Reallocation under Rationing: Evidence from Electricity Outages in South Africa

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Abstract

Rationing policies are often designed with equity considerations in mind, yet whether equalizing exposure delivers equal economic impacts remains underexplored. We study electricity outages in South Africa, where rationing equalizes exposure across locations. Combining high frequency outage data with geocoded transactions from over 11,000 firms from 2021 to 2023, we show that equal exposure does not imply equal impact. Average sales remain unchanged, but outages induce reallocation: below-median firms lose roughly 11 percent of average revenue, while above-median firms gain 10 percent. We provide novel evidence that consumer substitution drives these effects and that advance notice amplifies disparities.

JEL: O12, L11, Q41, D22, O55

Keywords: Electricity outages, rationing, reallocation, SMEs

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Electricity outages can impose substantial economic and social costs, and a growing literature documents their disruptive effects on firms and households (Dinkelman 2011; Allcott, Collard-Wexler, and O'Connell 2016; Mahadevan 2024; Cisse 2025). How essential services such as electricity are rationed has significant economic consequences, as allocation rules shape the distribution of welfare over space and time. A common approach is to allocate outages "equitably," distributing power cuts across locations so that no group bears a disproportionate burden.[1] Despite the intuitive appeal and widespread adoption of equitable rationing, such policies do not account for how consumers and firms jointly respond to shortages. In this paper, we show that outages induce consumers to reallocate spending across firms, generating unequal outcomes. Our results reveal a general mechanism through which policies designed to equalize access to scarce resources can instead amplify disparities in market outcomes.

We provide novel evidence on electricity rationing by studying firms and consumers in the context of a well-known example, electricity shortages in South Africa.[2] In 2023, national load shedding was active for roughly 72% of the calendar year as the grid struggled to keep pace with demand (Figure 1). To address these electricity shortages, policymakers implement "load shedding"—where the state utility, Eskom, divides areas into feeder-determined geographic blocks and cycles outages across these blocks based on published preset schedules. Whenever there is a shortage, municipal managers are required by law to shut off these blocks according to the rotational schedule, which balances exposure during peak hours and weekends, with the explicit goal of creating equitable rationing (NRS 2019).

We leverage an unusually rich, transaction-level dataset from a leading digital payments provider that captures a large share of small and medium-sized business activity in South Africa. The data include detailed information on firm characteristics (e.g., industry, location, and observable attributes at onboarding) as well as high-frequency transaction records, including time, location, purchase size, and payment method, allowing us to track both merchant performance and consumer purchasing behavior across establishments. The data cover 11,398 consumer-facing SMEs and approximately 8 million firm-day observations in Cape Town.[3] We combine these data with records of realized outages per geographic blocks measured in two-hour intervals from the City of Cape Town from 2021 to 2023.[4].

We exploit variation in outage exposure induced by the rationing schedule to identify the causal

[1]"Equitable" approaches to distributing power cuts has been common. Examples include: California in the 2000-2001 power crisis (California Public Utilities Commission 2001), Ecuador during a 2024 drought (Alexander 2024), Japan during the Fukushima incident (Fukue 2011), and Ukraine's ongoing energy crisis (Novikov 2024).

[2]South Africa's power crisis has received extensive coverage (Al Jazeera 2023; Sguazzin 2023; Ziady 2023).

[3]The platform processes approximately ZAR 38 billion (roughly USD 5 billion in PPP terms) annually across nearly 250,000 merchants—roughly fifteen percent of the formal business sector and 30 percent of point-of-sale terminals nationally—and 25 million consumer cards, covering approximately 70 percent of adult cardholders in the country (South African Reserve Bank 2024; World Bank 2025).

[4]We focus our analysis on the City of Cape Town as it publishes the most detailed and reliable information on outages in the country.

effect of electricity outages. Our research design relies on two features: (1) the severity of outages is set at the national level, driven largely by unplanned generator failures, and (2) the rationing rule is defined at a coarse geographic level and follows a predetermined schedule. The municipal schedule dictates which geographic block will lose power when there is a shortfall in electricity supply. The boundaries of these blocks are determined by the network of feeders.[5] This institutional setting generates a natural experiment where on any given day, a firm's exposure to electricity outages is plausibly exogenous to other determinants of firm performance.

We develop a parsimonious conceptual framework to organize our investigation by examining how firm heterogeneity in productivity and financial capacity shapes the distributional consequences of rationing. Existing models of electricity shortages predict that outages impose costs on affected firms through reduced input availability (Allcott, Collard-Wexler, and O'Connell 2016), but this prediction overlooks the demand reallocation channel when consumers can substitute across firms in local markets. Given our access to both firm-level and consumer-level data, we construct a model with CES demand and monopolistic competition. This generates endogenous reallocation of consumers as the set of active firms changes. The possibility that firm heterogeneity generates variation in impacts from ostensibly equal shocks has long been a consideration in the misallocation literature (e.g. Hsieh and Klenow (2009)). We build on this approach by deriving misallocation wedges through the interaction of infrastructure shocks and financial constraints.

If remaining operational during an outage requires not only high productivity but also sufficient financial capacity, and these two dimensions are imperfectly aligned, then rationing that is equal in exposure will be unequal in impact. We decompose the resulting welfare loss into a backup-power cost wedge, a variety loss from fewer active firms, and a misallocation term that arises when the "wrong" firms are selected into the operational set. This generates three testable predictions that motivate our empirical design: revenue reallocates toward operational firms, the distributional gap is driven by differential adoption of defensive technology in addition to firm type, and advance notice amplifies disparities because better-resourced firms are better able to translate warning into continued service. Our empirical results are consistent with these predictions.

Our main result is that electricity outages have virtually no effect on average firm performance. Daily revenue changes by just -R7 (less than 0.5 percent of the mean) and daily transactions by -0.02. However, this null average conceals large distributional effects. Outage exposure reduces daily revenue by R157 (approximately 11 percent of the sample mean) among below-median firms, while increasing revenue by approximately R150 (roughly 10 percent of the sample mean) among above-median firms.[6]

We find that these distributional effects are driven by consumers reallocating their spending

[5]The borders of these "load-shedding areas" are distinct from all other administrative borders, and are used for the sole purpose of rationing electricity.

[6]R150 is approximately USD20.18 in 2024 PPP-adjusted terms.

towards above-median firms. We provide direct evidence that consumers are substituting between below- and above-median firms using card-level data. When a consumer's regular below-median firm experiences an outage, their spending at all below-median merchants falls by 17 percent. Above-median firms capture roughly 28 percent of the displaced revenue. The asymmetry is stark in the other direction. Outages for above-median firms produce much smaller spending declines amongst its frequent consumers. Within-industry estimates yield larger magnitudes, with above-median firms recovering over 40 percent of displaced spending suggesting that competition within a local market exacerbates these distributional effects.

A natural question is whether the differential effects reflect inherent firm differences or the adoption of defensive technologies such as backup generators and inverter-battery systems. We use the type of network connection, WiFi versus cellular, over which transactions are transmitted during outages to proxy for whether a firm has adopted backup power, exploiting the fact that a functioning WiFi connection requires backup electricity. We use variation in the timing of adoption in an event-study design (Borusyak, Jaravel, and Spiess 2024). Following adoption, firms experience approximately R200 higher daily revenue and 0.75 additional transactions during outages relative to not-yet-adopters. This can substantially narrow the gap between above- and below-median firms on outage days.

These short-run distributional effects have longer-run consequences. We find that daily revenue losses for below-median firms with higher outage exposure aggregate to the weekly and monthly level. Examining exit from the platform, our evidence suggests that a one log-point increase in lagged outage duration raises the exit hazard by approximately 28 percent, with suggestive evidence that above median firms may be insulated from this effect. Examining new entry onto the platform, greater outage intensity selectively attracts higher-revenue entrants who survive longer on the platform. Together, these patterns suggest a compositional shift in market structure driven by electricity rationing.

Our findings raise the question of whether rationing policy can be designed to mitigate these distributional consequences. One increasingly common policy response to mitigate the adverse effects of shortages and extreme events is to deliver advance notices (Hallegatte 2012; Burlig et al. 2024). Advance notice can give firms time to prepare for outages by, for example, fueling generators, adjusting staffing, and activating backup systems. We exploit variation in the timing of Eskom's outage announcements, comparing outages that are announced in advance compared to those announced later. On average, Rather than narrowing distributional gaps, advance notice widens them. An additional day of notice ahead of the outage widens the effect of electricity outages between below- and above-median firms by R100 (roughly 60% of the average difference in the effect of outages between above- and below-median within this sample of outages). These patterns indicate that advance notice disproportionately benefits firms with greater adaptive capacity, amplifying rather than attenuating the performance gaps generated by rationing (Reguant, Wagner, and Weber 2025).

Our main contribution is to show that rationing policies designed to equalize exposure to electricity shortages can instead amplify disparities when consumers substitute across firms. Our results on the heterogeneous effects of equitably rationed outages are consistent with what prior research has documented on differential adaptation to rationed shortages by households (Mansur and Olmstead 2012; Gadenne 2020; Abajian et al. 2025) and firms (Abeberese, Ackah, and Asuming 2021; Hardy and McCasland 2021; Ryan and Sudarshan 2022) separately. To our knowledge, this is the first paper to document the mechanism of consumer substitution in response to firm adaptation to electricity shortages. Relative to the existing literature, which has focused almost exclusively on manufacturing, we provide evidence on the effects of electricity shortages in the market for services—the sector that increasingly drives structural transformation, productivity growth, and employment in developing economies (Rodrik 2016; Fan, Peters, and Zilibotti 2023; Nayyar, Hallward-Driemeier, and Davies 2021).

We join a rich literature on the effects of infrastructure on economic development, particularly on the effects of electricity access and reliability (Steinbuks and Foster 2010; Dinkelman 2011; Fisher-Vanden, Mansur, and Wang 2015; Allcott, Collard-Wexler, and O'Connell 2016; Gertler, Lee, and Mobarak 2017; Cole et al. 2018; Fried and Lagakos 2023; Burlig and Preonas 2024; Lin and Kassem 2025; Cisse 2025; Mahadevan 2026). Previous research has documented that electricity shortages impose significant economic costs on households and firms. Yet, measuring transactions on a ubiquitous digital platform coupled with frequent electricity outages, we find that when shortages are rationed, aggregate daily spending (at least in the market for services) remains unchanged as consumers can easily reallocate their spending between firms.

A nascent literature on designing policies to foster adaptation to shortages and extreme events finds that advance warnings can benefit adaptation behavior and improve welfare (Hallegatte 2012; Ferris and Newburn 2017; Downey, Lind, and Shrader 2023; Burlig et al. 2024; Pople et al. 2024; Rudder and Viviano 2024). This paper complements the literature that focuses on average benefits by asking for *whom* advance notice benefits. We find that anticipating shortages can lead to unequal outcomes through heterogeneous adaptation capacities, pointing to the role of complementary policies when equity is a priority.

This paper also contributes to a growing literature on the growth and survival of small and medium enterprises (SMEs) in developing economies, which emphasizes the role of managerial capacity, firm heterogeneity, and responses to uncertainty (Bloom et al. 2013; Hsieh and Olken 2014; McKenzie 2017; Quinn and Woodruff 2019). We extend this work by showing that in the presence of infrastructure shocks, policies designed to equitably allocate scarce resources can interact with firm heterogeneity to produce systematically unequal outcomes. In particular, we document that load shedding policies intended to equalize exposure instead induce demand reallocation that advantages higher revenue, more resources, and better managed firms and undermines the performance and survival of perhaps viable smaller enterprises. These findings speak to a broader literature on firm resilience and adaptation to shocks, highlighting how managerial capacity and existing financial resources interact with equitable policies to create unequal outcomes (Bloom 2009; Atkin, Khandelwal, and Osman 2017; Sterk, Sedláček, and Pugsley 2021). Our results suggest that the design of such policies must account for heterogeneity in firms' capacity to respond to uncertainty and infrastructure disruptions.

The paper proceeds as follows. Section I provides background on South Africa's electricity crisis and the institutional features of load shedding that enable identification. Section II describes our data sources and sample construction. Section III develops a conceptual framework that organizes the empirical findings. Section IV outlines our empirical strategy and presents the main results on the distributional effects of electricity rationing. Section V investigates the mechanisms driving these distributional effects, including consumer reallocation and firm adaptation. Section VI examines the longer-run effects on firm exit and entry, and Section VII analyzes the role of anticipation and its implications for policy design. Section VIII concludes.

I. Context and Background

South Africa's electricity shortfall originated in the years following democratization, when rising household connections were not matched by timely investment in new generation capacity or adequate maintenance of the existing coal fleet.[7] The utility-scale plants Medupi and Kusile came online many years late and far over budget, while policymakers repeatedly deferred opening the sector to independent power producers. Dependable capacity has consequently fallen short of even a largely stagnant demand, forcing the system operator to ration supply to protect the grid.[8] The number of hours South Africans spend without electricity rose by over 1,000% between 2018 and 2023 (Figure 1, panel A).

Eskom manages the national energy deficit through *load shedding*: centrally coordinated, rotational disconnections announced at the national level and executed by municipalities. Each "stage" represents an incremental gigawatt that must be shed—Stage 1 removes up to 1,000 MW, Stage 2 up to 2,000 MW, and so on—up to Stage 8, at which point a firm can expect twelve hours without power in a single day. The National Control Centre sets the stage, sometimes with only minutes of warning when a generating unit trips, and local distributors implement the published schedule.[9]

Within the City of Cape Town, consumers are assigned to one of sixteen feeder "blocks." The

[7] Khonjelwayo and Nthakheni (2020) estimate that investment in electricity infrastructure is insufficient and only 60% of what is required for adequate investment has been invested. This is equivalent to R10 billion in underinvestment per annum since 2011.

[8] Appendix Figure C.1 shows aggregate electricity consumption in South Africa from 2004 to 2021. Demand stagnated even before the frequent blackouts that began in 2021.

[9] Business owners sometimes receive fewer than twenty minutes of notice before an escalation. News24, June 2022

rotational design ensures that, within any given stage, every block is disconnected the same number of times provided the stage persists long enough. In practice, however, stage changes have been frequent, so exposure at any given period of time differs across blocks. Figure 2 illustrates this pattern for June–July 2023: both the severity and the geographic incidence of outages shift between consecutive days and weeks. The stage also determines how many blocks are simultaneously without power—one block in Stage 1, rising to eight of the sixteen in Stage 8.

Municipalities may request exemptions for critical infrastructure such as hospitals or water-treatment plants, but the radial structure of distribution networks limits the scope for such carve-outs. Court rulings in 2023 obliged the state to prioritize certain facilities; nonetheless, Eskom has argued that widespread exemptions would jeopardize system security. Most commercial feeders, including many serving historically disadvantaged townships, remain subject to the full rotation.

Two institutional features underpin our identification strategy. First, the assignment of feeders to blocks is fixed in advance and determined by network topology rather than by socio-economic characteristics; firms cannot sort into lower-outage blocks without physically relocating. Second, the decision to escalate from one stage to another responds to unplanned plant breakdowns at the national level—events that bear little relation to local economic conditions in Cape Town. Together, the predetermined spatial assignment and the quasi-random temporal shocks generate within-city, within-day variation that we exploit empirically.

The economic toll of the crisis has been substantial. National load shedding totaled roughly 530 hours in 2019 and surged to 6,830 hours in 2023, before easing to 4,169 hours in 2024 as modest improvements in coal-plant availability and a wave of private embedded generation narrowed the supply–demand gap.[10] Independent estimates place the cumulative output loss at ZAR 43.5 billion between 2007 and 2019 and ZAR 224 billion between 2020 and 2022 (Walsh, Theron, and Reeders 2024), while recent work links the outages to higher unemployment and firm exits (Bhorat and Köhler 2025), and even increased mortality (Budlender 2024).

II. Data

To study the effects of electricity outages on firm performance, we combine transaction-level data from South Africa's leading small-business payments platform with administrative outage records from the City of Cape Town.

Our primary dataset is the universe of transactions on South Africa's largest fintech payments platform for SMEs (hereafter the "platform"). The platform processes approximately ZAR 38 billion (roughly USD 5 billion in PPP terms) in transactions each year. Its merchants account for roughly

[10] Cape Town's outage hours fall below the national total because the City exclusively operates the 180-MW Steenbras Hydro Pumped Storage Scheme which it dispatches to shield City-supplied customers from up to two stages of Eskom's declared load shedding, leading to this reduction in exposure relative to the rest of the country.

30 percent of all point-of-sale terminals in the country, and the 25 million consumer cards linked to its transaction records cover about 70 percent of the country's adult cardholders (South African Reserve Bank 2024; World Bank 2025). South Africa's Small, Medium, and Micro-Enterprise (SMME) population totals approximately 2.3 million under the broadest definition (National Minimum Wage Commission 2021), but because the platform serves banked, card-accepting merchants, the formal-sector SMME count of roughly 0.77 million is the more relevant denominator (National Minimum Wage Commission 2024). The platform's 250,000-plus merchants therefore represent more than 15 percent of formal small businesses nationwide.

For each transaction, the data record the amount, geolocation, timestamp, payment method (card or cash), payment device, card identifier, and merchant identifier. We merge these records with firm-level information on industry and owner characteristics. Card transactions are recorded automatically by the platform; cash transactions are self-reported. Despite being self-reported, the cash measure captures real variation in cash reliance: Russel, Shi, and Clarke (2025) show that the average share of revenue recorded as cash in the platform data closely tracks independent survey-based cash-preference measures across South African provinces. In total, we observe over 470 million transactions from January 2021 to January 2024. We limit our focus to the 59 million transactions within the City of Cape Town.

We use a publicly available dataset from the City of Cape Town's Open Data Portal that records realized outages in each load shedding block, measured in two-hour intervals, from January 2020 to December 2023. For instance, an outage lasting from 1pm to 2pm appears as 60 minutes of outage within the 12pm–2pm interval. We combine this outage history with load shedding block boundaries to match each firm's location to its contemporaneous outage exposure. Both the boundaries and the outage records cover the 75% of Cape Town where the City—rather than Eskom—distributes electricity. While the stage of load shedding is set nationally, the implementation schedule is determined by the local electricity distributor. Boundaries of load shedding blocks that permit accurate measurement of outage exposure are, to our knowledge, publicly available only in Cape Town. In many municipalities, the exact boundaries of load shedding areas are not published even to residents, who must infer their block assignment from their own electricity meter. We also collect demographic data from the Open Data Portal, including average property values at the suburb level as of 2015.[11] The outage records on the Open Data Portal end in December 2023, and no updated version extending into 2024 or beyond is available. Although intensive daily load shedding continued through March 26, 2024, the absence of block-level outage data after December 2023 prevents us from assigning treatment status during the final months of the crisis. Our analysis period therefore ends in December 2023. This constraint also precludes studying the transition out of rationing or longer-run post-crisis effects.

[11] A "suburb" is an administrative unit akin to a neighborhood or census tract in the United States.

We also make direct use of the load shedding schedule published by the City of Cape Town.[12] Appendix Figure C.2 shows an example. The schedule specifies the order in which blocks would be disconnected at each stage, for every two-hour period on every day. We use this ordering to construct a block-level ranking. There are at most eight stages (i.e., at most eight blocks simultaneously without power). Suppose that at a given time and day the blocks are phased in from block 1 (disconnected first, in Stage 1) through block 8 (disconnected last, in Stage 8). We assign block 1 a rank of 1 and block 8 a rank of 8; blocks not at risk of disconnection at any active stage do not receive a ranking. Because the schedule rotates, each block's rank varies by day and time of day.

We conduct our main analysis at the firm-day level. We aggregate in-person transactions, outage exposure, and schedule-based rankings to the daily level and construct a balanced panel by firm and day from January 2021 to December 2023. We restrict the sample to firms with average monthly revenue exceeding ZAR 5,000—approximately the national median monthly wage—which excludes dormant and near-inactive accounts, and drop firms within 250 meters of a load shedding block boundary to account for localized spillover effects. The resulting sample contains 11,398 firms and approximately 8 million firm-day observations. Appendix B details the data construction.

II.A. Summary statistics

Summary statistics for the main analysis sample are reported in Table 1. The median firm earns approximately R20,400 (USD 1,120) per month and has been on the platform for 2.9 years. This median revenue is roughly four times the national median monthly wage of ZAR 5,200 (Statistics South Africa 2022), placing these firms well above subsistence scale. Outages are frequent: the median firm experiences 25.5 outages per month, each lasting two hours. Table 2 reports the industry composition: retail, hospitality, and healthcare and beauty services together comprise 77% of the sample. These consumer-facing sectors are overrepresented relative to the broader Cape Town economy, where retail and consumer services account for 47% of SMEs (Small Enterprise Development Agency 2023), reflecting the platform's orientation toward businesses that transact directly with end consumers.

Our sample occupies a middle ground between South Africa's large informal sector and the VAT-registered segment captured in tax data. Statistics South Africa reports that over half of informal firms turn over R1,500 or less per month, and most are sole proprietorships (Statistics South Africa 2023). By contrast, our sample median of R20,400 is well above informal benchmarks but below the R83,333 per month threshold that triggers mandatory VAT registration (R1-million per year).

