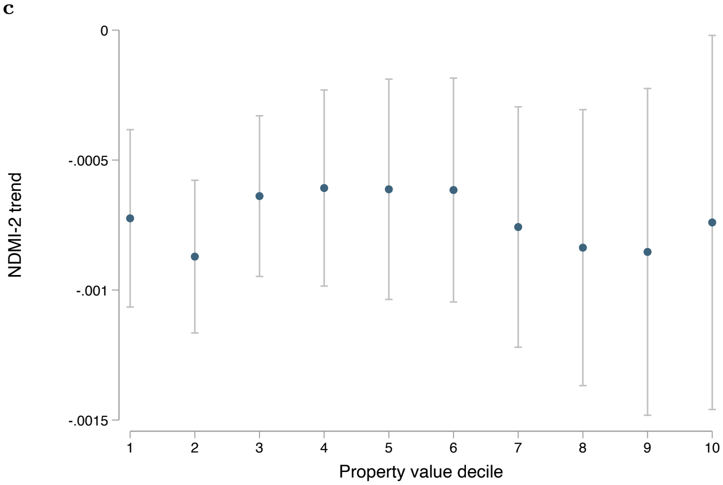
a



b

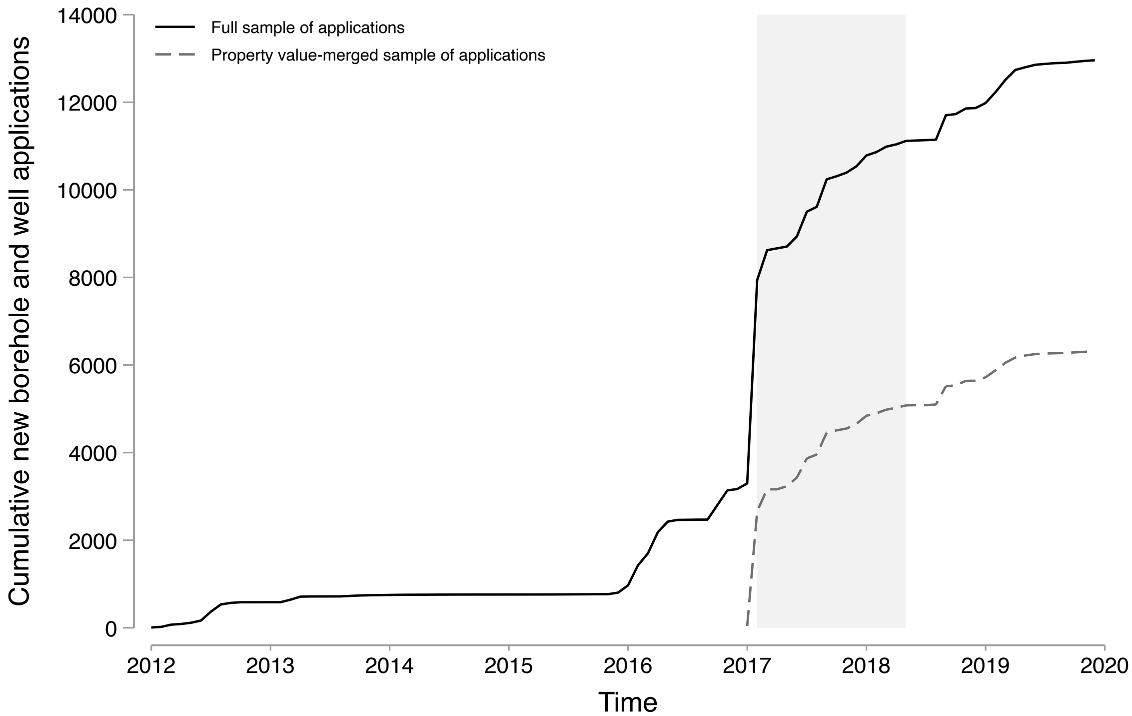


c



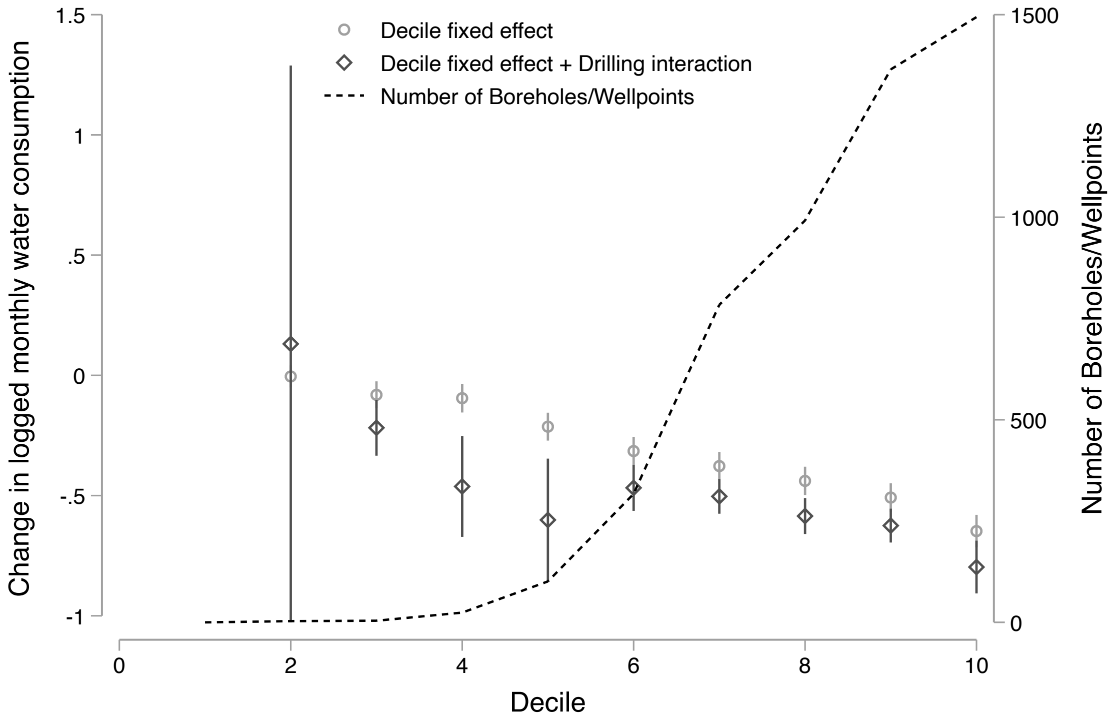
NOTES: Panels show regression coefficients of monthly remotely-sensed vegetation/moisture index on a linear trend for each property value decile. Coefficients jointly estimated using decile-by-month data from Jan. 2016 to Dec. 2019 in a model that includes decile-specific contemporaneous, 1-month lagged, and 2-month lagged rain effects and decile fixed effects. Standard errors are clustered at the monthly level and allows common serial correlation across deciles within a 12 month rolling window following Driscoll and Kraay (1998). 95% confidence intervals shown. Outcome is NDVI in panel (a), NDMI-1 in panel (b), and NDMI-2 in panel (c).