To enrich our analysis sample and shed light on mechanisms, we conducted an in-person survey of 259 firms across the Cape Town metropolitan area, including firms not on the platform. Survey respondents report median revenues in the range of R30,000–R75,000 per month and median

[12] https://www.capetown.gov.za/Loadshedding1/loadshedding/Load_Shedding_All_Areas_Schedule_and_Map.pdf

employment of 11–20 workers. Additional survey results appear in Appendix Table C.1. These firms are on the cusp of digitization: a slim majority (52%) report relying primarily on electronic payments, and 67% own a card machine. Visa executives have noted that contactless cards now account for over 60% of face-to-face transactions in South Africa, suggesting that our sample mirrors prevailing adoption patterns among small businesses.[13]

We do not directly observe employment, but micro and small firms account for nearly 90% of all registered businesses in South Africa (Tsebe et al. 2018), and the well-documented correlation between revenue and headcount (Statistics South Africa 2025) suggests that most firms in our sample fall below the survey median of 11–20 employees—consistent with spatial tax data for Cape Town, where the majority of firms employ fewer than 10 full-time equivalents (Appendix Figure C.9A). Our findings are therefore most directly transferable to consumer-facing urban micro-enterprises.

III. Conceptual Framework

This subsection provides a compact framework for interpreting the paper's main empirical patterns. The central idea is that outages temporarily shrink the set of firms that can serve customers, consumers then reallocate spending across differentiated firms within a local market, and the ability to remain operational depends not only on baseline firm performance but also on a separate financial-capacity margin. The framework is intentionally parsimonious: its primary role is to organize the evidence on reallocation, backup-power adoption, and anticipation. The setup also delivers a decomposition of potential welfare costs into backup-power input costs, variety loss, and misallocation arising when financial capacity is imperfectly aligned with firm performance.[14]

Baseline Environment. Consider a local market on a given day. Consumers have CES preferences with elasticity of substitution $\sigma > 1$ and allocate fixed nominal expenditure E across a continuum of differentiated firms $i \in [0, N]$, each supplying one variety.

Each firm is characterized by A_i, a parameter that summarizes the combination of productivity, quality, and demand appeal determining its revenue within a market. Under monopolistic competition with constant markups, prices are inversely related to A_i, so that baseline revenue is monotone in A_i. This motivates our use of non-outage revenue as the empirical proxy for firm performance.

Specifically, we define the baseline productive capacity, and then baseline revenue shares as:

$$M_0 \equiv \int_0^N A_i^{\sigma-1}\, di, \qquad s_i^0 = \frac{A_i^{\sigma-1}}{M_0}.$$

[13] Reuters, July 23, 2025

[14] Details of this decomposition are in Appendix A.

Outages and adoption. With some probability $q \in (0, 1)$, a firm may lose grid power during business hours. Before the outage state is realized, a firm can pay a fixed cost F to adopt backup power. Adoption is feasible only if the firm has enough financial capacity, denoted ω_i. We interpret ω_i as capturing internal funds, borrowing capacity, and related determinants of whether backup generation can be financed. Backup power allows the firm to continue operating during outages at a premium $\tau > 0$, as the price per kWh is higher than the price of grid power. We assume that the firm cannot operate during outages without backup power.

Let $\mathcal{G}$ be the set of firms who invest in alternative generation, and thus remain operational during an outage. Adoption requires two conditions: the firm must be productive enough that resilience is profitable, and it must be able to finance the fixed cost. Formally, $\mathcal{G} \equiv \{i : A_i \geq A^*, \ \omega_i \geq F\}$, where the cutoff A^* is determined endogenously because each firm's return depends on the total productive capacity of the firms that adapt.

We define the resilient productive capacity and revenue shares during outage states analogously: $M_{\mathcal{G}} \equiv \int_{i \in \mathcal{G}} A_i^{\sigma-1} di$ and $s_i^1 = A_i^{\sigma-1}/M_{\mathcal{G}}$. Since $M_{\mathcal{G}} \leq M_0$, each operational firm's outage-state revenue share weakly exceeds its baseline share. With variable profits being a constant fraction of revenue, the expected gain from adoption is thus:

$$\Delta\Pi_i = \frac{qE}{\sigma} \frac{A_i^{\sigma-1}}{M_{\mathcal{G}}} - F.$$

This structure clarifies why adaptation need not be perfectly aligned with baseline performance. Some high-A_i firms may fail to adopt because they are financially constrained, while some lower-A_i firms may adopt because they are better resourced.

Reallocation during outages. This structure delivers the paper's main redistribution result immediately. For any firm that remains operational during an outage, $R_i^1 = R_i^0 \frac{M_0}{M_{\mathcal{G}}}$ for firms $i \in \mathcal{G}$ while firms outside $\mathcal{G}$ earn zero. Aggregate nominal spending remains E by construction, but is reallocated away from firms that cannot serve customers and toward firms that can. The proportional revenue gain is uniform across all operational firms: it depends on the resilient capacity share $M_{\mathcal{G}}/M_0$, not on any individual firm's A_i. Since resilient firms are disproportionately above-median in baseline performance, this mechanism generates the pattern documented in Subsection IV.C and Section V of consumer substitution toward operational firms.

We can then show real consumption during outages satisfies $\frac{X_1}{X_0} = \frac{1}{(1+\tau)} \left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}$ so that aggregate output loss depends on two main factors: the operating cost premium and the resilient productive capacity share.

To isolate the welfare cost of this misalignment, define the efficient adaptation benchmark $\widetilde{M}_{\mathcal{G}}(m)$ as the resilient productive capacity that would obtain if the same m firms adopted, but selected on A_i alone. We then decompose the aggregate output loss into a backup-power cost wedge, a loss from fewer active varieties, and an additional misallocation term that arises when financial capacity is imperfectly aligned with baseline performance:

$$\mathcal{L} = 1 - \frac{X_1}{X_0} = 1 - \frac{1}{1+\tau}\left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}$$

$$(1) \qquad = \underbrace{\frac{\tau}{1+\tau}}_{\text{input cost wedge}} + \underbrace{\frac{1}{1+\tau}\left[1 - \left(\frac{\widetilde{M}(m)}{M_0}\right)^{\frac{1}{\sigma-1}}\right]}_{\text{variety loss}} + \underbrace{\frac{1}{1+\tau}\left[\left(\frac{\widetilde{M}(m)}{M_0}\right)^{\frac{1}{\sigma-1}} - \left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}\right]}_{\text{misallocation}}.$$

The first component captures the pure cost of operating on backup power, independent of which firms adopt. The second is the loss from reduced variety under efficient selection—the minimum variety cost given m adopters. The third term captures the additional loss when the adopting set $\mathcal{G}$ does not coincide with the top-m firms in A_i; it is strictly positive whenever financial capacity is imperfectly aligned with baseline performance.

The decomposition yields a sharp comparative static: the welfare cost of fixed adoption costs F is largest when financial capacity is imperfectly aligned with baseline performance. Section V confirms this: we find that there is a substantial overlap in the revenue distribution between adopting and non-adopting firms.

Finally, the framework extends naturally to anticipation. Suppose that, conditional on owning backup power, firm i is operational during a fraction $y_i(n)$ of outage windows, where n denotes advance notice and $y_i'(n) \geq 0$. Then effective resilient capacity becomes $M_{\mathcal{G}}(n) = \int_{i \in \mathcal{G}} y_i(n) A_i^{\sigma-1}\, di$. If better-resourced firms have a steeper activation response to notice, advance warning increases preparedness on average while also widening the gap between firms that can and cannot translate notice into continued service.

IV. The Effect of Electricity Rationing on Daily Firm Outcomes

Firm exposure to electricity outages may be correlated with other determinants of firm performance. Outages arise from a mismatch between electricity supply and demand, so they might coincide with periods of heightened economic activity. Moreover, institutional factors can distort the allocation of outages toward particular firms or geographies. Two institutional features of our setting in Cape Town allow us to overcome these challenges and estimate the causal effect of electricity rationing on firm performance.

IV.A. Estimation Strategy

First, rationing decisions are made at a national rather than regional level: the national utility rations electricity based on the country's aggregate shortfall, not on conditions specific to Cape Town or any individual firm. Although outages are more frequent during periods of higher economic activity, the national decision to ration is not driven by firm- or geography-specific factors, especially within a municipality. This motivates the inclusion of date fixed effects, possible because of the high-frequency nature of our data. The identifying variation comes from differences in outage exposure across firms within the same day.

Second, conditional on the national decision to implement outages at a given severity, Cape Town implements the outages according to a pre-specified rotation schedule. The schedule maps each combination of date, time, and severity level to specific geographic areas ("load shedding blocks") whose electricity supply is rationed. Because the rotation is determined in advance and published publicly, the local implementation of outages cannot, in theory, systematically favor particular firms or areas. Appendix Figure C.2 shows an example of the schedule—the stage of the outage determines the number of blocks that will receive an outage; and the schedule determines the order in which each load shedding block will receive an outage. Appendix Figure C.4 shows the empirical variation in outage probability given a load shedding block's ranking on the schedule.

Together, these two features imply that conditional on the day, a firm's outage exposure is determined by its fixed geographic location interacting with a mechanical schedule. The identifying assumption is that, conditional on the date, firm assignment to outage exposure is as good as random. This assumption would be violated if firms are able to select their location daily based on the outage schedule or try to locate in areas that receive less outages. The firms in our sample have brick-and-mortar stores, thus daily movements are not possible. Moreover, it is unlikely that the firm location decision is affected by differential outage exposure because outage exposure is ex-ante balanced. We confirm this in Figure 1, which shows that cumulative electricity outages over 2021-2023 were roughly uniform across Cape Town, making selection of firms into areas with less outages unlikely.

Our design implies that on any given day, the firm characteristics of the firms located in the blocks exposed to an electricity outage are similar to the firms located in unaffected blocks. We test this in Table 2, where we compare firm characteristics by outage exposure on any given day.[15] The table shows that most firm characteristics are balanced. While we find slightly higher (0.3%) property

[15] Concretely, for each firm characteristic, we run a regression that regresses firm characteristic X_i on whether a firm experienced an outage on day t and date fixed effects δ_t

$$X_i = \alpha \text{Outage}_{it} + \delta_t + \epsilon_{it}$$

This specification effectively stacks the cross-sectional comparison of firms across outage exposure across all of the days in our sample.

values for outage-exposed firms compared to non-exposed firms, these differences are small.[16]

Our main specification further includes firm fixed effects to absorb time-invariant firm heterogeneity and improve precision. We estimate variants of the following equation:

$$y_{it} = \beta \text{ Outage}_{it} + \delta_t + \gamma_i + \varepsilon_{it} \tag{2}$$

where δ_t are date fixed effects, γ_i are firm fixed effects, and Outage_{it} represents firm i's exposure to outages on day t. Standard errors are clustered at the industry-by-load-shedding-block level throughout our firm-level analysis. We estimate heterogeneous effects by interacting Outage_{it} with time-invariant firm characteristics X_i:

$$y_{it} = \beta \text{ Outage}_{it} + \varphi \text{ Outage}_{it} \times X_i + \delta_t + \gamma_i + \varepsilon_{it} \tag{3}$$

where β captures the effect of an outage for the omitted group and φ captures the differential effect for firms with characteristic X_i.

Our main specification considers a binary variable that measures whether the firm experienced any outages on any given day t. The dependent variable y_{it} measures daily revenue or daily transactions, where we specify the dependent variable in levels (Rand or transaction counts).[17] Our balanced panel imputes zeros on days when a firm records no transactions (but did not exit).

IV.B. Design Validity

Schedule Implementation. While the pre-specified schedule ensures that the *intended* allocation is not distorted by any institutional discretion, *realized* outages might not always follow the schedule. Indeed, this has been a challenge in the literature that employs a similar empirical strategy (Hardy and McCasland 2021; Abeberese, Ackah, and Asuming 2021). Our setting allows us to test the degree of compliance. Column 1 in Appendix Table C.5 shows that, in Cape Town, scheduled outage almost always predicts realized outage. They align 98% of the time during the analysis period of 2021–2023. Our main specification uses realized outage as the main explanatory variable, but Panel A of Table 4 shows the results from using scheduled outages as an instrument for realized outage. Given that the first stage is 98%, we find that the results from an IV approach to be identical. We further discuss the results of the robustness tests in Section IV.C.1.

[16] It is worth noting that we are testing 19 separate hypothesis—we might expect at least 1 of the differences to be significant purely from chance. We confirm this by stacking the balance regression we run for *all* covariates. The p-value on this joint-test is 0.441.

[17] One advantage of specifying our outcomes using levels is that we sidestep the discussion on logs in Chen and Roth (2024). However, daily revenue and transactions likely have long right tails. Thus across all specifications, we winsorize our outcomes at the top 1%.

Geographic Spillovers. Consumer substitution across block boundaries could affect firms in non-outage blocks because the rationing schedule operates at the level of geographic blocks. If customers displaced from an outage-affected block shift their spending to firms in adjacent non-outage blocks, the revenue of control firms would be inflated on days when neighboring blocks lose power. In our main analysis, we exclude all firms within 250 meters of a load shedding block boundary from the sample to minimize these spillover concerns.[18] Panel B of Table 4 shows that our results are robust to alternative distance cutoffs. To the extent that cross-boundary substitution is not mitigated by the alternative cutoffs, our estimate shows how electricity outages affect the *relative* outcomes among firms located in a block that received an outage and firms located in a block that did not.

IV.C. Results

We measure firm performance with two key metrics: daily revenue (in Rand) and daily transactions. Our main specifications consider the effect of exposure to *any* electricity outages on a given day. Table 3 reports estimates of the average effect of electricity outages on firm performance. The large differences between columns (1) and (2) illustrate how date fixed effects address the potential bias from a simple comparison of firm performance between outage and non-outage days. Column (1) confirms that outage days coincide with higher economic activity—on days with an electricity outage, the average firm records R242 higher daily revenue and roughly 0.9 more daily transactions. Columns (2)–(6) implement the empirical strategy described above.

In our baseline specification with firm and date fixed effects, electricity outages have virtually no effect on daily revenue (column (3), panel A) or transactions (column (3), panel B). The estimated effect on daily revenue is –R7 (less than 0.5 percent of the dependent variable mean of R1,471), and the effect on daily transactions is –0.02 (less than 0.4 percent of the mean of 5.5 transactions per day). Both estimates are statistically indistinguishable from zero. This null effect on average firm revenue suggest that the assumption on fixed daily expenditures E in Section III is an adequate approximation. Appendix Table C.9 finds that the average null effect aggregates to the market-day level, where a market is defined as load shedding block by industry. We discuss the implications of this market definition further below.

There are two potential explanations for the null average effect. First, given the frequency of outages in South Africa, all firms may be virtually unaffected due to widespread adoption of defensive technologies (e.g. uninterrupted power supplies, solar backup, or diesel generators). Second, outages may be impacting firms differentially. Revenue may be reallocated across firms: those that are more productive, larger, or better able to invest in defensive technologies capture unmet consumer demand during outage events. Under this interpretation, the null average effect implies that gains and losses across firms approximately offset—aggregate consumer spending

[18] Appendix Figure C.10 shows the results where we regress firm performance measures on an indicator for whether a firm's *adjacent* load shedding block is experiencing an outage. We find that positive and statistically significant estimates on daily revenue attenuate by 250 meters.

does not differ significantly between outage and non-outage areas, so any revenue gained by one set of firms comes at the expense of another. We turn to testing whether all firms or only a subset are unaffected by electricity outages.

We first consider heterogeneity by *absolute* performance, where we define a firm as "higher-performing" if its average daily revenue on non-outage days is above median.[19] The average effect masks substantial heterogeneity along this dimension. Exposure to an electricity outage reduces daily revenue by R157 (approximately 11 percent of the overall sample mean of daily revenue) among below-median firms, while the differential effect for above-median firms is R307 (column (4), panel A). The net effect for above-median firms is thus positive: outages *increase* daily revenue by approximately R150 (roughly 10 percent of the sample mean) among above-median firms. Likewise for daily transactions, exposure to an electricity outage reduces daily transactions by 0.41 (approximately 7 percent of the mean) for below-median firms while the differential for above-median firms is 0.80 transactions (column (4), panel B). These differential effects are statistically significant at the 1% level.

This stark pattern could reflect two distinct channels. This pattern could be driven by consumer substitution. The same consumers shift their consumption from below-median firms to above-median firms. Alternatively, this pattern can also reflect heterogeneity in consumer responses. For example, consumers located in lower-income areas, whose firms would likely be below-median in revenue, respond to outages by systematically *reducing* their spending. We now test these two explanations by constructing a market-specific (load-shedding block by industry) measure of median daily revenue. If we expect consumer substitution to be the driving force, we might expect a similar pattern to emerge within market. This market definition allows us to characterize heterogeneity in a way that is informative about local consumer substitution. In Section I, we note that load shedding block boundaries are determined solely by feeder network topology and do not coincide with any other administrative boundaries. It is therefore unlikely that there are market-level shocks (e.g. industry-by-block level) that correlate with outage exposure conditional on date and firm fixed effects.

Column (5) in panels A and B of Table 3 analyzes heterogeneity along *relative* performance. We define a firm as "relatively higher-performing" if its average daily revenue on non-outage days is above median within its market. Electricity outages reduce daily revenue by R152 (approximately 10 percent of the sample mean) among below-median firms and the differential for above-median firms is R293 (column (5), panel A). For daily transactions, below-median firms lose 0.37 transactions (approximately 7 percent) while the differential for above-median firms is 0.72 transactions (column

[19]This measure of "above-median" captures several dimensions that might be of interest. Firms with higher revenue will tend to be more productive, larger (in terms of employment), or have better credit access that allows them to make additional investments. While distinguishing between these dimensions would be of interest, we unfortunately lack the data to do so. We interpret daily revenue as a mix of productivity, size, and access to finance. In this interpretation, it is possible that a "low-revenue" firm might be productive but simply lack the credit access to grow their firm. Section V.B shows how this measure of performance relates to our proxies for self-generation and adaptation capacities.

(5), panel B). These differential effects are statistically significant at the 1% level. Columns (4) and (5) together suggest that the differential effect of outage exposure is not simply a result of differences in size or productivity, but reflects the role of *consumer substitution*. Column (6) suggests that cross-firm variation in size, productivity, and ability to invest in defensive technologies and consumer substitution play complementary roles. The symmetry of gains and losses is indicative of consumer reallocation rather than demand destruction, consistent with the reallocation predicted in Section III. When outages remove a fraction of firms from the active set, consumers do not reduce spending, but rather redirect it toward the remaining operational firms. The positive net effect for above-median firms implies that these firms are disproportionately represented in the resilient set $\mathcal{G}$, capturing revenue shares that previously accrued to firms that can no longer serve customers.

IV.C.1. Robustness

Imperfect schedule implementation. The main explanatory variable of interest in Table 3 is realized outages in a particular area, as measured by the City of Cape Town. However, realized outages could be endogenous to local economic conditions (e.g. transmission line or transformer failures due to localized demand shocks that overdraw power). Another concern is that the implementation of load shedding by the municipality deviates from the published schedule to favor certain areas over others. We use scheduled outages as implied by the load shedding schedule as an instrument for realized outages to address these concerns. This analysis uses only variation across firms in their positioning in the load shedding schedule and the severity of outages, which is set nationally and not locally. The instrument is constructed following the announced stage and the firm's positioning on the load shedding schedule. Table 4 Panel A shows that the IV results are very similar to those in Table 3. The alignment between the instrumental variable approach and the "natural experiment" approach is reassuring—the main source of electricity outages is national calls for electricity rationing, and the rationing is done following the proper procedure in Cape Town.[20]

Sample cutoff. Table 4 Panel B shows the robustness of our main results to different cutoffs to drop firms near load shedding borders. The first column includes the full sample and does not drop firms within 250 meters. We then drop firms within 500 (columns 2 and 5) and 1,000 meters (columns 3 and 6) of the load shedding border. Across all sub-samples, we find that the pattern and magnitude of the coefficients are remarkably similar to the main result where we dropped firms within 250 meters of the load shedding border.

[20]While not common, deviations from published load shedding schedules do occur. For example, Eskom has taken control over the implementation of load shedding in the a different city due to its inability to properly follow the published schedule (see https://www.sabcnews.com/sabcnews/922739-2/). Interviews with city officials suggest that they do this to favor industrial sections of the city. Such practice introduces clear selection bias when estimating Equation 2 since areas that experience outages are likely to be lower-revenue compared to areas without electricity outages. To our knowledge, there have been no such incidents in Cape Town.

Pre-period performance measure. One potential concern is that a firm's performance classification may itself be affected by outage exposure, since we use the non-outage daily revenues. In this case, our heterogeneity measure may simply be conditioning on the (heterogeneous) dynamic effects of outages rather than reflecting any other differences in firm "type." Table 4 Panel C addresses this by defining above-median performance using revenue from January–December 2021, a period preceding the most intense load shedding. We restrict the sample to January–December 2023 and to firms that have been active since 2021. The differential effects remain similar to our main results, indicating that the heterogeneous effects are not an artifact of contemporaneous performance classification.

Intensive margin outage days. Appendix Table C.4 shows the results by restricting the sample to only days with any electricity outages. This table provides a straightforward comparison between areas that have an electricity outage vs. areas that do not on any days with electricity rationing. While the magnitudes differ (as we lose the comparison to days without any outages at all), the qualitative pattern remains the same. Below-median firms lose revenue and transactions while above-median firms gain.

Outage definitions. The primary measure of outage exposure is binary. We also examine whether the results are robust to using continuous measures of outage exposure. We consider two measures: number of outages in a day and the total duration of outages. Results for these exercises are reported in Appendix Table C.8. In each alternative specification of outage exposure, the overall pattern of estimated treatment effects remains the same: outage exposure has negligible average effects with underlying losses by low-performing firms and positive gains by high-performing firms.

Cash Transactions. Another concern is that firms might simply switch to cash transactions and fail to record them, since cash revenue is self-reported. As noted in Section II, Russel, Shi, and Clarke (2025) validate that the platform's self-reported cash measure tracks independent survey-based cash-preference measures across provinces. Businesses can report cash transactions on the platform; however, they do so at varying rates. In particular, cash substitution might be driving the heterogeneous effects if below median firms are more likely to have their revenue shift toward cash.

To assess whether firms shift transactions to cash rather than recording them on the platform, we restrict to the subset of firms whose lifetime cash revenue is at least 10% of its total revenue. If such substitution occurs, it is most likely to be detected within this subset where cash revenue reporting is consistent. We examine whether outages shift the cash share of revenue and transactions in this subsample, conditional on a firm having any transactions. Appendix Table C.11 reports the results. We find that cash substitution cannot explain our results. If anything, above-median firms are *more likely* to have cash revenue and transactions during outage periods.

V. Mechanisms

V.A. Estimating consumer reallocation

To provide direct evidence of consumer substitution, we examine whether *the same consumer* substitutes toward a different firm when the firm they intended to visit experiences an outage. We use de-identified card-level data in this analysis, where we assume that each unique card corresponds to a unique consumer. While it is possible that consumers might have multiple cards, this would bias our estimates of consumer substitution towards zero.

One challenge is that we do not observe which firms a consumer might "intend" to visit on any given day. We approximate this by considering a set of firms that a card regularly visits. We construct a measure of a "regular firm"—a merchant that the consumer frequents (visits at least twice) during 2021. We limit the sample to cards for whom we can identify at least two regular firms within any one industry and we drop firms within 250 meters of the load shedding border. We then test whether an outage to the consumer's identified regular firm affects the consumer's spending at different firms from January 2022–December 2023. We estimate variants of the following equation on a balanced panel at the card-day level:

$$y_{ct} = \beta \text{ Regular Firm Outage}_{ct} + \delta_t + \kappa_c + \varepsilon_{ct} \tag{4}$$

where β measures the effect of whether any one of card c's regular merchant experienced an electricity outage on day t on outcome y_{ct}, conditional on day fixed effects δ_t and card fixed effects κ_c. To characterize the nature and extent of substitution, we consider the effects of a regular firm outage on the consumer's daily spending on above-median (high-performing) and below-median (low-performing) firms. We estimate Equation 4 on a balanced sample at the card-day level where we impute zeros for days with no transactions. Each card's "entry" and "exit" is characterized by the day of its first and last observed transaction.

Appendix Table C.3 shows the summary statistics of the card-level data for the analysis sample. We are able to identify 106,296 unique cards with an average of 3.5 identified "regular" merchant for each card. The average card records 32 total transactions. Conditional on transacting, we observe that each card spends R334 (20 USD) per day—87% of this spending is on above-median firms.

Table 5 presents the results. Panel A presents results at the card-day level. We estimate that when one of a consumer's identified regular firm that is below median experiences an outage, they reduce their spending at *all* below-median merchants by R0.43 (column 1), or 17% of the average daily spending at below-median firms (R2.50). In contrast, they raise their spending at above-median firms by R0.12; which is 28% of the lost revenue (column 3). In contrast, we find that when a consumer's above-median regular firm experiences an outage, spending at *all* above-median merchants reduce by R0.19 (1.6% of average daily spending at above-median firms; Column 4) while we detect no statistically significant increases in their spending at below-median merchants.

Panel B further narrows in on the substitution channel by considering within-card and within-industry changes in spending at below- and above-median merchants. While Panel A can capture cross-industry substitution, it might also understate the degree of *direct* substitution.[21] The sample of cards in Panels A and B are the same. We augment Equation 4 to accommodate the new data structure, which is a balanced panel at the card by industry by day level, and include card by industry fixed effect:

$$y_{cit} = \beta \text{ Regular Firm Outage}_{cit} + \delta_t + \kappa_{ci} + \varepsilon_{cit} \tag{5}$$

We find larger magnitudes when we restrict our attention to within-industry substitution: when a below-median regular firm experiences an outage, daily spending at below median merchants within the same industry decreases by 37%; and spending at above-median merchants captures 41.2% of the card's displaced spending (columns 1 and 3). In this specification, we estimate a positive substitution for cards whose above-median regular merchants experiences an outage: their spending at above-median firms decreases by 1.6%; this spending is fully captured by below-median firms. However, below-median firms only recoup 22.5% of their outage-induced loss while above-median firms are, on net, *gaining* revenue.

Across panels A and B in Table 5, the stark asymmetry in magnitudes suggests that consumers substitute far more when a below-median regular firm experiences an outage than when an above-median regular firm does.[22] This pattern is consistent with below-median firms being unable to serve their customers during outage hours—consumers turn to other firms that can—while above-median firms remain largely able to serve their consumers, so that outages to their locations do not trigger the same displacement.

These patterns map directly onto the reallocation channel in the framework: when a firm is removed from the active set, its revenue share is redistributed to operational firms in proportion to their productive capacity $A_i^{\sigma-1}$. The asymmetry we document—a 17% decline in spending at below-median firms relative to baseline, of which above-median firms capture 28%—is consistent with resilient firms having higher A_i.

We note that the magnitudes in the card-level analysis in Table 5 do not align with the firm-day

[21] Spending decreases at origin firms experiencing the outages (columns 1 and 4) are fully captured because the regular firm is on the platform by construction, but spending increases at destination firms (columns 2 and 3) are attenuated if consumers substitute toward firms on other platforms, making column (3) a lower bound on the true reallocation toward above-median firms.

[22] This specification blends the extensive and intensive margin, Appendix Table C.6 separately estimates the effect of a regular firm outage on whether a card transacts; and conditional on transacting, how much they are spending. We observe that the magnitudes that we see in Table 5 are primarily driven by the intensive margin—an outage only decreases transaction probabilities by 1% (0.08 percentage points).

level results in Table 3, which found close to perfect reallocation between above and below median merchants. In the card-level analysis, we estimate the effect of exposure to outages from regular firms, defined as a merchant that the consumer has visited at least twice in 2021. This may lead to an estimate of imperfect substitution for two reasons. First, the regular merchant may no longer be in the consumer's consideration set—the consumer would not be affected by an outage to that firm. Second, other firms in the consumer's choice set may be affected by outages as well that we do not observe, leading to attenuation in our estimate for substitution. While the card-level specification necessarily conditions on a subset of the consumer's choice set, it provides direct evidence that the reallocation channel operates through consumer substitution toward above-median firms.

V.B. Adaptation to outages

Throughout, we have hypothesized that consumers are substituting toward above-median firms over below-median firms because above-median firms are able to better serve these consumers during electricity outages. This suggests a degree of differential adaptation capacity to electricity outages between below- and above-median firms. This subsection investigates this hypothesis directly. We first develop a proxy for whether a firm has adopted a defensive technology using the granular nature of the transaction data. We then document heterogeneity in which firms adopt these technologies and estimate the causal effect of adoption on firm performance during outages using an event-study design that exploits variation in the timing of adoption.

V.B.1. Proxying for adaptation

One data limitation is that we do not have data on whether a firm has a backup generator, inverter-battery system, or other adaptation technologies that allow merchants to continue operating during electricity outages as if they were still being supplied electricity from the grid. As a result, we cannot directly observe which firm might have access to self-generated electricity during outage periods.

We use the granular nature of the transaction data to infer whether a firm has adopted a defensive technology using the *type* of network over which the transaction was transmitted. The data record whether each transaction was transmitted via "WiFi" or "Cellular." Our strategy relies on the observation that a viable WiFi connection requires electricity. If we observe a firm transmitting a transaction over WiFi instead of a cellular connection during a power outage, we can conclude that the firm has adopted some form of defensive technology that keeps its WiFi operational during outages.[23] While we are able to proxy for *any* adaptation, we cannot distinguish between the specific technologies: we can only observe whether the firm's WiFi connection is operating during

[23] Popular investments include backup generators or inverter-battery systems. Inverter-battery systems charge while electricity is flowing, and output electricity during electricity outages to specific outlets.

electricity outages.

Appendix Table C.2 shows the summary statistics for firms that we classify as having ever adopted any adaptation technology (Outage WiFi) compared to those for whom we do not observe any adaptation (No Outage WiFi). We observe that 61% of firms in our sample (6,929 out of 11,398) have transacted with a WiFi signal during power outages. The differences in WiFi usage during outages are not solely driven by differences in WiFi usage during non-outage periods: 45% of firms in the "No Outage WiFi" sample transacts over WiFi during non-outage periods.

Heterogeneity in adaptation behavior. Firms that adapt are observably different than those that do not: Adapting firms tend to be female-owned, less informal, and located in a wealthier neighborhood. Importantly, we find that adapting firms earn roughly R700 (64%) more daily and have nearly double the daily transactions compared to non-adapting firms.[24] Despite the mean differences, we find that there is substantial overlap in the revenue and transactions distribution between adopting and non-adopting firms (Appendix Figure C.8). This overlap is precisely the source of the misallocation in the welfare decomposition in Section III.

V.B.2. The effect of adopting defensive technologies

Whether the patterns we observe are due to differences between firm types or to defensive technologies has large implications for policy design and understanding the distributional consequences of rationing policies. To distinguish between these two explanations, we use the variation in timing of adaptation to estimate the effects of adopting any type of defensive technologies with an event-study design. Specifically, we aim to estimate whether we observe there are *differential* impact of an electricity outage among firms that adapt compared to firms that do not.

Denote the first day that we observe the firm transact with a WiFi connection during a power outage as the day of adoption. We consider the following equation:

$$y_{it} = \sum_{k \neq -1} \alpha^k \text{ Relative Day } k_{it} + \sum_{k \neq -1} \beta^k \text{ Relative Day } k_{it} \times \text{Outage}_{it} + \delta_t + \gamma_i + \varepsilon_{it} \tag{6}$$

where Relative Day k_{it} is a series of indicators equal to one when an observation is k days from the adoption date. We denote $k = 0$ as the observed adoption date. The coefficients of interest are β^k, which capture the differential effect of outages before and after the firm adopts a defensive technology.[25]

[24] The comparison is similar if we restrict to non-adapting firms that uses WiFi in non-outage periods. The average daily revenue in that sample is R975 and the average daily transactions is 3.93.

[25] We do not report the estimated coefficient on the day of adoption (Relative Days$_{it}$ = 0) since it is mechanically always a day with a power outage. We cannot separately identify the "pure" effect of adoption relative to the differential effect during outage days.

We restrict the analysis to firms for whom we observe to have ever conducted a transaction via WiFi during a power outage—thus comparing earlier-adopters to later-adopters. To address the staggered nature of the treatment, we estimate the parameters β^k specified in Equation 6 following the imputation procedure of Borusyak, Jaravel, and Spiess (2024). The first stage estimates untreated potential outcomes by regressing the outcome on the outage indicator, firm fixed effects, and date fixed effects using only pre-adoption observations. We then impute counterfactual outcomes for post-adoption observations and compute treatment effects as the weighted average of residuals at each event-time horizon, separately for outage and non-outage days. We residualize outcomes on within-firm day-of-week effects to absorb weekly seasonality patterns that the daily fixed effects do not fully capture in a pre-estimation step. Standard errors are obtained via a cluster bootstrap of 1,500 draws at the industry-by-load-shedding-block level, which jointly accounts for uncertainty from the imputation and the pre-estimation residualization.

Figure 3 plots the estimated $\hat{\beta}^k$ coefficients from Equation 6. We first test for differential pre-trends in the effect of an outage prior to adoption following the procedure in Borusyak, Jaravel, and Spiess (2024). The F-statistics are 0.977 and 1.124 for daily sales and transactions, respectively. The p-value of these tests are 0.446 and 0.345. Following the adoption of a defensive technology, we observe a persistent difference in the effect of electricity outages between adopting and not-yet-adopting firms. Figure 3 suggests that adopting firms experience substantially higher daily revenue (panel A) and more daily transactions (panel B) during outages compared to not-yet-adopters. The estimated effect of adopting a defensive technology (R200 and 0.75 transactions per day) is similar in magnitude to the differential effect of an electricity outage between high- and low-performers, implying that defensive technology adoption can substantially narrow the gap between high- and low-performers observed on outage days.

Mismeasurement. Given that we only observe a proxy of adoption, it is possible that the estimate might be biased. First, it is possible that some firms might not actually have adopted any defensive technologies even if we observe them to have transacted using WiFi during periods of outages. For example, if a firm uses the WiFi of a neighboring firm, we would misclassify them. To the extent that adaptation is mismeasured, this would bias our estimates *downwards*, making our estimates a lower bound on the true effect.

Second, the adoption date is conditional on transaction and an outage—thus the event time might be mismeasured. We note that the high frequency of outages in this setting compresses the gap between a firm's actual adoption and the first observed WiFi transaction during an outage. A firm that invests in backup power has an immediate incentive to use it at the next outage, and with a median of more than 25 outages per month (Table 1), opportunities for detection arise almost daily. A simple calculation illustrates the point. The median firm records approximately two transactions per day over roughly ten business hours. A two-hour outage window therefore coincides with at least one transaction with a probability of approximately one-third. Compounding across the more than six outages a typical firm faces per week, the probability of remaining undetected after one week is below ten percent and falls below one percent within two weeks. The lag between true adoption and first detection is thus measured in days, not weeks, well within the resolution of the seven-day event study window.

To alleviate measurement concerns, we repeat our analysis at the weekly level—where we consider the differential effect of having adopted a defensive technology on the effect of having experienced an *above-median* week of outage duration. Appendix Figure C.11 shows results that are similar to the Figure 3.

VI. Long run effects of frequent outages

The preceding sections documented large short-run distributional effects of electricity outages. Although the conceptual framework in Section III is static, the within-period reallocation it describes—repeated revenue losses for non-resilient firms and corresponding gains for resilient ones—can erode the financial position of marginal firms over time, shifting market composition toward more resilient incumbents.

VI.A. Longer run estimates

We first estimate whether the short-run effects that we estimate in Sections IV and V aggregate. One hypothesis might be that consumers substitute inter-temporally such that firms' total revenue over the course of a week, or a month, do not change. We test this by estimating Equation 3 at the firm-week and firm-month level in Appendix Table C.10. We ask whether firms that are more exposed to outages over a given week or month also experience losses to revenue and transactions. We find that the daily short-run effects aggregate to longer-run losses at both the weekly and monthly level for below-median firms; and longer-run *gains* for above-median firms.

These results suggest that *frequent* outages are not transitory disruptions whose effects wash out over longer horizons. If electricity outages were rare or one-time events, we might expect consumers to substitute inter-temporally—delaying a purchase during an outage and returning to their regular firm the following day or week. But under chronic exposure, where firms and consumers face recurring outages multiple times per week, the incentive to wait diminishes: consumers cannot perpetually defer spending, and each successive outage reinforces the habit of patronizing firms that remain operational. Consistent with this, we find no evidence of inter-temporal substitution at the weekly or monthly level. Revenue lost by below-median firms during outage hours is not recovered in subsequent days, while the gains accruing to above-median firms persist. The within-day reallocation documented in Section V therefore compounds with outage frequency, progressively widening the cumulative revenue gap between resilient and non-resilient firms.

This distinction is important for interpreting the economic costs of electricity outages. Many firms in low- and middle-income countries experience endemic outages: the average firm experiences roughly nine electricity outages per month in sub-Saharan Africa (World Bank 2024). Our results suggest that in these settings, the distributional effects of outages accumulate. This raises the possibility that sustained exposure reshapes not only firm revenues but also market composition.

VI.B. Suggestive evidence on entry and exits

If repeated revenue losses cause below-median firms to exit at higher rates, the long-run consequences of frequent outages may be substantially larger than the within-day reallocation we have documented. Moreover, periods of frequent outages might discourage entry of particular firms, shifting market composition toward more resilient incumbents. Because entry and exit may respond to the *expectation* of future outage paths rather than contemporaneous exposure alone, we view our results in this section as suggestive since the empirical strategy presented in Section IV.A do not directly apply.

Our empirical approach models platform exit at the firm level and entry at the market level. For exit, the population at risk is observed—every active firm in a given month can potentially exit—making firm-level linear probability and hazard models a natural specification. We estimate linear probability models of platform exit at the firm-month level with firm and month fixed effects, interacting block-level log outage duration with an above-median indicator to test for heterogeneous exit responses. Because exit reflects accumulated financial stress rather than a single day's shock, we estimate a one-month lagged specification as our preferred estimates.

Table 7 presents the results. Columns (1)–(3) report log-hazard coefficients from estimating Cox proportional hazard models with block $\times$ industry fixed effects stratified by above- and below-median firms; columns (4)–(6) report linear probability models with firm and month fixed effects. All specifications use lagged block-month outage duration as the treatment.

The Cox proportional hazard models indicate that outage exposure is associated with higher rates of firm exit. In the uninteracted specification (column (1)), a one log-point increase in lagged outage duration raises the hazard of exit by approximately 28 percent. When the effect is allowed to vary by firm performance (columns (2) and (3)), the interaction terms are negative, suggesting that above-median firms may be less exposed to outage-induced exit, but they are not statistically distinguishable from zero and the main effect loses precision once the sample is stratified.

The linear probability models with firm fixed effects sharpen this pattern. Column (5) estimates that a one log-point increase in the prior month's outage duration raises the exit probability of below-median firms by 0.25 percentage points, approximately 25 percent of the mean monthly exit rate of

0.95 percent. The differential for above-median firms is –0.11 percentage points, offsetting roughly half of the baseline effect. The pattern is nearly identical when above-median status is defined within industry $\times$ block cells (column (6)). In both specifications, the interaction is significant at the 1% level.

The LPM specification requires that outage exposure be predetermined relative to exit. This assumption is supported by the fact that load shedding schedules are driven by supply-side grid constraints rather than individual firm trajectories. Because exit is an absorbing state, however, the within-firm estimator identifies the effect of outage exposure on the *timing* of exit among firms that ultimately fail, and the inclusion of never-exiting firms in the estimation mechanically attenuates the main coefficient toward zero. The LPM estimates in columns (4)–(6) should therefore be interpreted as a complement to the Cox specification rather than as population-level exit probabilities, and the sharper statistical significance of the interaction terms partly reflects the restricted margin of identifying variation.

We next examine whether outage exposure shapes platform entry. In this case, the set of potential entrants is unobserved, so we aggregate entry counts to the block-month level (Dunne, Roberts, and Samuelson 1988; Hjort and Poulsen 2019). Panel A of Table 8 estimates the effect of outage intensity on entry counts at the block-month level, separately for above- and below-median entrants. Contemporaneous outage duration has no significant average effect on the number of entrants (column (1)). The lagged specification, however, reveals a compositional shift: a one log-point increase in lagged outage intensity differentially raises above-median entry by 0.34 firms per block-month, while below-median entry is unaffected (column (4)). This differential effect is statistically significant at the 1% level. Outage exposure thus selectively expands the presence of higher-performing firms at the entry margin, mirroring the exit-side finding.

Panel B of Table 8 examines entrant composition conditional on entry. Firms that enter blocks with greater outage intensity have significantly higher initial revenue: a one log-point increase in outage duration at entry is associated with 0.20 log points higher first-month revenue (column (1)). These entrants are also somewhat more likely to be above-median performers, though this effect is only marginally significant (column (2)). Moreover, entrants in higher-outage blocks are 3.3 percentage points less likely to exit the platform over the sample period (approximately 16 percent of the mean exit rate among entrants; column (3)).

Taken together, the exit and entry results point to a compositional shift in platform participants driven by electricity rationing. On the exit margin, outage exposure raises the overall hazard of firm exit, with suggestive evidence that this effect may be concentrated among below-median incumbents. On the entry margin, outage intensity selectively attracts above-median entrants who start larger and survive longer. The net effect is a reallocation of platform activity away from less-resilient firms and toward better-positioned competitors.

This pattern is consistent with the extension of our framework in which a firm remains in the market only if its expected outage-state revenue exceeds its outside option. Because non-resilient firms earn zero during outages, chronic exposure reduces their expected revenue in proportion to outage probability q, pushing marginal firms below the viability threshold. The increase in exit risk following outage months, and its concentration among below-median incumbents, is consistent with q accumulating over time to erode the financial position of the least resilient firms, while the selection of more resilient entrants reflects the same mechanism operating on the other margin of market composition.

These results carry an important caveat. Entry and exit are defined by appearance on and disappearance from the payments platform, and we cannot directly observe transactions outside it. High-performing firms, having greater financial sophistication, are more likely than lower-performing peers to use alternative payment systems, as evidenced by survey responses reported in Table C.14. It may be possible that observed exits by high-performers are simply migration to another platform rather than truly exiting the market. This implies that the differential exit rates documented here are, if anything, a lower bound on the true reallocation of market presence toward baseline higher-performing firms. Moreover, this compositional shift need not imply improved market efficiency. The framework in Section III highlights that outages select for firms that can finance resilience rather than those with the highest underlying productivity or growth potential, meaning below-median firms may have low current revenue only because they are young or credit-constrained, not because they lack the capacity to grow. Thus, the misallocation component of the welfare loss may increase even as observable market composition (via our measures) appears to strengthen.

VII. The role of anticipation and implications for policy design

The previous sections show that the ex-ante equal rationing of electricity outages generates unequal effects in Cape Town. These unequal effects are driven by firm heterogeneity in the capacity to adapt and consumers consequently substituting toward firms with the ability to serve them. We investigate the role of anticipation in the effects of rationing and discuss its implications for the design of rationing policies. We use data on the timing of electricity outage announcements and perform heterogeneity analysis by the days of advance notice given.