Figure D.10: Cumulative new borehole and well applications



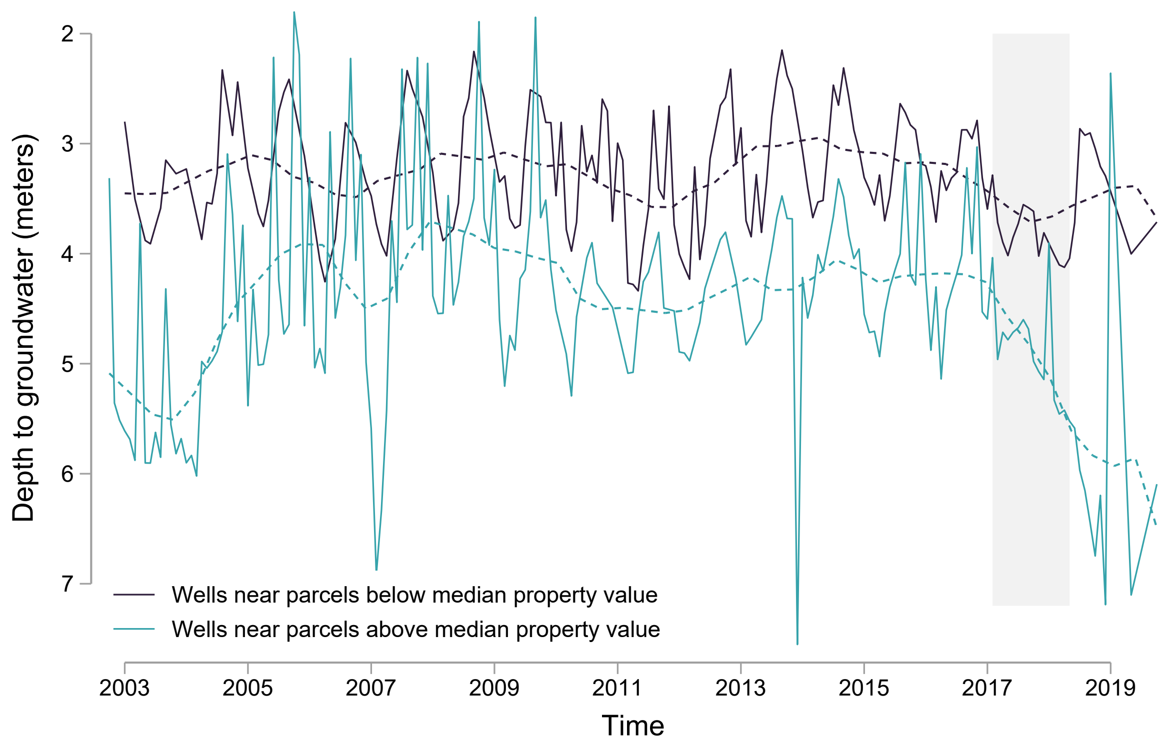
Notes: Monthly cumulative applications for new boreholes and wells by property value decile for full sample of applications (since January 2012, solid line) and sample of applications merged to property values (since January 2017, dashed line).

Figure D.11: Decile-specific change in log municipal water use, 2016-2019



NOTES: Point estimates for decile fixed effects on water use changes (circles) and the sum of decile fixed effects and decile-specific effect of groundwater access (diamonds). 95% confidence intervals shown. The dashed line represents the number of registered boreholes and wellpoints by decile.

Figure D.12: Cape Town groundwater levels: raw data



NOTES: Black (green) line shows monthly groundwater levels averaged across monitoring wells located near poorer (richer) land parcels, defined as whether average 2016 property values for parcels within a 1km radius of the well is below (above) the median. Dotted lines show a local polynomial fit with an Epanechnikov kernel and a rule-of-thumb bandwidth following Fan and Gijbels (1996). Gray-shaded area marks the February 2017 to May 2018 water crisis. Figure 4 panel (c) shows an analogous figure using the cleaned groundwater well data that drops outliers and interpolates missing values.

E Appendix Tables

Table E.1: Timeline of Cape Town marginal water prices

	Tariff Block (kL)						Indigent
Start Month	0-6	6-10.5	10.5-20	20-35	35-50	50+	Grant
July 2014	0	11.23	16.09	23.84	29.43	38.83	103.27
July 2015	0	11.86	17.00	25.18	31.11	41.02	104.69
January 2016	0	12.32	19.28	31.45	47.99	89.96	109.17
July 2016	0	15.84	20.23	33.00	50.36	94.39	133.57
November 2016	0	16.57	23.58	41.04	66.53	200.54	139.95*
July 2017	4.41 (0)	17.16	25.11	42.24	110.22	292.24	145.62
February 2018	28.22 (0)	49.46 (16.74)	107.51	322.54	860.09	860.09	164.33**
July 2018	30.29 (0)	48.21 (0)	126.05	126.05	1048.06	1048.06	0
October 2018	22.03 (0)	35.80 (0)	54.47	54.47	311.92	311.92	0
December 2018	14.22 (0)	20.23 (0)	28.73	28.73	63.07	63.07	0
July 2019	15.04 (0)	21.40 (0)	30.39	30.39	66.70	66.70	0