The framework in Section III identifies a specific channel through which advance notice can amplify these disparities. Owning backup power is necessary but not sufficient for continued operation—firms must also fuel generators, adjust staffing, and take other preparatory steps. Advance notice gives firms time to take these steps, raising the fraction of outage windows during which a firm with backup power is fully operational. If better-resourced firms are able to respond more effectively, notice raises average resilient capacity while widening the gap between firms that can and cannot translate warning into continued service. Appendix A provides more details on these predictions.

We scrape Eskom's announcement page to collect information on each load shedding announcement and measure the number of days between the announcement and the outage event using the publishing date. Appendix Figure C.5 shows an example announcement. Eskom does not necessarily publish all announcements on its website, and not all outage events are accompanied by an announcement. We therefore limit the sample to the outage events that we can link to an Eskom announcement and to the outage events where Eskom announced an *increase* in severity. Appendix Figure C.6 shows the distribution of the days between the announcement date and the outage events in this sample.

We first consider whether this sample of outages are selected relative to the full sample of electricity outages. We replicate the key results from Table 3 in Appendix Table C.7, where we include only the outage days that were accompanied with an announcement and days without any outages. We find that the magnitudes in this sample are roughly 60% of the estimated magnitudes in Table 3. While the sample of outages appear to be a selective set, the mechanisms we observe within this sample remains similar to the larger set of outages.

We augment Equations 2 and 3 with an additional interaction for the days of notice associated with the day's outages:

$$
\begin{aligned}
y_{it} =& \beta_1 \text{ Outage}_{it} + \beta_2 \text{ Outage}_{it} \times \text{Days of Notice}_t + \beta_3 \text{ Outage}_{it} \times X_i + \\
& \beta_4 X_i \times \text{Days of Notice}_t + \beta_5 \text{ Outage}_{it} \times X_i \times \text{Days of Notice}_t + \delta_t + \gamma_i + \varepsilon_{it}
\end{aligned}
\tag{7}
$$

Notice that "Days of notice" varies at the day-level as we take the latest announcement available for each day's outages.

Table 6 shows the results. Columns (1) and (3) decompose these averages by absolute performance, revealing that the gains from advance notice accrue entirely to above-median firms. We find that the effect of an outage between above and below-median firms widens when there are additional days of notice for the outage. An additional day of notice widens the differences in the outage effect by roughly R100 and 0.2 transactions. We estimate noisy negative effects of outages for below-median firms when an announcement is made on the same day. Similarly, we do not estimate meaningful differences in the effect of an outage announced on the same day between above and below-median firms. These noisy estimates are plausibly from same-day announcements that declare electricity outages at night (e.g. 10pm-12am). It is not the case that this selected sample of outages do not affect below-median firms: Appendix Table C.7 estimates that outages reduces revenue by R91 and transactions by 0.2 transactions for below-median firms. Columns (2) and (4) confirm that the results are robust to measuring relative performance within industry-by-block.

It is possible that advance notice might also reflect different *types* of outages. An outage announced on the same day might be more severe than the a planned outage due to plant maintenance. Appendix Table C.12 shows that these effects are not driven by "selection" of outages that receive advance notice—the estimated coefficients remain similar in magnitude and statistical significance even when controlling for the severity and duration of the outages.

These results reveal a complementarity between advance notice and adaptation capacity. Firms without defensive technology are entirely outside the resilient set and have nothing to activate when warned; for them, advance notice is inoperative. Above-median firms—which are disproportionately likely to have invested in backup power—can use notice to prepare for outages, and the activation margin $y_i(n)$ described in Appendix Section A.E translates additional lead time into a higher fraction of outage windows during which they remain fully operational. This does not expand the set $\mathcal{G}$ of firms with backup power, but it raises each member's activation probability $y_i(n)$, leading to an increase in effective resilient capacity $M_{\mathcal{G}}(n)$, thus amplifying the reallocation toward already-resilient firms.

It is therefore not that advance notice harms below-median firms—their losses are unchanged. But that its benefits are conditional on adaptation capacity, so they accrue exclusively to firms that already have it. We view policies that broaden adaptation capacity are particularly important when rationing is accompanied by advance warning.

VIII. Conclusion

South Africa's rotational load shedding regime offers a clean setting for observing how equal rationing move through local product markets. Exploiting the quasi-random timing and geography of Cape Town's load shedding schedule, we find that a single day of power loss does not depress aggregate SME sales, with daily revenue and transactions unchanged on average. This aggregate figure hides stark distributional effects. outages reduce revenue for baseline low-performing firms by roughly eleven percent of the sample mean of daily revenue while raising sales for high-performing firms by a similar magnitude, widening an existing performance gap. The divergence stems from consumer reallocation rather than demand destruction; consumers shift spending from lower-performing businesses to higher-performing competitors able to keep the lights on. Advance notice amplifies this pattern through a complementarity with adaptation capacity: its benefits accrue entirely to above-median firms that can translate warning into preparation, while below-median firms' losses are unchanged. These short-run reallocations appear to accumulate over time: outage exposure raises the hazard of firm exit and this effect is concentrated among less-resilient incumbents, while entrants during high-outage periods are disproportionately drawn from better-capitalized firms. These differential effects imply that the welfare costs of rationing fall most heavily on marginal firms and the workers and consumers they serve, even as aggregate market activity undergoes a compositional change.

The conceptual framework allows us to quantify these welfare costs through a back-of-the-envelope calculation. Calibrating the CES model to realized revenue shares and adoption in our data, we estimate that consumer welfare falls by approximately one-third during outage hours at moderate parameter values, with the annualized cost reaching roughly 4% of platform consumption when scaled by the fraction of business activity hours affected by outages (Appendix A.G). The decomposition reveals that misallocation accounts for a relatively large share of the welfare loss due to adoption being only weakly correlated with baseline productivity. Further, static consumer welfare losses likely understate the full cost: firms that exit account for 3.9 times as much productive capacity as would be lost under efficient selection from the bottom of the revenue distribution upwards, suggesting that the documented reallocation dynamics carry substantial aggregate consequences.

These findings have direct implications for policy, and the conceptual framework identifies three levers that interact. First, formally equal rotation schedules do not yield equal outcomes because staying operational depends on both baseline performance and financial capacity. Reducing the fixed cost of backup power, through subsidies, shared energy hubs, or standardized solutions, broadens the set of resilient firms and narrows the inequality that results from consumer substitution. Second, relaxing the financial-capacity constraint, through matching grants, concessional finance, or landlord-incentive programs, can bring high-potential but financially constrained firms into the resilient set, reducing the misalignment between adaptation and baseline performance that the framework highlights. Third, the design of outage communication matters: advance notice is a complement to adaptation capacity, raising effective resilient capacity among firms that already have the ability to act while doing nothing for those without it. Long lead times should therefore be paired with complementary support that enables disadvantaged firms to translate notice into continued service. Because these levers interact—notice is most beneficial when firms can afford to act on it—policy packages that combine cost reduction, financial access, and communication design are likely to be more effective than any single intervention.

Our results have implications beyond Cape Town; they take on particular significance given the changing nature of structural transformation in the developing world. As manufacturing's role as an engine of convergence has diminished (Rodrik 2016), productivity growth in consumer services—retail, hospitality, personal care—has become central to development prospects (Fan, Peters, and Zilibotti 2023; Nayyar, Hallward-Driemeier, and Davies 2021). Small and young firms in these sectors are disproportionately responsible for net job creation (Ayyagari, Demirgüç-Kunt, and Maksimovic 2011) yet they are precisely the firms most vulnerable to the reallocation dynamics we document. As climate change and aging infrastructure increase the frequency of essential-service shortages across emerging markets, understanding whether ostensibly equal rationing produces systematically unequal outcomes among these firms is of first-order importance for both growth and equity.

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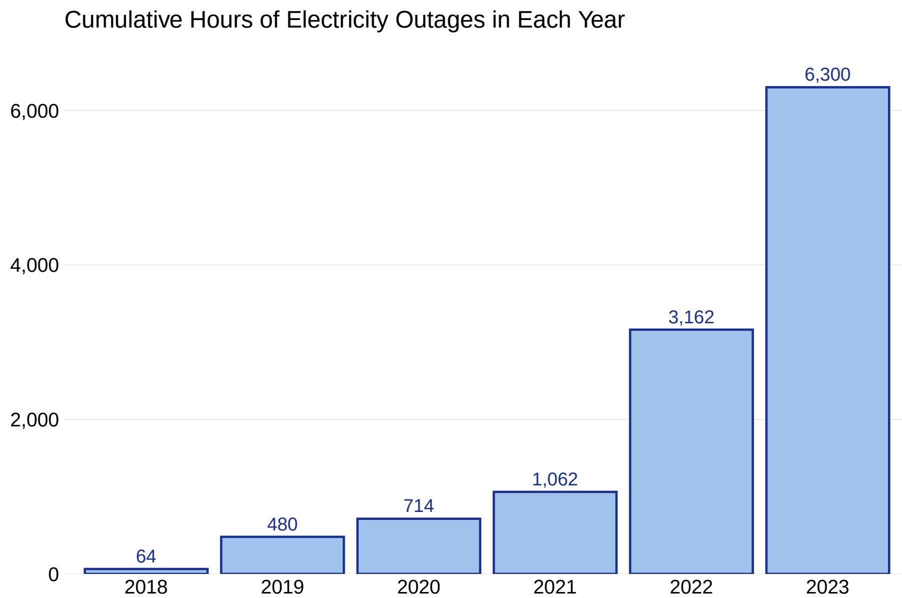
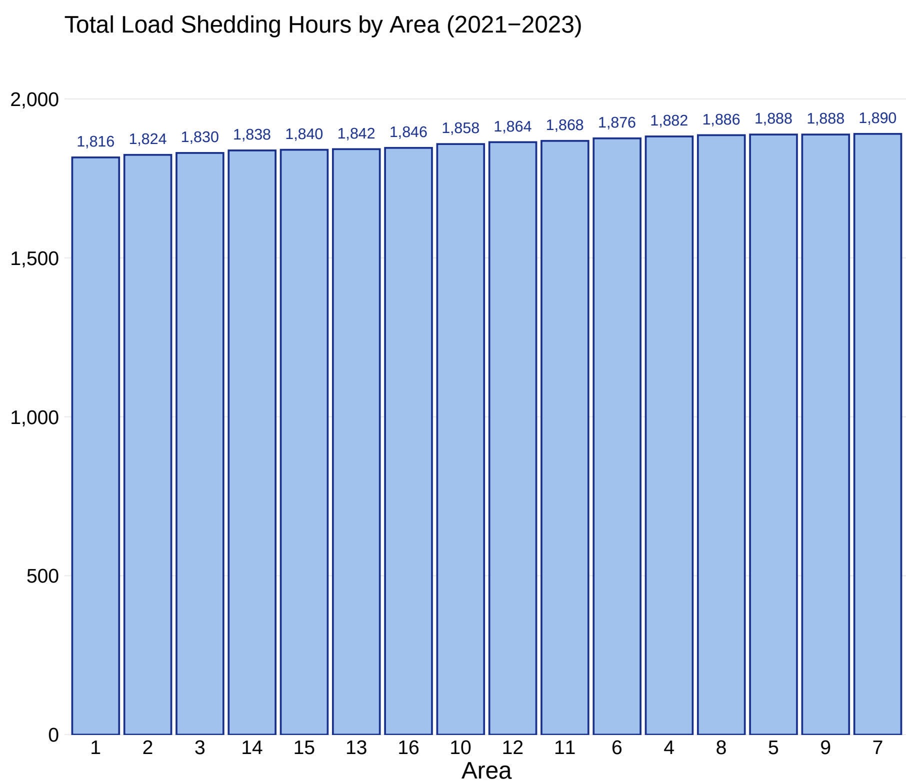
Figures

FIGURE 1. Outage Severity Across Time and Geography

A. Hours of Electricity Outages in Cape Town 2018–2023



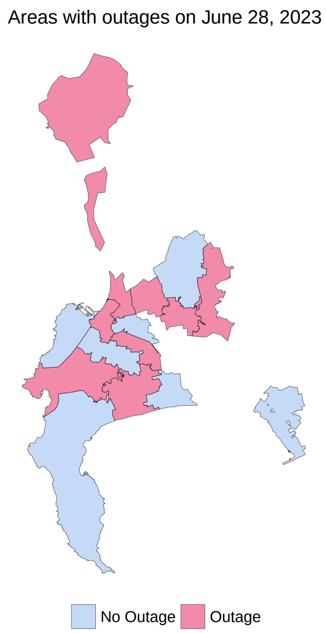
B. Hours of Electricity Outages Across Load Shedding Blocks 2021-2023



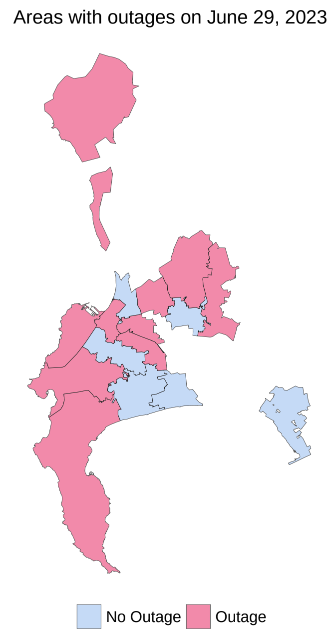
Note: This figure shows distribution of outages in Cape Town across time. Panel A plots the cumulative hours with electricity outages from 2018–2023. Panel B plots the cumulative hours of electricity outages experienced by each load shedding block during our analysis period of 2021–2023.

FIGURE 2. Daily and Weekly Variation in Electricity Outages

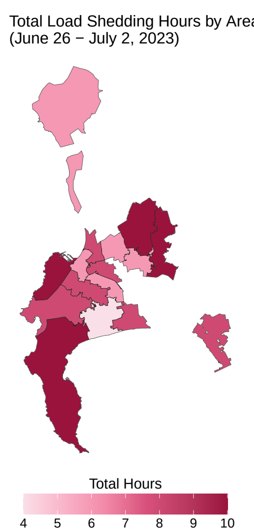
A. Areas with Electricity Outages on 2023-06-28



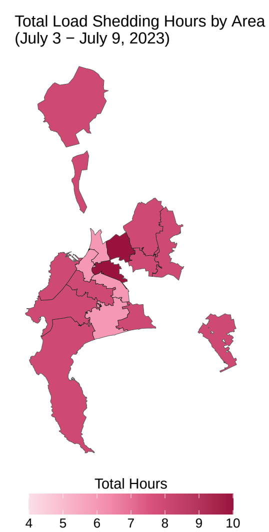
B. Areas with Electricity Outages on 2023-06-29



C. Cumulative Hours of Outages, Week 1 June 2023



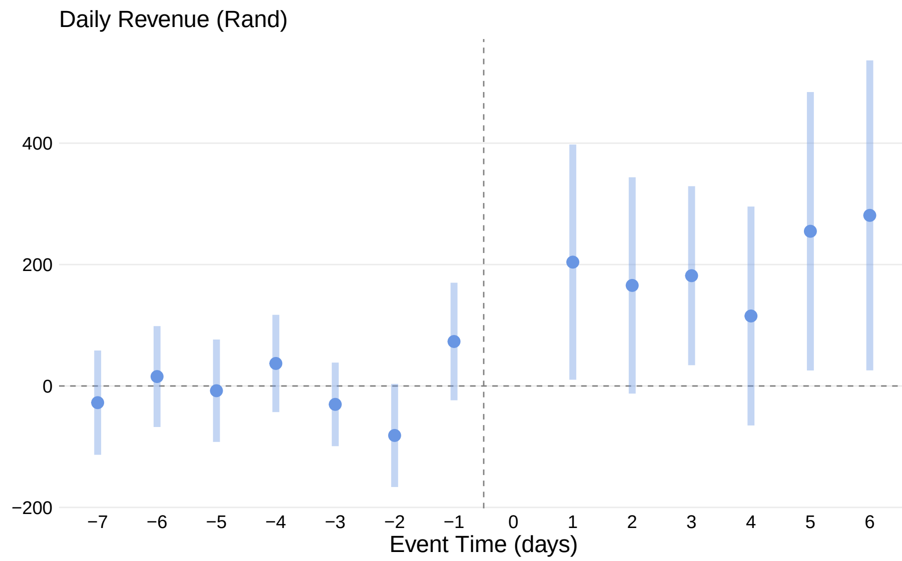
D. Cumulative Hours of Outages, Week 2 July 2023



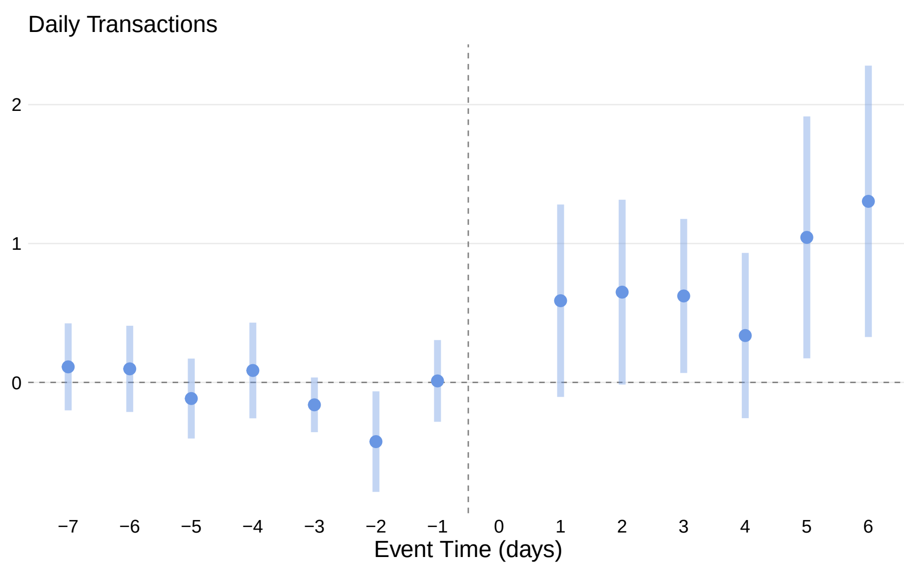
Note: This figure illustrates daily and weekly geographic variation in electricity outages in Cape Town. Panels A and B map the areas experiencing an electricity outage on two consecutive days: 2023/06/28 and 2023/06/29. Panels C and D show cumulative outage hours by load shedding block for two different weeks: June 26–July 2, 2023 and July 3–July 9, 2023. On both days, the severity (the “stage” which determines the number of areas with an outage) and the geography (specific areas with an outage) differ, reflecting the rotational nature of the load shedding schedule.

FIGURE 3. Event Study of Defensive Technology Adoption

A. Daily Sales



B. Daily Transactions



Note: This figure plots the estimated $\hat{\beta}^k$ coefficients from Equation 6, which capture the differential effect of an electricity outage on firm performance before and after the adoption of a defensive technology (e.g., backup power). Panel A plots the effect on daily sales and Panel B plots the effect on daily transactions. The event date ($k = 0$) is defined as the first day a firm is observed transacting via WiFi during a power outage. We omit the event-date coefficient since it is mechanically a day with a power outage. Standard errors are bootstrapped with 1,500 draws. Dashed lines indicate 95% confidence intervals.

Tables

TABLE 1. Summary Statistics

	N	Mean	SD	Min	P25	P50	P75	Max
Daily								
Revenue	11398	1682.65	4514.36	163.08	355.9	713.52	1634.9	318933.12
Card Revenue	11398	1630.74	4478.68	0	338.37	682.2	1570.44	318933.12
Cash Revenue	11398	103.43	5221.26	0	0	0	1.17	556122.53
Transactions	11398	6.7	23.78	0.02	0.71	1.93	5.84	1833.91
Card Transactions	11398	6.21	23.32	0	0.68	1.81	5.26	1833.91
Cash Transactions	11398	0.49	2.98	0	0	0	0	129.64
Outages	11398	0.95	0.39	0	0.82	0.85	1.2	3.18
Monthly								
Revenue	11398	46977.8	94955.33	5000.02	10131.81	20406.58	46564.59	2900284.34
Card Revenue	11398	45500.67	93681.13	0	9606.01	19390.54	44420.46	2900284.34
Cash Revenue	11398	3060.88	161767.71	0	0	0	33	17239796.17
Transactions	11398	184.86	455.97	0.67	20.45	54.55	164.67	23125.38
Card Transactions	11398	170.7	438.14	0	19.56	51.73	149.02	23125.38
Cash Transactions	11398	14.15	82.25	0	0	0	0.11	2417.51
Outages	11398	27.97	11.41	0	24.84	25.54	35.52	66.5
Lifetime								
Revenue	11398	1190789.6	2772182.57	6500	198666.72	431742.38	1106538.57	89059413.43
Card Revenue	11398	1154043.75	2723359.45	0	190074.9	415916.16	1069135.9	89059413.43
Cash Revenue	11398	94458.43	5981254.56	0	0	0	775.72	637872458.46
Transactions	11398	4517.67	13937.17	2	376.2	1110.95	3463.75	855638.92
Card Transactions	11398	4186.59	13462.43	0	359	1038.9	3213	855638.92
Cash Transactions	11398	330.97	2123.43	0	0	0	2.98	56509.58
Outages	11398	676.01	330.32	0	425	873	921	945
Other Establishment Characteristics								
Property Value in Suburb (Thousand Rand)	10287	2177.12	1674.03	63.86	1000	1600	3250	19050
Age of Firm	11398	1160.94	670.95	31	632	1044	1613	2518
$\mathbb{1}$(Mobile Industry)	11398	0.17	0.37					
$\mathbb{1}$(Uses WiFi)	11398	0.74	0.44					
$\mathbb{1}$(Informal)	11398	0.17	0.37					
$\mathbb{1}$(Foreign-Owned)	11398	0.13	0.33					
Age of Owner	10334	48.08	12.31	19	39	47	57	98
$\mathbb{1}$(Female-Owned)	10334	0.48	0.5					

Note: This table shows the summary statistics of the 11,398 unique firms in our main analysis sample with monthly revenue exceeding 5,000 ZAR that excludes any firms within 250 meters of the load shedding border. We summarize firms by their average daily and monthly revenue and transactions, total lifetime revenue, and other firm characteristics. Note that we first present the daily and monthly averages at the firm level. We report the outcome means at the firm-day and firm-month levels in the subsequent regression tables.

TABLE 2. Balance table

	No blackouts $N = 4,355,261$		Blackouts $N = 3,613,788$		
	Mean	SD	Mean	SD	p
Panel A: Firm Characteristics					
Average Daily Revenue (Rand)	1469.987	2063.808	1471.638	2066.863	0.168
Average Daily Transactions	5.441	9.768	5.549	9.937	0.533
Number of Days on Platform	1520.574	616.168	1391.906	622.556	0.155
$\mathbb{1}$(Informal)	0.155	0.362	0.163	0.369	0.341
$\mathbb{1}$(Services)	0.481	0.500	0.480	0.500	0.854
Age of Owner	48.949	12.043	48.787	12.208	0.761
$\mathbb{1}$(Female-Owned)	0.500	0.500	0.491	0.500	0.744
$\mathbb{1}$(Owner is Citizen)	0.879	0.326	0.873	0.333	0.121
Property Value in Suburb (Thousand Rand)	2173.039	1630.517	2180.167	1677.995	0.014
$\mathbb{1}$(Uses WiFi)	0.819	0.385	0.779	0.415	0.150
Panel B: Industry Composition					
Food, drink, and hospitality	0.245	0.430	0.250	0.433	0.883
Healthcare, Beauty, and Fitness	0.257	0.437	0.251	0.434	0.944
Home and Repair	0.069	0.253	0.067	0.251	0.727
Leisure and Entertainment	0.020	0.141	0.023	0.150	0.823
Personal Services	0.035	0.183	0.035	0.185	0.859
Professional Services	0.063	0.243	0.059	0.236	0.861
Retail	0.274	0.446	0.269	0.444	0.965
Transportation	0.012	0.111	0.017	0.128	0.777
Travel and Tourism	0.025	0.157	0.027	0.163	0.791

Note: This table presents a test of covariate balance across firms experiencing an electricity outage vs. firms that are not on any given day. We report the means and standard deviations by each group and the p-value of the difference between the two groups. The p-values are calculated by regressing each covariate against an indicator for whether the firm experiences an outage on a particular day, conditional on date fixed effects. Panel A shows key firm characteristics while Panel B shows the industry composition between the two groups. We also run a stacked regression of all the covariates against whether a firm experiences an electricity outage on any given day. The p-value on a joint test is 0.441.

TABLE 3. Effect of outages on firm revenue and transactions

Panel A: Daily Sales						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	241.9***	6.802	-6.842	-157.4***	-151.6***	-166.5***
	(24.36)	(10.31)	(4.962)	(20.91)	(19.35)	(22.87)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				307.0***		209.5***
				(35.51)		(23.28)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					292.5***	114.9***
					(37.49)	(35.75)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,470.7	1,470.7	1,470.7	1,470.7	1,470.7	1,470.7
R^2	0.00146	0.01813	0.44834	0.44888	0.44883	0.44890
Observations	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049

Panel B: Daily Transactions						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.8697***	0.0395	-0.0169	-0.4081***	-0.3741***	-0.4209***
	(0.1375)	(0.0940)	(0.0215)	(0.0953)	(0.0786)	(0.0967)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)				0.7978***		0.6613***
				(0.1752)		(0.2004)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)					0.7215***	0.1610
					(0.1494)	(0.1212)
Date FE	No	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.4899	5.4899	5.4899	5.4899	5.4899	5.4899
R^2	0.00108	0.01199	0.57052	0.57073	0.57069	0.57074
Observations	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on daily sales (panel A) and daily transactions (panel B). The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage in columns 1–3 of panels A and B. In columns 4–6, the coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage for below-median firms and the coefficient on $\mathbb{1}$(Outage) interacted with either $\mathbb{1}$(Above Median) or $\mathbb{1}$(Above Median in Industry × Block) represents the differential effect of an outage for above-median firms relative to below-median firms. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 4. Robustness

Panel A: Instrumental Variables Estimates

	Daily Sales			Daily Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-6.534	-157.1***	-151.2***	-0.0174	-0.4082***	-0.3731***
	(4.478)	(21.06)	(19.48)	(0.0217)	(0.0951)	(0.0785)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)		307.0***			0.7969***	
		(35.44)			(0.1749)	
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)			292.3***			0.7186***
			(37.35)			(0.1484)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,470.7	1,470.7	1,470.7	5.4899	5.4899	5.4899
Observations	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049

Panel B: Alternative Border Cutoffs

	Daily Sales			Daily Transactions		
	All	$\geq$ 500m	$\geq$ 1km	All	$\geq$ 500m	$\geq$ 1km
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-147.9***	-155.9***	-166.8***	-0.3707***	-0.3914***	-0.4136***
	(18.20)	(20.59)	(23.06)	(0.0702)	(0.0842)	(0.0934)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)	286.4***	299.2***	314.6***	0.7230***	0.7530***	0.7864***
	(35.40)	(39.57)	(44.62)	(0.1381)	(0.1599)	(0.1779)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,455.5	1,489.7	1,533.0	5.4052	5.5645	5.6817
R^2	0.44539	0.45096	0.45496	0.56565	0.57247	0.58014
Observations	8,844,929	7,279,628	5,955,427	8,844,929	7,279,628	5,955,427

Panel C: Pre-Period Above-Median Definition

	Daily Sales			Daily Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	3.655	-144.1***	-134.2***	-0.0284	-0.3324***	-0.2991***
	(13.86)	(21.06)	(20.61)	(0.0412)	(0.0915)	(0.0904)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)		270.2***			0.5560***	
		(24.28)			(0.1383)	
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)			244.7***			0.4804***
			(27.04)			(0.1306)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2,576.0	2,576.0	2,576.0	9.2499	9.2499	9.2499
R^2	0.59975	0.59995	0.59992	0.73805	0.73810	0.73808
Observations	690,315	690,315	690,315	690,315	690,315	690,315

Note: This table presents robustness checks. Panel A reports instrumental variable estimates using the load shedding schedule as an instrument for realized outage exposure. We construct the instrument by considering whether a firm's position on the schedule is at or below the stage cut-off. Appendix Table C.5 shows the first-stage. Panel B reports estimates from Equation 3 for varying border exclusion distances to assess sensitivity to potential SUTVA violations. Panel C reports estimates using a pre-period definition of above-median performance. We limit the analysis to January 2023 – December 2023 and firms who have been active since 2021. We use revenue from January – December 2021 as the pre-period revenue. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5. Effect of outages on consumer substitution

Panel A: Card-Day Level

	Below Median Merchant Spending		Above Median Merchant Spending	
	(1)	(2)	(3)	(4)
$\mathbb{1}(\leq$P50 Regular Firm Outage)	-0.4254***		0.1226**	
	(0.0575)		(0.0495)	
$\mathbb{1}(>$P50 Regular Firm Outage)		0.0365		-0.1899***
		(0.0510)		(0.0365)
Date FE	Yes	Yes	Yes	Yes
Card FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.4822	2.4822	11.299	11.299
R^2	0.01101	0.01100	0.05552	0.05552
Observations	40,787,210	40,787,210	40,787,210	40,787,210

Panel B: Card-Industry-Day Level

	Spending at Below Median Merchant		Spending at Above Median Merchant	
	(1)	(2)	(3)	(4)
$\mathbb{1}(\leq$P50 Regular Firm Outage)	-0.3554***		0.1466***	
	(0.0399)		(0.0229)	
$\mathbb{1}(>$P50 Regular Firm Outage)		0.0801***		-0.0711***
		(0.0260)		(0.0157)
Date FE	Yes	Yes	Yes	Yes
Card-Industry FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.94147	0.94147	4.4584	4.4584
R^2	0.01256	0.01255	0.06085	0.06085
Observations	45,951,631	45,951,631	45,951,631	45,951,631

Note: This table presents estimates from Equation 4 and Equation 5 on the effect of an electricity outage to a card's regular firm on two outcomes: Average daily spending at below and above median average daily revenue merchants. We consider two cases of a "regular firm outage": if the outage is to a regular firm that is below-median or above-median in daily revenue. Panel A examines within-card substitution across all firms and Panel B examines within-card-industry substitution (i.e., substitution within the same industry). In both panels, we restrict to the same set of cards for whom we are able to identify at least 2 regular merchants *within* the same industry. Standard errors are clustered at the card level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6. Effect of outages on firm revenue and transactions by announcement date

	Daily Sales		Daily Transactions	
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Outage)	-25.21	-22.33	-0.0053	0.0044
	(26.55)	(26.17)	(0.0973)	(0.0954)
$\mathbb{1}$(Outage) $\times$ Days of Notice	-29.54	-28.37	-0.0640	-0.0538
	(20.56)	(20.60)	(0.0600)	(0.0676)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)	-0.8673		-0.0694	
	(18.05)		(0.0564)	
Days of Notice $\times$ $\mathbb{1}$(Above Median)	86.04***		0.2960***	
	(18.34)		(0.0857)	
$\mathbb{1}$(Outage) $\times$ Days of Notice $\times$ $\mathbb{1}$(Above Median)	101.4***		0.1883***	
	(19.18)		(0.0526)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)		-7.917		-0.0920*
		(17.90)		(0.0478)
Days of Notice $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)		81.66***		0.2735***
		(18.30)		(0.0798)
$\mathbb{1}$(Outage) $\times$ Days of Notice $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)		99.91***		0.1712***
		(17.38)		(0.0601)
Firm FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,373.7	1,373.7	5.1294	5.1294
R^2	0.43921	0.43919	0.56501	0.56500
Observations	4,919,137	4,919,137	4,919,137	4,919,137

Notes: This table presents estimates from Equation 7. We limit the sample of electricity outages to those for which we observe an announcement of worsening severity. We measure "Days of Notice" as the difference between the date of the announced outage and the announcement date. Across all columns, $\mathbb{1}$(Outage) captures the effect of an outage with zero days of notice for below-median firms; $\mathbb{1}$(Outage) $\times$ Days of Notice captures how an additional day of notice changes the outage effect for a below-median firm. $\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median) captures the differential outage effect for above-median firms relative to below-median firms when days of notice is zero; $\mathbb{1}$(Above Median) $\times$ Days of Notice captures differential trends in the outcome by firm type on days with more advance warning, independent of outage exposure. $\mathbb{1}$(Outage) $\times$ Days of Notice $\times$ $\mathbb{1}$(Above Median) captures how the effect of an additional day of advance notice during an outage differs between above- and below-median firms. The dependent variable is daily sales in columns (1)–(2) and daily transactions in columns (3)–(4). Standard errors are clustered at the industry-by-load-shedding-block level.***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 7. Exits

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Log Outage Duration	0.2447**	0.2934*	0.3163**	0.0020**	0.0025**	0.0027**
	(0.1209)	(0.1581)	(0.1574)	(0.0010)	(1e-03)	(1e-03)
Lagged Log Outage Duration × Above Median		-0.1161			-0.0011***	
		(0.2364)			(3e-04)	
Lagged Log Outage Duration × Above Median (Ind × Block)			-0.1722			-0.0012***
			(0.2362)			(3e-04)
Observations	236,875	236,875	236,875	236,679	236,679	236,679
R^2	–	–	–	0.1199	0.1199	0.1200
Adj. R^2	–	–	–	0.0776	0.0776	0.0777
Month FE	No	No	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes	Yes	Yes
Block × Industry FE	Yes	Yes	Yes	No	No	No
Dep. Var. Mean	–	–	–	0.0095	0.0095	0.0095
Estimator	Cox PH	Cox PH	Cox PH	LPM	LPM	LPM

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: This table presents estimates of the effect of load shedding on firm exit. Columns (1)–(3) report Cox proportional hazard models stratified for above and below median firms, clustered at the industry × block level. Coefficients reported are log-hazard coefficients. Columns (4)–(6) report linear probability models with firm and month fixed effects, also clustered at the industry × block level. The dependent variable is an indicator for firm exit in a given month; firms leave the sample upon exit. The outage duration measure is the lagged block-month level outage, logged as $\log(1+x)$. The above median indicator equals one if a firm's average monthly revenue exceeds the sample median, computed within the analysis sample after applying the 5,000 ZAR/month revenue filter. In columns (3) and (6), the above median indicator is instead computed within industry × block cells. The Cox models report log-hazard coefficients in the coefficient column; the LPM models report marginal effects on the probability of exit. Because exit is an absorbing state, the LPM identifies the effect of outage exposure on exit timing among firms that eventually exit. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8. Entry Effects

Panel A: Entry Counts

	Number of Entries			
	(1)	(2)	(3)	(4)
Log Outage Duration	-0.0508	-0.1585		
	(0.4023)	(0.4067)		
Log Outage Duration × $\mathbb{1}$(Above Median)		0.2152*		
		(0.1076)		
$\mathbb{1}$(Above Median)		-1.194**		-1.587**
		(0.4355)		(0.6589)
Lagged Log Outage Duration			0.2412	0.0718
			(0.2954)	(0.2909)
Lagged Log Outage Duration × $\mathbb{1}$(Above Median)				0.3389***
				(0.0713)
Month FE	Yes	Yes	Yes	Yes
Block FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	5.6900	5.6900	5.7483	5.7483
R^2	0.67902	0.68277	0.68232	0.68744
Observations	1,184	1,184	1,152	1,152

Panel B: Entrant Composition

	Log Sales	Above Med.	Ever Exit
	(1)	(2)	(3)
Log Outage Duration at Entry	0.1959***	0.0074*	-0.0329***
	(0.0156)	(0.0040)	(0.0025)
Block FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Dep. Var. Mean	8.2472	0.47647	0.20261
R^2	0.02898	0.03136	0.04851
Observations	6,737	6,737	6,737

Note: Panel A presents estimates of the effect of load shedding on firm entry counts at the block-month level, split by above/below median firm performance. The dependent variable is the number of entries per block-month-performance group. Panel B examines entrant composition conditional on entry. The dependent variable in column (1) is the log of entry-month sales; in column (2), an indicator for whether the entrant's average revenue exceeds the sample median; and in column (3), an indicator for whether the entrant subsequently exits during the sample period. The outage measure in Panel B is the block-level log outage duration in the firm's entry month. All logged variables are defined as $\log(1 + x)$. Standard errors are clustered at the load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Supplemental Appendix to: "Reallocation Under Rationing: Evidence from Electricity Outages in South Africa"

Rowan Clarke, F. Christopher Eaglin, Zachary Kuloszewski, and Jun Wong

Appendix A. Conceptual framework details and proofs

This appendix develops the framework from Section III in more detail. The model is interpretive: it isolates the mechanisms drive within-market revenue reallocation, unequal adaptation, and amplification through advance notice.

A.A. Setup

Consider a local market with a representative consumer who allocates nominal expenditure $E > 0$ across a continuum of differentiated firms $i \in [0, N]$. Preferences are CES:

$$X = \left(\int_0^N x_i^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 1.$$

For any active set $\mathcal{A} \subseteq [0, N]$, the corresponding price index is

$$P(\mathcal{A}) = \left(\int_{i \in \mathcal{A}} p_i^{1-\sigma} \, di \right)^{\frac{1}{1-\sigma}},$$

and, given expenditure E, variety-level expenditure shares are

$$s_i(\mathcal{A}) = \frac{p_i x_i}{E} = \left(\frac{p_i}{P(\mathcal{A})} \right)^{1-\sigma}.$$

Real consumption is $X = E/P(\mathcal{A})$.

Each firm has a baseline-performance parameter $A_i > 0$. This object should be interpreted broadly: it bundles productivity, quality, and demand appeal into a single sufficient statistic for baseline within-market performance. Let the common factor-price index be Γ, so a firm's unit cost under grid power is $c_i = \Gamma / A_i$. Under monopolistic competition with elasticity σ, baseline prices are constant markups over marginal cost,

$$p_i^0 = \mu c_i = \frac{\sigma}{\sigma - 1} \frac{\Gamma}{A_i}.$$

Define the baseline productivity aggregate

$$M_0 \equiv \int_0^N A_i^{\sigma-1} \, di.$$

Outages occur with probability $q \in (0, 1)$. Before the outage state is realized, a firm can adopt backup power at fixed cost $F > 0$. Adoption is feasible only if the firm has financial capacity $\omega_i \geq F$. During an outage, an adopting firm remains active but pays an operating-cost premium $\tau > 0$, so its outage price is

$$p_i^1 = \frac{\sigma}{\sigma - 1} \frac{(1+\tau)\Gamma}{A_i}.$$

A non-adopting firm is inactive during the outage window and earns zero outage revenue.

Let $\mathcal{G}$ denote the set of firms that adopt backup power, and define resilient productive capacity

$$M_{\mathcal{G}} \equiv \int_{i \in \mathcal{G}} A_i^{\sigma-1} \, di.$$

Throughout, assume $0 < M_{\mathcal{G}} < M_0$ in nondegenerate outage states.

A.B. Revenue shares and profits

The CES structure implies that baseline revenue shares are proportional to $A_i^{\sigma-1}$.

LEMMA A1 (Revenue shares under inverse-performance pricing). *Suppose all firms in an active set $\mathcal{A}$ price according to $p_i = \kappa / A_i$ for some common $\kappa > 0$. Define*

$$M(\mathcal{A}) \equiv \int_{i \in \mathcal{A}} A_i^{\sigma-1} \, di.$$

Then

$$P(\mathcal{A}) = \kappa M(\mathcal{A})^{-1/(\sigma-1)}, \qquad s_i(\mathcal{A}) = \frac{A_i^{\sigma-1}}{M(\mathcal{A})}, \qquad R_i(\mathcal{A}) = \frac{A_i^{\sigma-1}}{M(\mathcal{A})} E.$$

PROOF. Using the CES price index,

$$P(\mathcal{A})^{1-\sigma} = \int_{i \in \mathcal{A}} \left(\frac{\kappa}{A_i} \right)^{1-\sigma} di = \kappa^{1-\sigma} \int_{i \in \mathcal{A}} A_i^{\sigma-1} di = \kappa^{1-\sigma} M(\mathcal{A}),$$

which implies $P(\mathcal{A}) = \kappa M(\mathcal{A})^{-1/(\sigma-1)}$. Substituting into the expenditure-share formula gives

$$s_i(\mathcal{A}) = \frac{p_i^{1-\sigma}}{P(\mathcal{A})^{1-\sigma}} = \frac{(\kappa/A_i)^{1-\sigma}}{\kappa^{1-\sigma} M(\mathcal{A})} = \frac{A_i^{\sigma-1}}{M(\mathcal{A})}.$$

Revenue is $R_i(\mathcal{A}) = s_i(\mathcal{A}) E$. $\square$

Applying Lemma A1 to the baseline state yields

$$s_i^0 = \frac{A_i^{\sigma-1}}{M_0}, \qquad R_i^0 = \frac{A_i^{\sigma-1}}{M_0} E.$$

Thus, baseline revenue rankings are monotone in A_i.

A.C. Outage-state allocation and adoption

In the outage state, only firms in $\mathcal{G}$ are active. Since all active firms face the same proportional operating-cost increase $(1+\tau)$, their outage-state prices are again of the form κ/A_i.

PROPOSITION A1 (Common operating-cost shocks do not affect outage-state revenue shares or adoption incentives). *Let $\mathcal{G}$ be the set of adopting firms. Outage-state revenue shares and revenues among active firms are*

$$s_i^1 = \frac{A_i^{\sigma-1}}{M_{\mathcal{G}}}, \qquad R_i^1 = \frac{A_i^{\sigma-1}}{M_{\mathcal{G}}} E, \qquad i \in \mathcal{G},$$

and are independent of τ. Consequently, the common operating-cost premium affects real consumption through the price index but does not affect relative revenue shares or the adoption threshold under fixed nominal expenditure.

PROOF. Set $\kappa_1 = \frac{\sigma}{\sigma-1}(1+\tau)\Gamma$. For any $i \in \mathcal{G}$, outage prices satisfy $p_i^1 = \kappa_1/A_i$. Applying Lemma A1 with active set $\mathcal{G}$ yields the stated revenue expressions, which do not depend on κ_1 and therefore do not depend on τ. □

PROPOSITION A2 (Threshold structure of adoption). *Fix an adoption set $\mathcal{G}$ with $M_{\mathcal{G}} > 0$. Then the profitability component of adoption is strictly increasing in A_i, so there exists a cutoff A^* such that adoption is privately profitable if and only if $A_i \geq A^*$. Combining profitability and feasibility,*

$$\mathcal{G} = \{i : A_i \geq A^*,\ \omega_i \geq F\}.$$

Moreover, any equilibrium cutoff satisfies

$$\text{(A1)} \qquad \frac{qE}{\sigma} \frac{(A^*)^{\sigma-1}}{M_{\mathcal{G}}(A^*, F)} = F,$$

where

$$M_{\mathcal{G}}(A^*, F) = \int_0^N A_i^{\sigma-1} \mathbf{1}\{A_i \geq A^*,\ \omega_i \geq F\}\, di.$$

PROOF. For fixed $M_{\mathcal{G}}$, the function $A_i \mapsto \Delta\Pi_i$ is strictly increasing because $\sigma > 1$. Hence profitability is characterized by a threshold A^*. Feasibility requires $\omega_i \geq F$. Substituting the marginal adopter condition $\Delta\Pi_i = 0$ into the expression for expected net gains yields equation (A1). □

To guarantee existence and uniqueness of the cutoff, impose the following regularity conditions: (i) $\int_0^N A_i^{\sigma-1} di < \infty$; (ii) the joint distribution of (A_i, ω_i) is absolutely continuous on $(0, \infty)^2$; and (iii) for every $a > 0$, the set of firms with $A_i \geq a$ and $\omega_i \geq F$ has positive measure.