NOTES: Values in the table are converted to December 2019 ZAR by applying South African CPI to the starting month of each tariff. Where indigent pricing differs from non-indigent pricing, indigent prices are given in parentheses. *The change in the indigent grant corresponding to the November 2016 tariff change took place one month later, in December 2016. **The change in the indigent grant corresponding to the February 2018 tariff change took place one month earlier, in January 2018.

Table E.2: Day Zero timeline

Feb 2017	Level 3b: 1 hr of outdoor watering per day w/ bucket
May 2017	First mention of "Day Zero" when capacity <13.5%
June 2017	Level 4: 100 liters/day/person
July 2017	Large tariff increases
Sept 2017	Level 5: 87 liters/day/person, ban outdoor use
Dec 2017	Day Zero estimated at April 22, 2018
Feb 2018	Level 6B: 50 liters/day/person
Feb 2018	Day Zero estimated at July 9, 2018
Jun 2018	DZ canceled for 2018

Table E.3: Average pre-water crisis remotely-sensed water index values by decile

Decile	NDVI	NDMI-1	NDMI-2
1st	.193	-.0495	.0208
2nd	.184	-.0622	.00283
3rd	.188	-.0668	.00175
4th	.209	-.0545	.0197
5th	.24	-.038	.0444
6th	.263	-.0197	.0722
7th	.284	.000965	.1
8th	.314	.0279	.135
9th	.354	.0609	.181
10th	.38	.0891	.217

NOTES: Table shows the area-weighted NDVI, NDMI-1, and NDMI-2 values across parcels within a property value decile averaged across monthly values during January 2016-December 2016.

Table E.4: Remotely-sensed water indices and parcel characteristics

	(1)	(2)	(3)
		Outcome is	
	NDVI	NDMI1	NDMI2
Property value (in million ZAR)	0.1003	0.0684	0.1051
	(0.0124)	(0.0109)	(0.0154)
	[0.0000]	[0.0000]	[0.0000]
Outdoor space with low water demand	0.0162	0.0128	0.0259
	(0.0146)	(0.0110)	(0.0143)
	[0.2680]	[0.2439]	[0.0699]
Outdoor space with high water demand	0.0349	0.0246	0.0396
	(0.0080)	(0.0059)	(0.0076)
	[0.0000]	[0.0000]	[0.0000]
Number of observations	542	542	542

NOTES: Table shows regressions of parcel-level averaged month 2016 remotely-sensed water indices on parcel property value and dummy variables for whether a parcel has outdoor space (e.g., lawn or garden) with low water demand land cover (e.g., uncared-for garden or lawn, pavement, concrete, dirt, artificial turf, drought-tolerant plants) or high water demand land cover (e.g., grass, plants, flowers). Omitted category is parcel without outdoor space. Standard errors in parentheses robust to heteroskedasticity. p-values in brackets.

Table E.5: Remotely-sensed water indices and rainfall

Outcome: NDVI	(1)	(2)	(3)	(4)
$\text{rain}_t \times$ decile=1	0.0007	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=1		0.0007	0.0005	0.0005
		(0.0000)	(0.0001)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=1			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=1				0.0001
				(0.0000)
				[0.0106]
$\text{rain}_t \times$ decile=2	0.0007	0.0003	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=2		0.0006	0.0004	0.0004
		(0.0001)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=2			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=2				0.0001
				(0.0000)
				[0.0954]
$\text{rain}_t \times$ decile=3	0.0006	0.0003	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=3		0.0006	0.0004	0.0004
		(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=3			0.0004	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=3				0.0000
				(0.0000)
				[0.2784]
$\text{rain}_t \times$ decile=4	0.0007	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=4		0.0006	0.0004	0.0004
		(0.0000)	(0.0000)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=4			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=4				0.0001
				(0.0000)
				[0.1702]
$\text{rain}_t \times$ decile=5	0.0008	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=5		0.0008	0.0005	0.0005
		(0.0000)	(0.0001)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=5			0.0005	0.0005
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=5				0.0001
				(0.0000)
				[0.0725]

Table E.5: Remotely-sensed water indices and rainfall, continued...