PROPOSITION A3 (Existence and uniqueness of the adoption cutoff). *Under the regularity conditions above, there exists a unique cutoff $A^* \in (0, \infty)$ satisfying equation (A1).*

PROOF. Define

$$H(a) \equiv \frac{qE}{\sigma} \frac{a^{\sigma-1}}{M_{\mathcal{G}}(a, F)}.$$

By assumption, $M_{\mathcal{G}}(a, F) > 0$ for every $a > 0$. As a rises, the numerator $a^{\sigma-1}$ increases strictly while the denominator weakly decreases because the set of firms satisfying $A_i \geq a$ shrinks. Therefore $H(a)$ is strictly increasing. Absolute continuity and dominated convergence imply continuity. Finally, $H(a) \to 0$ as $a \downarrow 0$ and $H(a) \to \infty$ as $a \uparrow \infty$. The intermediate value theorem therefore yields existence, and strict monotonicity yields uniqueness. □

Note that the equilibrium mass of adopters $m = |\mathcal{G}|$ is determined jointly with A^*: higher outage probability q raises the expected return to adoption and thus lowers the cutoff, expanding $\mathcal{G}$ and increasing m. The efficient-selection benchmark $\widetilde{M}_{\mathcal{G}}(m)$ holds m fixed to isolate the composition margin, whether the *right* firms adopt, from the extensive margin of how *many* firms adopt. The variety loss component of the decomposition captures the latter, while the misallocation component captures the former.

A.D. Reallocation and real consumption

The model's main redistribution result is immediate.

PROPOSITION A4 (Outages reallocate nominal spending toward operational firms). *For any firm that remains operational during the outage window,*

$$R_i^1 = R_i^0 \frac{M_0}{M_{\mathcal{G}}}, \qquad i \in \mathcal{G},$$

while $R_i^1 = 0$ for $i \notin \mathcal{G}$. Thus all operational firms receive the same proportional revenue expansion, governed by the inverse resilient-capacity share $M_{\mathcal{G}}/M_0$.

PROOF. From Lemma A1,

$$R_i^0 = \frac{A_i^{\sigma-1}}{M_0}E \qquad \text{and} \qquad R_i^1 = \frac{A_i^{\sigma-1}}{M_{\mathcal{G}}}E \quad \text{for } i \in \mathcal{G}.$$

Taking the ratio gives the result. Firms outside $\mathcal{G}$ are inactive by assumption. □

The framework also implies a simple expression for real consumption losses.

PROPOSITION A5 (Real consumption under outages). *Let X_0 denote real consumption under grid power and X_1 denote real consumption in the outage state. Then*

$$\frac{X_1}{X_0} = \frac{1}{1+\tau}\left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}.$$

PROOF. Under grid power, the common price coefficient is $\kappa_0 = \frac{\sigma}{\sigma-1}\Gamma$, so Lemma A1 implies

$$P_0 = \kappa_0 M_0^{-1/(\sigma-1)}.$$

Under outages, the active set is $\mathcal{G}$ and the coefficient is $\kappa_1 = \frac{\sigma}{\sigma-1}(1+\tau)\Gamma$, so

$$P_1 = \kappa_1 M_{\mathcal{G}}^{-1/(\sigma-1)}.$$

Since real consumption equals $X = E/P$,

$$\frac{X_1}{X_0} = \frac{P_0}{P_1} = \frac{1}{1+\tau}\left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}.$$

□

Equation (A2) below separates pure output loss from misallocation in adoption. Let $m = |\mathcal{G}|$ denote the mass of adopting firms and define the efficient-selection benchmark

$$\widetilde{M}(m) \equiv \sup_{\mathcal{S}:\,|\mathcal{S}|=m} \int_{i\in\mathcal{S}} A_i^{\sigma-1}\,di,$$

that is, the resilient productive capacity that would be obtained if the same number of firms adopted, but adoption were assigned to maximize productive capacity.

Proposition A6 (Misallocation from imperfectly aligned financial capacity). *For any adoption set* $\mathcal{G}$ *with mass* m*, we have*

$$\widetilde{M}(m) \geq M_{\mathcal{G}}.$$

Equality holds if adoption is perfectly aligned with baseline performance in the sense that the adopting set is a top-m *set in* A_i*. If financial capacity prevents some higher-*A_i *firms from adopting while allowing some lower-*A_i *firms to adopt, then the inequality is strict.*

Proof. Because the function $a \mapsto a^{\sigma-1}$ is strictly increasing for $\sigma > 1$, the integral of $A_i^{\sigma-1}$ over any measurable set of mass m is maximized by selecting the firms with the highest values of A_i. Therefore $\widetilde{M}(m)$ weakly exceeds the productive capacity of any feasible adoption set of the same mass, including $\mathcal{G}$. Equality holds exactly when $\mathcal{G}$ is itself a top-m set. If the adoption set excludes some firm with higher A_i and includes another with lower A_i, strict monotonicity implies strict inequality. □

Using Proposition A6, the outage-state real consumption loss can be written as

$$\mathcal{L} = 1 - \frac{X_1}{X_0} = 1 - \frac{1}{1+\tau}\left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}$$

(A2)

$$= \underbrace{\frac{\tau}{1+\tau}}_{\text{backup-power cost wedge}} + \underbrace{\frac{1}{1+\tau}\left[1 - \left(\frac{\widetilde{M}(m)}{M_0}\right)^{\frac{1}{\sigma-1}}\right]}_{\text{variety loss}} + \underbrace{\frac{1}{1+\tau}\left[\left(\frac{\widetilde{M}(m)}{M_0}\right)^{\frac{1}{\sigma-1}} - \left(\frac{M_{\mathcal{G}}}{M_0}\right)^{\frac{1}{\sigma-1}}\right]}_{\text{misallocation}}.$$

The final term is weakly positive by Proposition A6. In the paper, this decomposition is used only as a conceptual accounting device. A full welfare quantification would require additional information on the cost wedge, the mapping from observed resilience proxies to operational capacity, and off-platform and intertemporal substitution margins that lie outside the data.

A.E. Extension: advance notice and activation

The baseline model treats a firm with backup power as fully operational in the outage state. To capture the role of anticipation, let $n \geq 0$ denote advance notice and suppose that, conditional on adopting backup power, firm i is operational during a fraction $y_i(n) \in [0, 1]$

of outage windows, where $y_i'(n) \geq 0$. Then effective resilient productive capacity becomes

$$M_{\mathcal{G}}(n) \equiv \int_{i \in \mathcal{G}} y_i(n) A_i^{\sigma-1} \, di.$$

All expressions above continue to hold after replacing $M_{\mathcal{G}}$ with $M_{\mathcal{G}}(n)$. In particular, average outage revenue across outage windows is

$$\bar{R}_i^1(n) = \frac{y_i(n) A_i^{\sigma-1}}{M_{\mathcal{G}}(n)} E, \qquad \frac{X_1(n)}{X_0} = \frac{1}{1+\tau} \left(\frac{M_{\mathcal{G}}(n)}{M_0} \right)^{\frac{1}{\sigma-1}}.$$

If higher-capacity firms have larger increases in $y_i(n)$ when notice improves, then notice raises effective resilient capacity and amplifies the relative revenue gains of firms that are better able to prepare, staff, fuel, or switch onto backup systems. This gives the model a simple channel through which advance warning can improve average preparedness while widening cross-firm disparities.

A.F. Empirical mapping

The framework maps directly to the empirical objects in the paper. The baseline-performance object A_i is proxied by non-outage revenue within market. Financial capacity ω_i is not directly observed, but is reflected in correlates of defensive-technology adoption such as neighborhood wealth and formality. The indicator $\mathbf{1}\{i \in \mathcal{G}\}$ corresponds to the firm's ability to remain operational during outages and is proxied empirically by observing WiFi-based transactions during outage windows, regardless of whether the underlying technology is a generator, inverter-battery system, or another backup-power arrangement. The resilient-capacity share $M_{\mathcal{G}}/M_0$ is the baseline revenue share of firms that remain operational during outages, and $y_i(n)$ captures the activation margin created by advance notice. This mapping is intended to guide interpretation rather than to impose a structural estimation exercise on the reduced-form designs.

A.G. Welfare Calibration

We quantify the consumer welfare cost of electricity outages using the CES monopolistic competition framework developed in Section III. During outage hours, the welfare loss $1 - X_1/X_0$ decomposes into three terms: a cost wedge from backup power operation at premium τ; a variety loss from the reduction in active firms; and a misallocation loss from the gap between the actual resilient set $\mathcal{G}$ and the efficient selection of the highest-productivity firms.

Data Inputs. We identify adopting firms ($i \in \mathcal{G}$) as those which transact over Wi-Fi during an outage period at any point during the sample period. Under CES with constant markups, baseline revenue shares are proportional to $A_i^{\sigma-1}$, so the key model inputs, $M_{\mathcal{G}}/M_0$ and $M^e(m)/M_0$, are directly observable as revenue ratios during non-outage periods and do not depend on σ. We construct these ratios across 134 markets defined as industry $\times$ load-shedding block cells, retaining markets with at least 5 firms. The sample comprises 11,350 firms after applying the same restrictions as in the main analysis.

The expenditure-weighted resilient capacity share is $M_{\mathcal{G}}/M_0 = 0.629$: adopters account for 61% of firms and 63% of baseline revenue. The efficient benchmark is substantially higher at $M^e(m)/M_0 = 0.892$, indicating that if the same number of firms adopted but selection were by non-outage performance rank, the resilient set would capture nearly 90% of productive capacity. This gap is the data moment that drives the misallocation term in Equation A2. With these ratios anchored in the data, can then directly compute total welfare loss and each component of Equation A2 for varying values of σ and τ.

Parameter grid and calibration. While we can observe adoption, we cannot directly observe firm-costs or consumer preferences to estimate elasticities. As an exercise to bound the welfare impacts of outages, we sweep over a plausible grid of these values $\sigma \in \{2, 3, 4, 5, 7, 10\}$ and $\tau \in \{0.05, 0.1, 0.2, 0.3, 0.5\}$ and calculate consumer welfare losses for each combination.[26] Figure C.12 reports the full grid of conditional welfare losses. We assume an electricity share of total variable costs ranging roughly from 1.25% to 25% to establish our range for τ.

At moderate parameter values ($\sigma = 3$, $\tau = 0.2$), the conditional welfare loss is 35.3% of real consumption during outage hours: the cost wedge accounts for 16.7 percentage points (49% of the total), misallocation for 13.9 p.p. (41%), and variety loss for 4.7 p.p. (14%).[27] The cost wedge dominates because it applies uniformly to all surviving firms, while the misallocation channel reflects the large gap between $M_{\mathcal{G}}/M_0$ and the efficient benchmark. Figure C.13 shows how the composition of welfare loss varies with σ: at low elasticities, misallocation accounts for over half of the total loss, while the cost wedge dominates as goods become more substitutable.

To annualize these impacts, we scale by the outage probability q, computed as the frac-

[26] The range of σ values is motivated by trade and IO literature findings Broda and Weinstein (2006); Hottman, Redding, and Weinstein (2016) of elasticities ranging from 2 to 7 for most categories of end consumer goods. Parameter ranges for τ are based on estimates of backup generation costs in sub-Saharan Africa from Fried and Lagakos (2023) of USD0.44/kWh, or approximately 3-5 times the cost of grid electricity.

[27] Note that these values are expenditure-weighted averages of market-level welfare losses computed across 134 markets using Equation A2. Because the welfare formula is non-linear in the capacity ratios, evaluating welfare components using the aggregate ratios yields slightly different values.

tion of business-hour windows (8am–6pm) with recorded outages over 2021–2023. At the expenditure-weighted aggregate of $\bar{q} = 0.121$, the annualized welfare loss at the preferred specification is 4.15% of annual platform consumption.

Validation from reduced-form evidence. The model delivers a testable prediction that is independent of the welfare parameters (σ, τ). Proposition A4 implies that an adopter's revenue rate during outage hours equals $M_0/M_{\mathcal{G}} \approx 1.59$ times its baseline revenue rate. Mapping this to the daily event study in Figure 3, the model-predicted post-adoption outage-day gain is

$$\hat{\beta}^k_{\text{model}} = \frac{h}{H} \cdot \left(\frac{M_0}{M_{\mathcal{G}}} - 1 \right) \cdot \bar{R}^0 \approx 0.29 \times 0.59 \times 1{,}747 \approx \text{R}299,$$

where $h/H = 0.29$ is the mean fraction of business hours affected conditional on an outage day and $\bar{R}^0 = \text{R}1{,}747$ is the mean non-outage-day revenue of eventual adopters. The event study estimates a post-adoption gain of approximately R200 per outage day. The model prediction exceeds the estimate by a factor of roughly 1.5, consistent with potential downward bias from proxy-based adoption measurement: many control firms classified as not-yet-adopters likely possess backup power but have not yet been detected via WiFi transactions, attenuating the estimated differential toward zero. Beyond measurement attenuation, the model abstracts from partial operation by non-adopters and demand absorption by non-platform firms, each of which would reduce the predicted differential.

Firm-side extensions. Three features of the data discipline the model's predictions. First, the adoption-performance gradient is remarkably flat: adoption rates rise from 56% in the bottom revenue decile to only 67% in the top decile. This near-uniform adoption rate suggests a low correlation between productivity and financial capacity, generating the large misallocation gap. Second, exit rates decline with baseline revenue but non-adopters exit at 7–8 percentage points higher rates than adopters throughout the distribution. Exiting firms account for 17.7% of aggregate baseline revenue, compared to 4.6% under an efficient-exit benchmark. This ratio of $3.9x$ suggests substantial dynamic costs beyond the static framework. Third, the revenue multiplier for adopters during outages, $M_0/M_{\mathcal{G}} \approx 1.59$, exceeds 1 by construction whenever some firms exit the active set, consistent with the reduced-form evidence that surviving firms capture meaningful demand reallocation.

Appendix B. Data Construction

We aggregate in-person transactions, outage exposure, and constructed rankings to the daily level and construct a balanced panel by firm and day from January 2021 to December 2023.[28] From the transaction-level dataset, we construct total daily sales and revenue by summing up the transactions and the amount of each transactions. We construct several measures of outage exposure: The main analysis focuses on an indicator that is equal to one when the location that the firm is located in has been assigned any electricity outages over the course of the day, and zero otherwise. We also construct alternative measures of outage exposure, such as the total number of outage events during the day and the total duration of outages during the day. We aggregate the firm's ranking in the loadshedding schedule by taking the *maximum* ranking in the load shedding schedule during business hours for each firm. The maximum daily ranking is informative of the firm's highest probability of receiving an electricity outage during that day.

We impose the following restrictions to construct the main analysis sample. The dataset contains over 470 million transactions to 250,000 unique firms. First, we remove "trial firms" from the analysis sample, which we define as firms that transact less than 100 times with a total lifetime revenue of 1,000 Rand, and firms that are younger than 30 days. This restriction removes any firms that are not active on the Platform and might be operating using other payment processing platforms. This leaves 466 million transactions from approximately 146,000 distinct firms.

Next, we restrict the transactions data from the Platform only to firms within the Cape Town metro area whose electricity distributor is the City of Cape Town since we are only able to observed realized electricity outages for this set of firms. We merge the transactions and outage data by overlapping the firm location with the shapefile of the load shedding blocks. This leaves over 59 million transactions from approximately 20,100 distinct firms. We further subset the firms to those earning at least R5,000 per month. This leaves over 57 million transactions from 13,034 firms.

Finally, we remove firms whose locations are within 250 meters of the load shedding border to minimize contamination in the control group from spillovers. This leaves 52 million transactions from 11,709 distinct firms.[29] We also remove online-only firms and

[28] We classify whether a transaction is online or in person based on the payment type (e.g. if the transaction was conducted via Shopify, it is an online transaction). Thus, the analysis that follows represent the effect of electricity outages on in-store revenue.

[29] Appendix Figure C.3 shows the distribution of distances to adjacent load shedding border across firms.

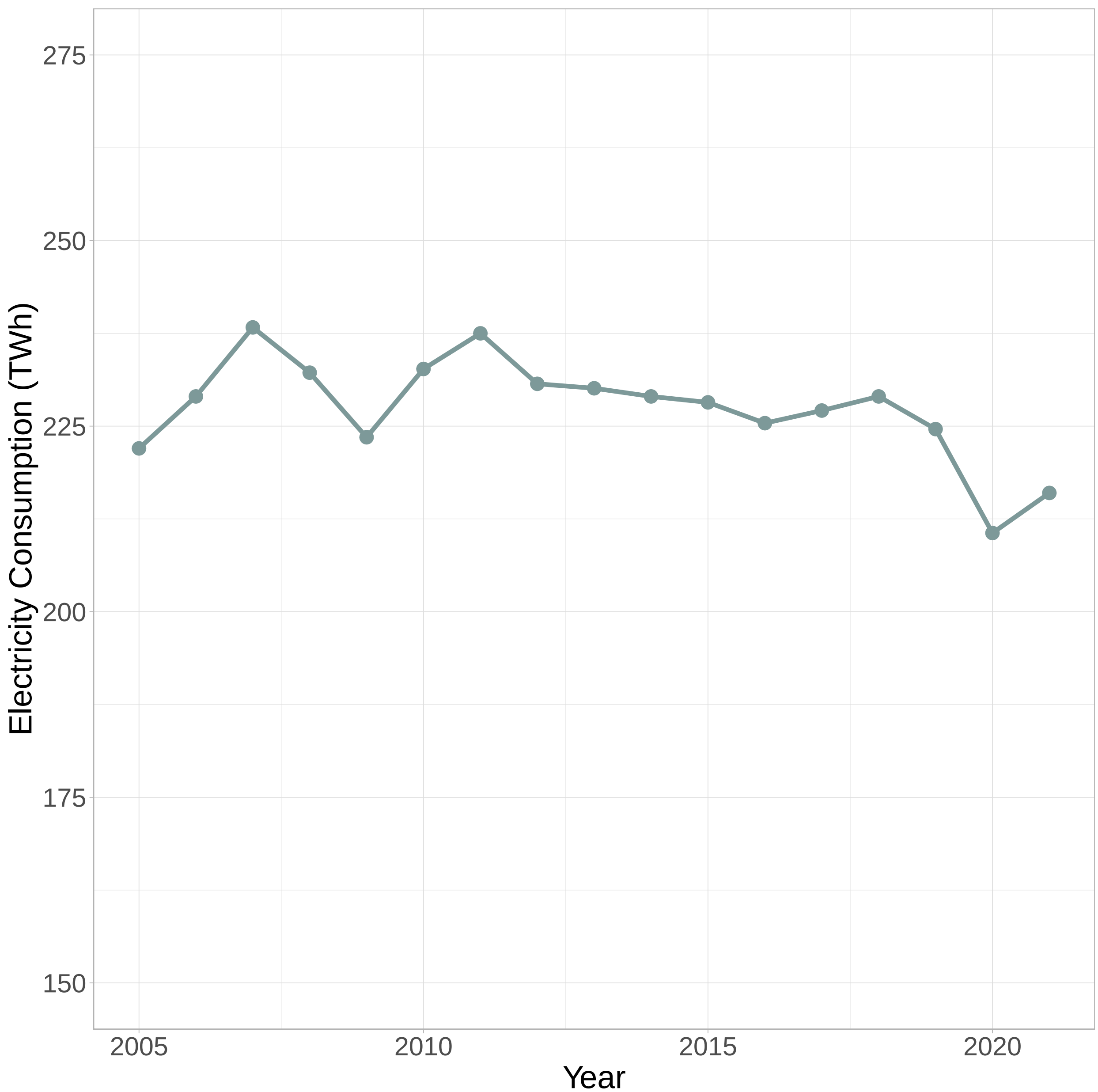
non-profit organizations from the main analysis sample.[30] Most of the firms in the data are service-oriented firms. This leaves over 51 million transactions from 11,398 distinct firms.

We expand the aggregated firm-day level data (which is unbalanced) to a balanced panel where we impute any days without any transactions as the firm recording zero revenue and transactions from January 2021 to December 2023. We restrict the balanced panel at the firm and day level to only active firms. That is, we drop the observation if the firm has exited or if the firm has not entered yet. We define the date of entry as the date of the firm's first non-zero transaction and the date of exit as the date of the firm's last non-zero transaction. The ultimate dataset contains 7,969,049 observations, where we observe each of the 11,398 firms for an average of 699 days.

[30] We remove the non-profit organization industry which might be soliciting donations via the Platform and not relevant to the research question.

Appendix C. Additional Tables and Figures

FIGURE C.1. Aggregate Electricity Consumption



Note: This figure reports the total electricity consumption in TWh in South Africa from 2004 to 2021. Data is from Enerdata.

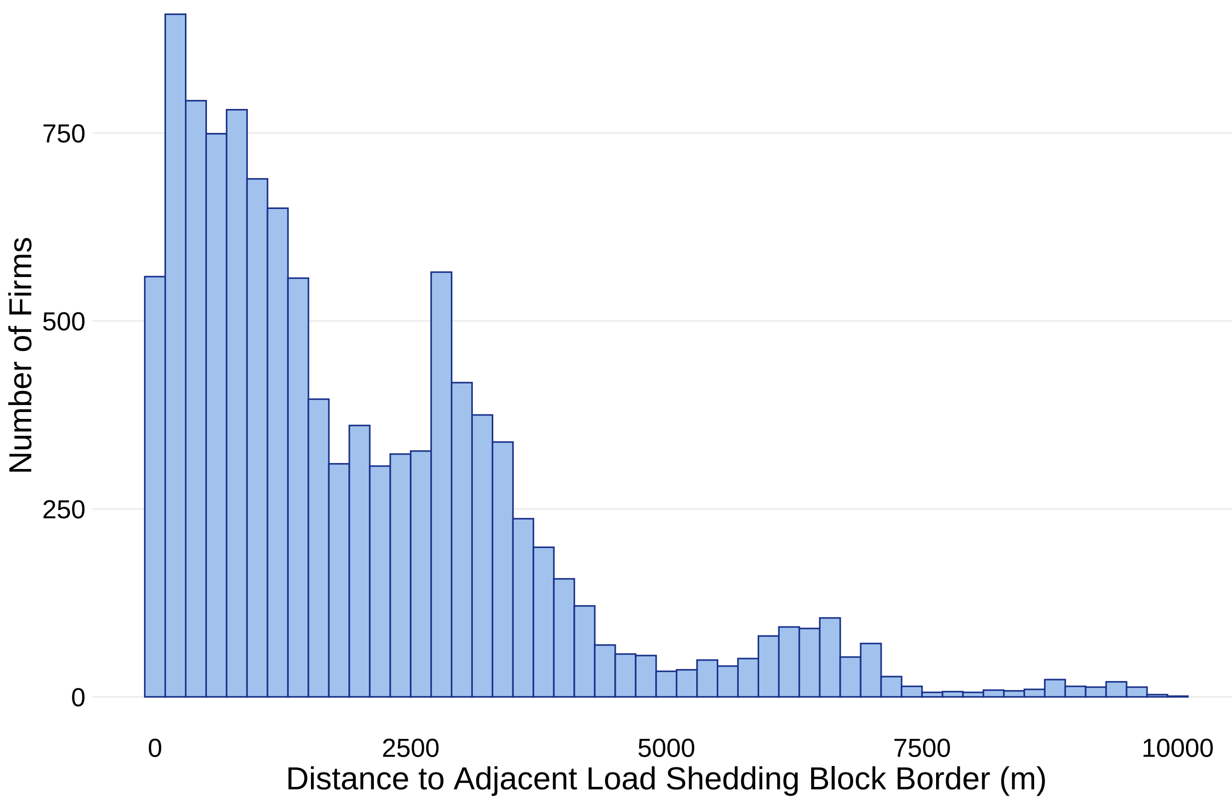
FIGURE C.2. Example of a loadshedding schedule for Stage 3

STAGE 3

DAYS OF THE MONTH		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th	14th	15th	16th
		17th	18th	19th	20th	21st	22nd	23rd	24th	25th	26th	27th	28th	29th	30th	31st	
FROM	TO	AREAS THAT WILL BE LOAD-SHED BETWEEN THE TIMES, TO THE LEFT, ON THE DAY OF THE MONTH ABOVE															
00:00	02:30	1, 9, 13	13, 5, 9	1, 9, 5	13, 5, 1	2, 10, 14	14, 6, 10	2, 10, 6	14, 6, 2	3, 11, 15	15, 7, 11	3, 11, 7	15, 7, 3	4,12, 16	16, 8, 12	4,12, 8	16, 8, 4
02:00	04:30	2, 10, 14	14, 6, 10	2, 10, 6	14, 6, 2	3, 11, 15	15, 7, 11	3, 11, 7	15, 7, 3	4, 12, 16	16, 8, 12	4, 12, 8	16, 8, 4	5, 13, 1	1, 9, 13	5, 13, 9	1, 9, 5
04:00	06:30	3, 11, 15	15, 7, 11	3, 11, 7	15, 7, 3	4, 12, 16	16, 8, 12	4, 12, 8	16, 8, 4	5, 13, 1	1, 9, 13	5, 13, 9	1, 9, 5	6, 14, 2	2, 10, 14	6, 14, 10	2, 10, 6
06:00	08:30	4, 12, 16	16, 8, 12	4, 12, 8	16, 8, 4	5, 13, 1	1, 9, 13	5, 13, 9	1, 9, 5	6, 14, 2	2, 10, 14	6, 14, 10	2, 10, 6	7, 15, 3	3, 11, 15	7, 15, 11	3, 11, 7
08:00	10:30	5, 13, 1	1, 9, 13	5, 13, 9	1, 9, 5	6, 14, 2	2, 10, 14	6, 14, 10	2, 10, 6	7, 15, 3	3, 11, 15	7, 15, 11	3, 11, 7	8, 16, 4	4, 12, 16	8, 16, 12	4, 12, 8
10:00	12:30	6, 14, 2	2, 10, 14	6, 14, 10	2, 10, 6	7, 15, 3	3, 11, 15	7, 15, 11	3, 11, 7	8, 16, 4	4, 12, 16	8, 16, 12	4, 12, 8	9, 1, 5	5, 13, 1	9, 1, 13	5, 13, 9
12:00	14:30	7, 15, 3	3, 11, 15	7, 15, 11	3, 11, 7	8, 16, 4	4, 12, 16	8, 16, 12	4, 12, 8	9, 1, 5	5, 13, 1	9, 1, 13	5, 13, 9	10, 2, 6	6, 14, 2	10, 2, 14	6, 14, 10
14:00	16:30	8, 16, 4	4, 12, 16	8, 16, 12	4, 12, 8	9, 1, 5	5, 13, 1	9, 1, 13	5, 13, 9	10, 2, 6	6, 14, 2	10, 2, 14	6, 14, 10	11, 3, 7	7, 15, 3	11, 3, 15	7, 15, 11
16:00	18:30	9, 1, 5	5, 13, 1	9, 1, 13	5, 13, 9	10, 2, 6	6, 14, 2	10, 2, 14	6, 14, 10	11, 3, 7	7, 15, 3	11, 3, 15	7, 15, 11	12, 4, 8	8, 16, 4	12, 4, 16	8, 16, 12
18:00	20:30	10, 2, 6	6, 14, 2	10, 2, 14	6, 14, 10	11, 3, 7	7, 15, 3	11, 3, 15	7, 15, 11	12, 4, 8	8, 16, 4	12, 4, 16	8, 16, 12	13, 5, 9	9, 1, 5	13, 5, 1	9, 1, 13
20:00	22:30	11, 3, 7	7, 15, 3	11, 3, 15	7, 15, 11	12, 4, 8	8, 16, 4	12, 4, 16	8, 16, 12	13, 5, 9	9, 1, 5	13, 5, 1	9, 1, 13	14, 6, 10	10, 2, 6	14, 6, 2	10, 2, 14
22:00	0:30	12, 4, 8	8, 16, 4	12, 4, 16	8, 16, 12	13, 5, 9	9, 1, 5	13, 5, 1	9, 1, 13	14, 6, 10	10, 2, 6	14, 6, 2	10, 2, 14	15, 7, 11	11, 3, 7	15, 7, 3	11, 3, 15

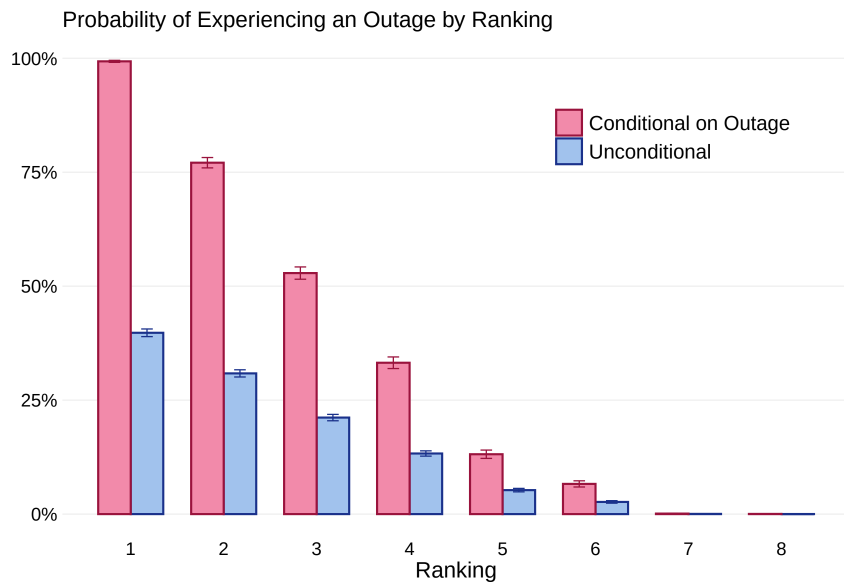
Note: This figure shows a screenshot from Cape Town's load shedding schedule. We show the schedule for stage 3, of which there are 8 total stages. Each cell indicates the load shedding block number that will experience an outage if a stage 3 outage event was declared on the days of the month indicated in the top two rows and during the 2.5 hour period during the left two columns. The full schedule can be found at `https://www.capetown.gov.za/Loadshedding1/loadshedding/Load_Shedding_All_Areas_Schedule_and_Map.pdf`.

FIGURE C.3. Distribution of Distance to Adjacent Load Shedding Border



Note: This figure shows the distribution of all firms' (N = 13, 034) distance to the nearest load shedding border. Note that the main analysis sample (N = 11, 398) drops all firms within 250 meters of the load shedding border.

FIGURE C.4. Outage Probability by Load Shedding Schedule Ranking



Note: This figure reports a load shedding block's outage probability by their load shedding schedule ranking. We transform the load shedding schedule into a ranking from 1–8. Rank 8 indicates that the firm would only receive an outage in the most severe stage of stage 8. Rank 1 implies that the firm would receive an outage, starting from the least severe stage of stage 1. We drop area that are not scheduled to receive an outage at a particular time and day. We show both the unconditional (across all time and days; in blue) and conditional (on any outage; in pink) probabilities.

FIGURE C.5. Example announcement from Eskom

Eskom

POWER ALERT 1

Loadshedding will be increased to Stage 6 from 12:00 until 05:00 on Monday.

Friday, 24 November 2023: Due to the loss of five generating units over the past 24 hours resulting in a shortage of generation capacity, as well as the need to replenish our emergency reserves, Stage 6 loadshedding will be implemented from 12:00 midday until 05:00 on Monday.

Eskom will closely monitor the power system and communicate any changes to loadshedding should it be required.

Unplanned outages are currently at 15 901MW of generating capacity, while the capacity out of service for planned maintenance is 5 822MW.

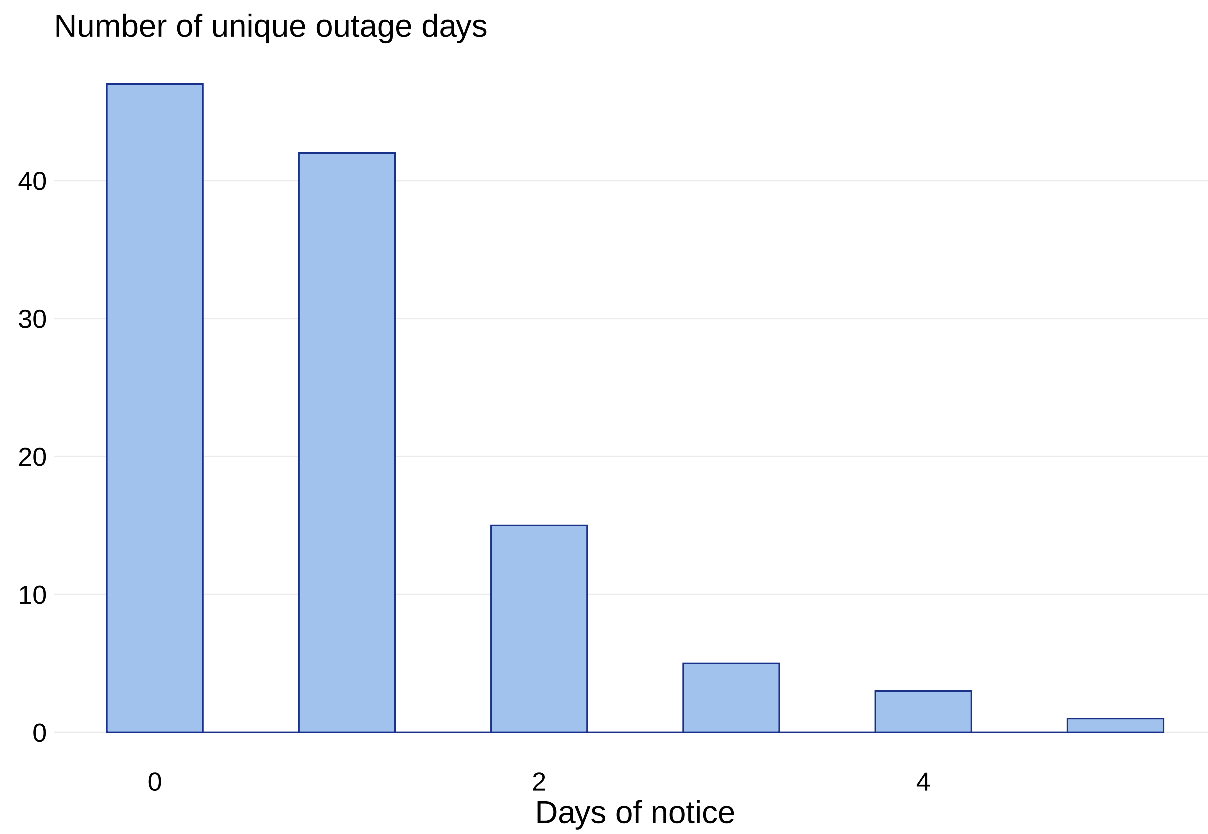
Eskom teams are working tirelessly to ensure that this additional generating units are returned to service as soon as possible.

Eskom's load forecast for the evening peak demand is 27 206MW. We would like to thank those who do heed the call to use electricity sparingly and efficiently, including switching off geysers and pool pumps from **17:00 to 21:00**, as this lowers demand and helps in alleviating the pressure on the power system and contributes to lower stages of loadshedding.

ENDS

Note: This figure shows an example announcement of an escalation in outage severity from Eskom on the same day. The date of the announcement is highlighted in bold. All announcements are obtained from https://www.eskom.co.za/category/news/.

FIGURE C.6. Distribution of difference between announcement and outage days



Note: This figure shows the distribution of the number of days in between the outage announcement and the outage event by Eskom for 113 distinct outage events.

FIGURE C.7. Outage Effects by Industry

A. Heterogeneous Effects on Daily Revenue by Industry

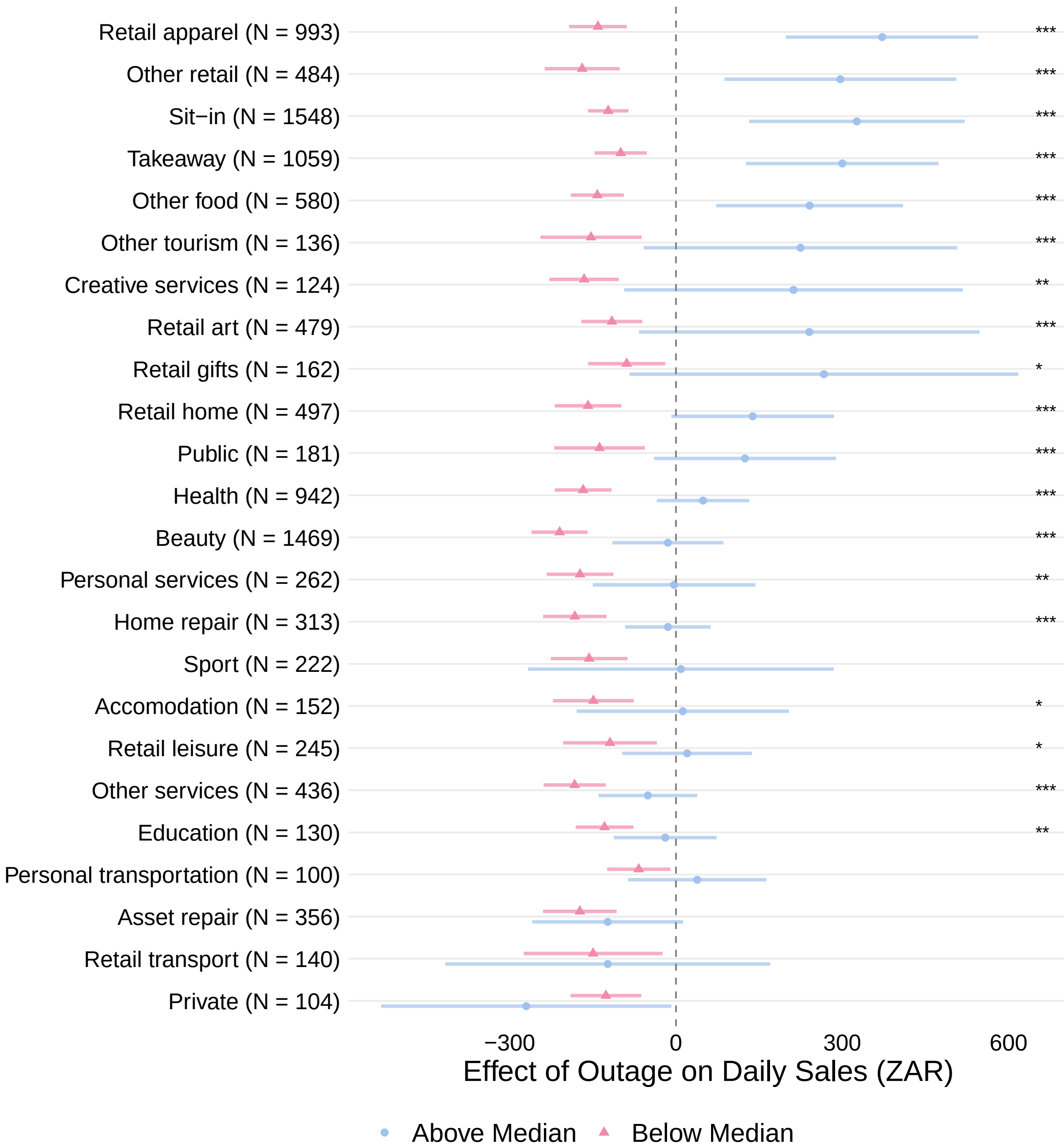
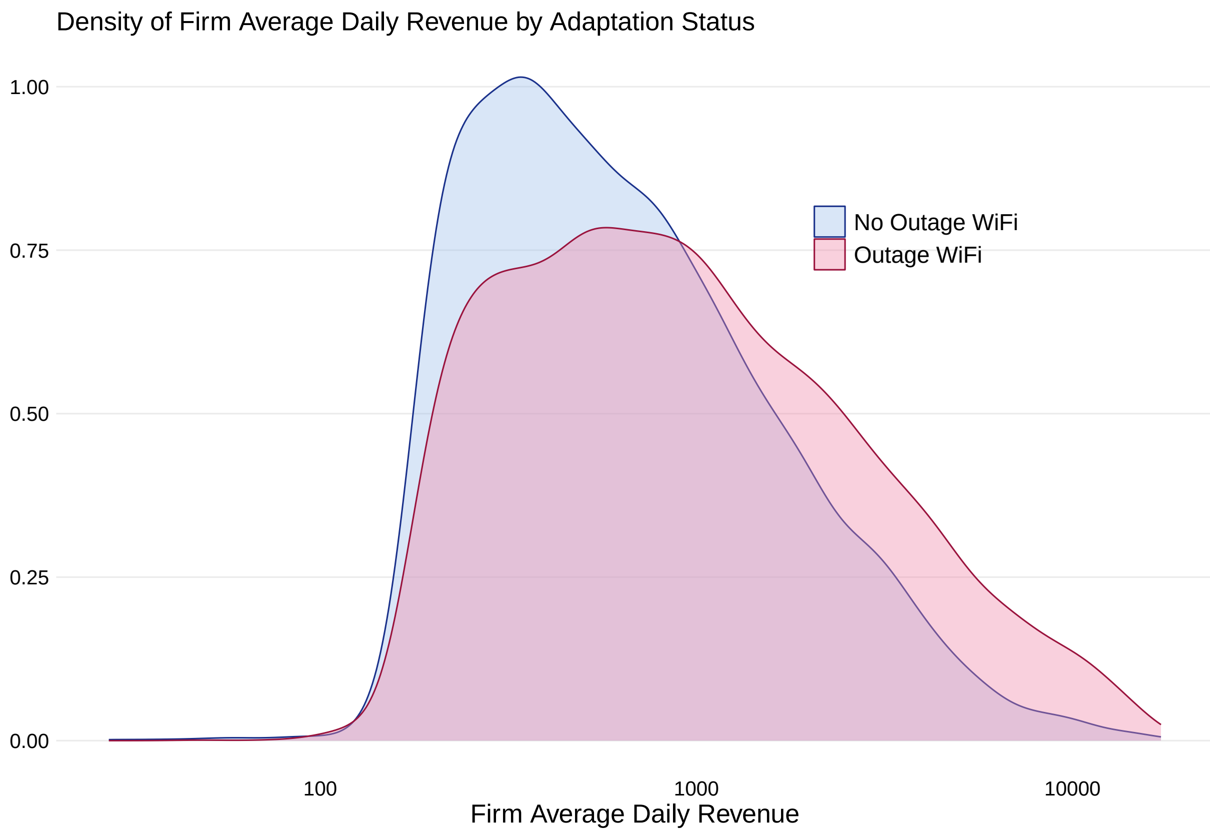


FIGURE C.7. Outage Effects by Industry

B. Heterogeneous Effects on Daily Transactions by Industry

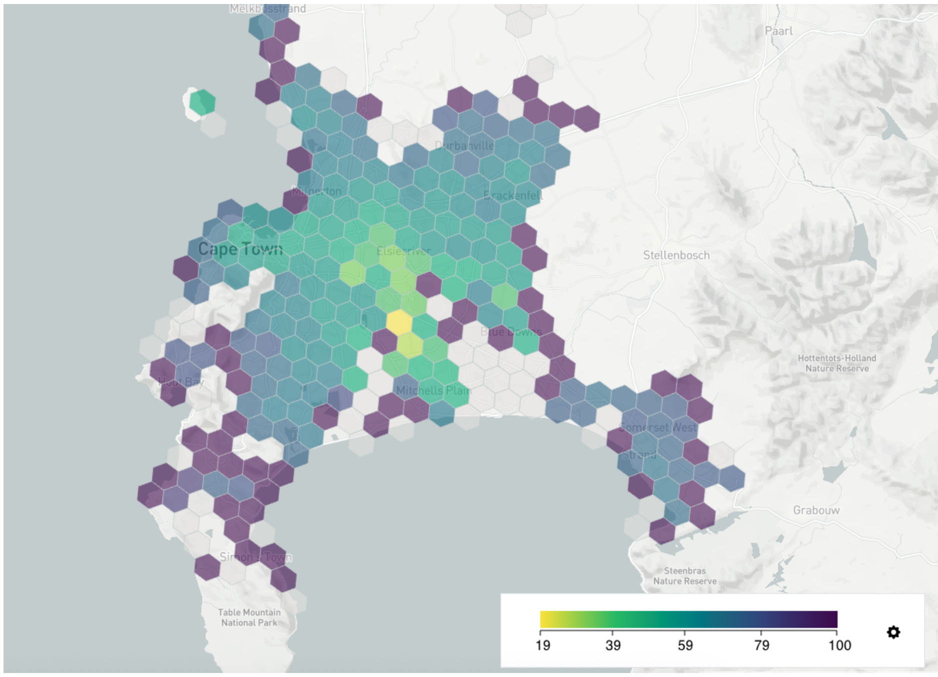
Note: This figure reports results from estimating 3, split by industry. Panel A reports the heterogeneity results on daily revenue; while Panel B reports the results on daily transactions. Standard errors are clustered at the block level, and used to construct the 95% confidence intervals displayed.