Outcome: NDVI	(1)	(2)	(3)	(4)
$\text{rain}_t \times$ decile=6	0.0007	0.0003	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=6		0.0008	0.0005	0.0005
		(0.0001)	(0.0001)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=6			0.0005	0.0005
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=6				0.0001
				(0.0000)
				[0.0184]
$\text{rain}_t \times$ decile=7	0.0007	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=7		0.0007	0.0005	0.0004
		(0.0001)	(0.0001)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=7			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=7				0.0001
				(0.0001)
				[0.0177]
$\text{rain}_t \times$ decile=8	0.0008	0.0004	0.0004	0.0004
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=8		0.0007	0.0004	0.0004
		(0.0001)	(0.0001)	(0.0000)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=8			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=8				0.0001
				(0.0001)
				[0.0330]
$\text{rain}_t \times$ decile=9	0.0009	0.0005	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=9		0.0008	0.0005	0.0005
		(0.0001)	(0.0001)	(0.0001)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=9			0.0006	0.0005
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=9				0.0002
				(0.0001)
				[0.0414]
$\text{rain}_t \times$ decile=10	0.0008	0.0004	0.0005	0.0005
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-1} \times$ decile=10		0.0007	0.0005	0.0005
		(0.0001)	(0.0001)	(0.0001)
		[0.0000]	[0.0000]	[0.0000]
$\text{rain}_{t-2} \times$ decile=10			0.0005	0.0004
			(0.0000)	(0.0000)
			[0.0000]	[0.0000]
$\text{rain}_{t-3} \times$ decile=10				0.0002
				(0.0001)
				[0.0413]
AIC	-1791.332	-2061.462	-2304.454	-2265.759
BIC	-1749.594	-1978.407	-2180.517	-2101.389
Number of observations	480	470	460	450

NOTES: Table shows regressions of monthly NDVI indices on monthly contemporaneous and lagged rainfall interacted with property value deciles. Models include decile fixed effects. Sample period is January 2016 to December 2019. Standard errors are clustered at the monthly level and allows for common serial correlation across deciles within a 12 month rolling window following Driscoll and Kraay (1998). *p*-values in brackets. Results also shown in Figure D.7.

Table E.6: Household municipal water use change and applications for boreholes and wells

	3-year difference in logged average monthly municipal water use (2016 to 2019)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Boreholes and Wells		Boreholes		Wells	
Boreholes and/or Wells		-0.142		-0.143		-0.135	
		(0.014)		(0.019)		(0.019)	
		[0.000]		[0.000]		[0.000]	
2nd Decile	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
	[0.848]	[0.849]	[0.848]	[0.849]	[0.848]	[0.849]	[0.849]
Boreholes and/or Wells × 2nd Decile			0.135		0.351		-0.296
			(0.586)		(0.728)		(0.026)
			[0.818]		[0.630]		[0.000]
3rd Decile	-0.081	-0.081	-0.081	-0.081	-0.081	-0.081	-0.081
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Boreholes and/or Wells × 3rd Decile			-0.137		-0.705		0.052
			(0.053)		(0.017)		(0.097)
			[0.010]		[0.000]		[0.591]
4th Decile	-0.095	-0.095	-0.095	-0.095	-0.095	-0.095	-0.095
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Boreholes and/or Wells × 4th Decile			-0.367		-0.521		-0.078
			(0.104)		(0.138)		(0.090)
			[0.000]		[0.000]		[0.384]
5th Decile	-0.214	-0.214	-0.213	-0.214	-0.213	-0.214	-0.214
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 5th Decile			-0.388		-0.395		-0.448
			(0.126)		(0.147)		(0.140)
			[0.002]		[0.007]		[0.001]
6th Decile	-0.316	-0.315	-0.315	-0.315	-0.315	-0.316	-0.316
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 6th Decile			-0.153		-0.158		-0.142
			(0.039)		(0.043)		(0.065)
			[0.000]		[0.000]		[0.029]
7th Decile	-0.379	-0.377	-0.377	-0.378	-0.378	-0.378	-0.379
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 7th Decile			-0.126		-0.125		-0.128
			(0.021)		(0.028)		(0.040)
			[0.000]		[0.000]		[0.001]
8th Decile	-0.442	-0.439	-0.439	-0.440	-0.441	-0.441	-0.440
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 8th Decile			-0.146		-0.088		-0.210
			(0.024)		(0.023)		(0.036)
			[0.000]		[0.000]		[0.000]
9th Decile	-0.511	-0.507	-0.508	-0.509	-0.510	-0.510	-0.510
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 9th Decile			-0.117		-0.108		-0.120
			(0.020)		(0.025)		(0.030)
			[0.000]		[0.000]		[0.000]
10th Decile	-0.653	-0.648	-0.648	-0.650	-0.649	-0.651	-0.651
	(0.035)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.035)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Boreholes and/or Wells × 10th Decile			-0.150		-0.185		-0.086
			(0.039)		(0.052)		(0.043)
			[0.000]		[0.000]		[0.046]
N (Households)	443367	443367	443367	443367	443367	443367	443367

NOTES: Coefficients from household-level regressions of difference between 2019 and 2016 log of average monthly municipal water use on property value decile (column 1), property value decile and any new applications for either boreholes or wells during 2017-2018 (column 2), and their interaction (column 3). Columns (4)-(5) replicate columns (2)-(3) for any new borehole applications. Columns (6)-(7) replicate columns (2)-(3) for any new well applications. Standard errors clustered at the neighborhood level are in parentheses and *p*-values are in brackets.

Table E.7: Pre-water crisis groundwater-rain relationship

	Outcome is groundwater depth	
	(1)	(2)
Rain	0.002	0.003
	(0.001)	(0.000)
	[0.000]	[0.000]
Constant	-3.480	-4.492
	(0.096)	(0.062)
	[0.000]	[0.000]
Number of months	109	109
Sample	below median	above median

NOTES: Table shows regression coefficients of monthly groundwater levels on monthly rainfall for sample monitoring wells between January 2008 and December 2016, before the water crisis. Column 1 (2) examines monthly interpolated groundwater depths averaged across wells for wells located near poorer (richer) land parcels, defined as whether average 2016 property values for parcels within a 1km radius of the well is below (above) the median. Rainfall is the average value across the six largest dams supplying municipal water to Cape Town. Serial correlation and heteroscedasticity robust Newey-West standard errors with optimal bandwidth in parentheses. p-values in brackets.

Table E.8: Groundwater level trend break estimates

	Outcome is groundwater depth					
	(1)	(2)	(3)	(4)	(5)	(6)
Above median value × post-crisis × month	-.0964	-.0801	-.113	-.0921	-.113	-.0921
	(.019)	(.0145)	(.0249)	(.0182)	(.0249)	(.0182)
	[1.04e-06]	[9.36e-08]	[.0000107]	[9.80e-07]	[.0000107]	[9.80e-07]
Observations	1431	2080	1431	2080	1431	2080
Dist. to well (km)	0.5	0.5	1	1	1.5	1.5
Drop outliers & interpolate?	No	Yes	No	Yes	No	Yes

NOTES: Table shows estimates of β_3 from the differential linear trend break model in eq. C.1 for radii distances of 0.5, 1, and 1.5 km to a well when constructing P_i and with and without dropping outliers and interpolating missing values in groundwater depth data. Standard errors in parentheses clustered at the month-level and allows for common serial correlation across wells within a 12 month rolling window following Driscoll and Kraay (1998). p-values in brackets.