FIGURE C.8. Distribution of Revenue by Adaptation Status

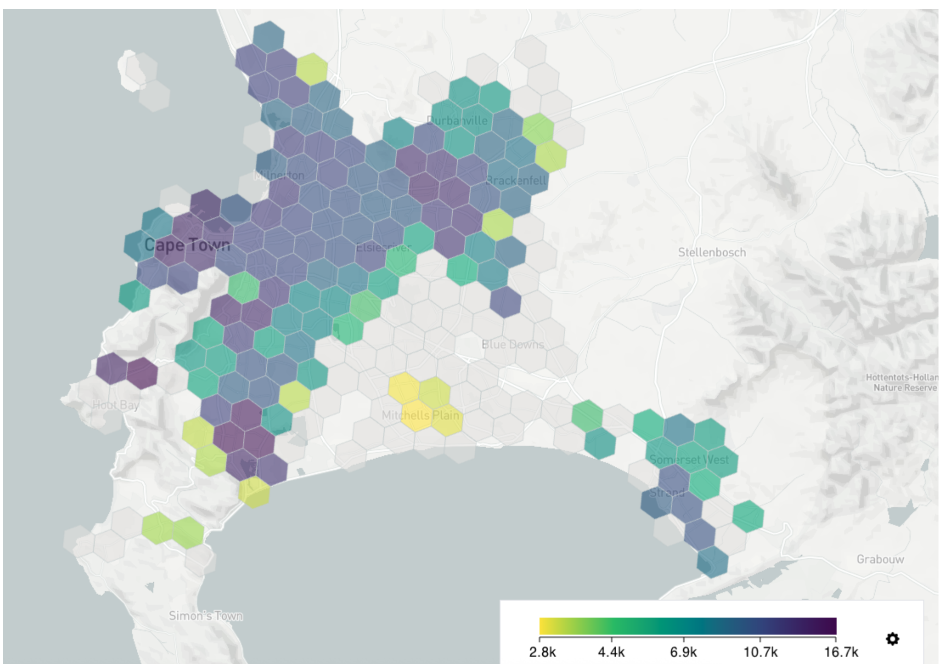


Note: This figure plots the distribution of average daily revenue by whether a firm has been observed to have transacted over WiFi during an outage period.

FIGURE C.9. South African Spatial Tax Data Sample



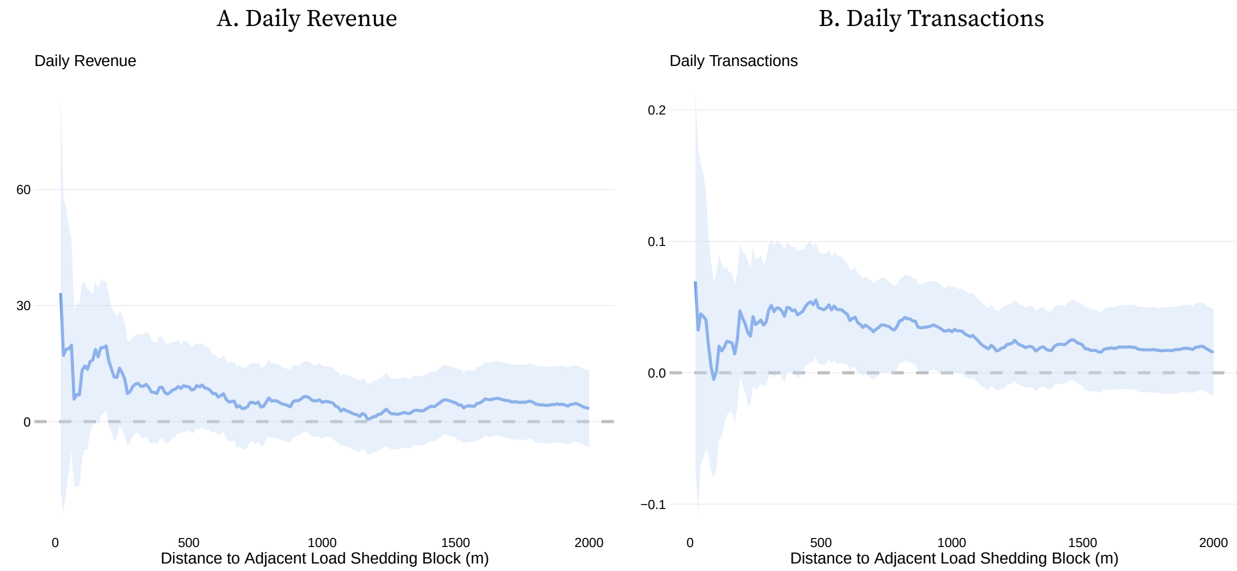
A. Location Share of Firms Under 10 FTE Employees, 2024



B. Average Monthly Income (Wages) in Retail Sector, 2024

Note: These figures report spatial distribution of Micro-enterprises (Panel A) and average wage income for employees in the Wholesale and Retail Trade industries (Panel B) from the Spatial Economic Activity Data (SEAD-SA) for 2024.

FIGURE C.10. Effect of *neighboring* outages on firm performance



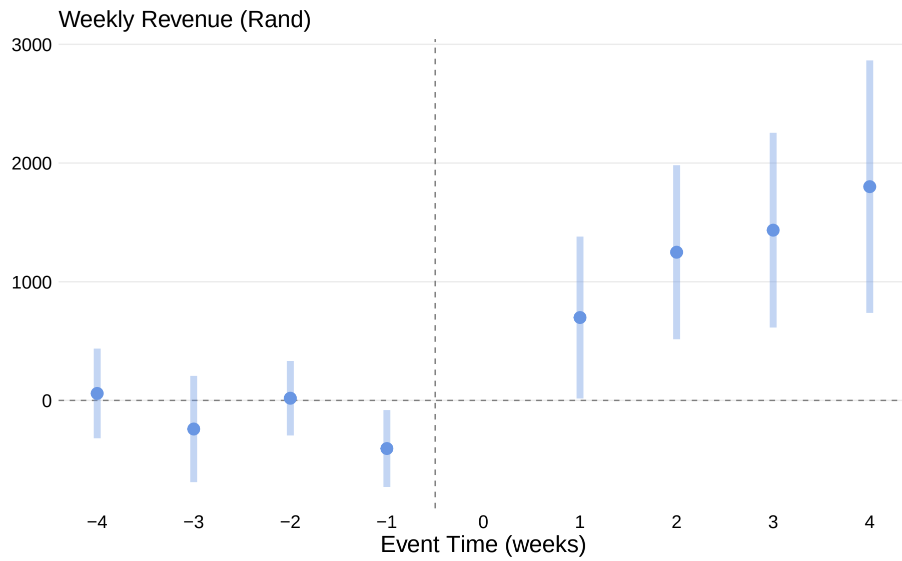
Note: This figure shows the estimated coefficients $\hat{\beta}$ from estimating the following equation:

$$y_{it} = \beta \text{ Adjacent Outage}_{it} + \delta_t + \gamma_i + \varepsilon_{it}$$

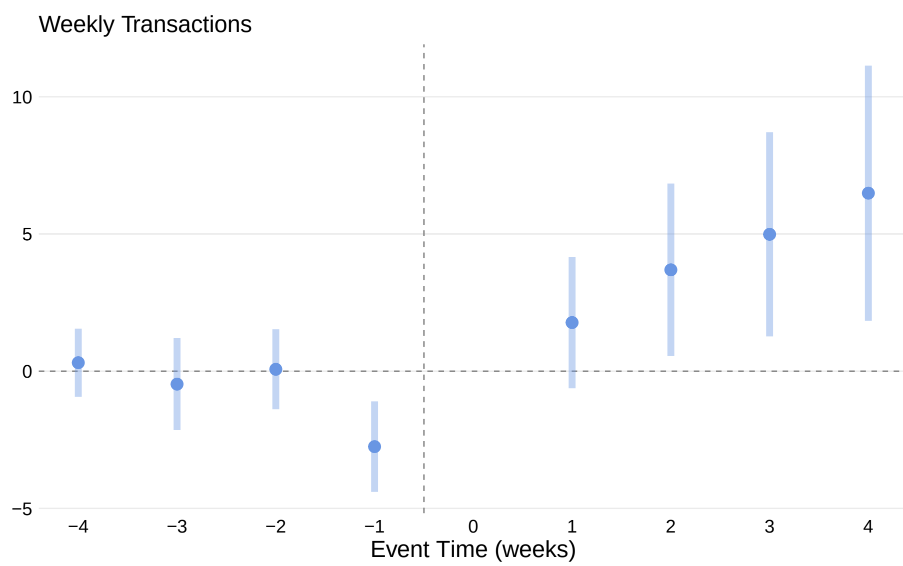
200 times. The estimated coefficient at each point includes firms that are within $x \in \{10, 2000\}$ meters to the load shedding border. The figure connects these 200 coefficients with a line. Panel A shows the estimated coefficients on daily sales and Panel B shows the coefficients for daily transactions. The shaded area represent 90% confidence intervals. We consider the effects of whether an adjacent load shedding block is affected by an outage, restricting the sample to days in which the own firm's block is not experiencing an outage.

FIGURE C.11. Weekly Event Studies

A. Weekly Sales

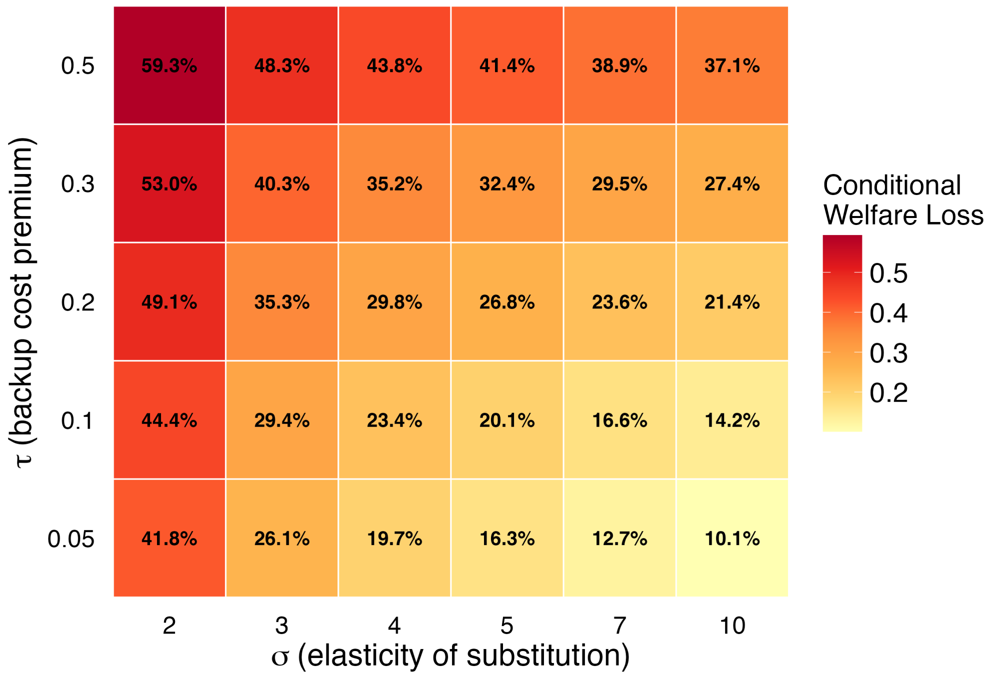


B. Weekly Transactions



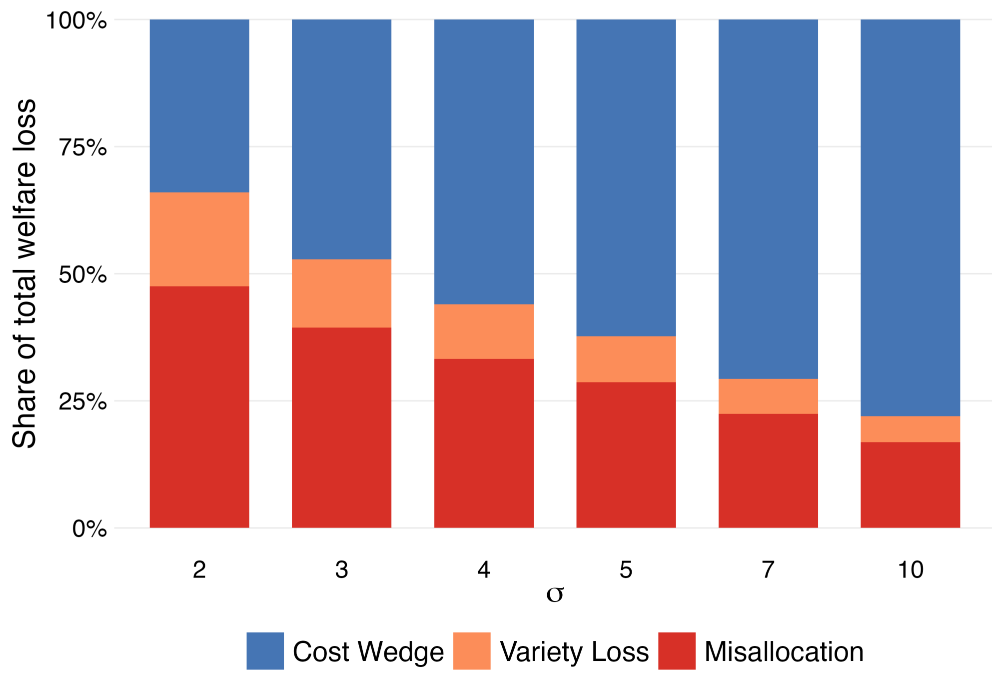
Note: This figure plots the estimated $\hat{\beta}^k$ coefficients from Equation 6, which capture the differential effect of an electricity outage on firm performance before and after the adoption of a defensive technology (e.g., backup power) at the weekly level. Here, we measure the effect of an electricity outage at the weekly level by considering an above-median outage duration on any given week. Panel A plots the effect on weekly sales and Panel B plots the effect on weekly transactions. The event week ($k = 0$) is defined as the first week a firm is observed transacting via WiFi during a power outage. Standard errors are bootstrapped with 1,500 draws. Dashed lines indicate 95% confidence intervals.

FIGURE C.12. Calibrated Conditional Consumer Welfare Loss



Note: This figure shows conditional (during outage hours) welfare loss $\mathcal{L} = 1 - X_1/X_0$ across a (σ, τ) parameter grid, estimated using the revenue shares of the realized set of adopting firms $M_{\mathcal{G}}$-those who are observed to transact over Wi-Fi during outages- and the "efficient adoption benchmark" $M^e(m)$-the same m number of firms in $M_{\mathcal{G}}$ selected on baseline performance alone. All values are expenditure-weighted averages across 134 markets, defined as block $\times$ industry.

FIGURE C.13. Welfare Loss Decomposition



Note: This figure shows Share of conditional welfare loss attributable to each component at $\tau = 0.2$. Misallocation reflects the gap between the efficient adoption benchmark $M^e(m)/M_0$ and the actual resilient capacity share $M_{\mathcal{G}}/M_0$. As σ increases, the exponent $1/(\sigma - 1)$ compresses revenue-share differences, reducing the variety and misallocation channels relative to the cost wedge $\tau/(1+\tau)$.

TABLE C.1. SME Survey Summary Statistics

Variable	Mean	Mean (Above-med.)	Mean (Below-med.)	p-value
Has access to external funding	0.186	0.209	0.159	0.272
Has backup generation	0.797	0.871	0.710	0.001
Has a card machine	0.668	0.785	0.529	0.000
Mostly electronic payments	0.518	0.577	0.449	0.028
Mostly physical payments	0.435	0.368	0.514	0.011
Can anticipate loadshedding events	0.694	0.693	0.696	0.964
Experienced loss of sales due to loadshedding	0.372	0.362	0.384	0.694
Experienced disruptions due to power outages	0.306	0.344	0.261	0.119
Customers assume shops are closed during loadshedding	0.309	0.344	0.268	0.157
Customers use cash instead of card during loadshedding	0.332	0.374	0.283	0.091
N = 259				

Note: This table reports group means from a survey of 259 Cape Town SMEs. The sample both includes firms who use the Platform and those who use other payment methods, including other electronic platforms. Firms in the Above Median group report monthly revenue of ZAR 10,001-30,000 or greater.

TABLE C.2. Summary Statistics by Observed WiFi During Outage

	No Outage WiFi $N = 4,469$		Outage WiFi $N = 6,929$		
	Mean	SD	Mean	SD	p
Panel A: Firm Characteristics					
Average Daily Revenue	1044.713	1401.550	1716.464	2310.088	0.000
Average Daily Transactions	3.947	6.713	6.818	11.135	0.000
$\mathbb{1}$(Informal)	0.201	0.401	0.146	0.353	0.000
$\mathbb{1}$(Services)	0.441	0.497	0.465	0.499	0.284
Age of Owner	48.310	12.591	47.932	12.120	0.218
$\mathbb{1}$(Female-Owned)	0.450	0.498	0.497	0.500	0.004
$\mathbb{1}$(Owner is Citizen)	0.865	0.342	0.872	0.334	0.442
Property Value in Suburb (Thousand Rand)	2010.982	1584.158	2284.856	1721.344	0.000
$\mathbb{1}$(Uses WiFi)	0.450	0.498	1.000	0.017	0.000
Panel B: Industry Composition					
Food, drink, and hospitality	0.261	0.439	0.292	0.455	0.165
Healthcare, Beauty, and Fitness	0.189	0.391	0.258	0.438	0.001
Home and Repair	0.084	0.277	0.056	0.230	0.003
Leisure and Entertainment	0.035	0.184	0.019	0.135	0.005
Personal Services	0.034	0.181	0.035	0.183	0.909
Professional Services	0.051	0.220	0.058	0.235	0.183
Retail	0.299	0.458	0.244	0.429	0.000
Transportation	0.024	0.154	0.012	0.107	0.008
Travel and Tourism	0.024	0.152	0.027	0.162	0.388

Note: This table presents summary statistics of firms for whom we observe transactions over WiFi during an electricity outage and those for whom we do not. We report the means and standard deviations by each group and the p-value of the difference between the two groups. The p-values are calculated by regressing each covariate against an indicator for whether the firm is ever observed to have used WiFi during an outage. Panel A shows key firm characteristics while Panel B shows the industry composition between the two groups.

TABLE C.3. Summary Statistics on Card Sample

	N	Mean	SD	Min	P25	P50	P75	Max
Card-Level Summary								
Number of Identified Regular Firms	106296	3.56	2.04	2	2	3	4	37
Lifetime Total Transactions	106296	31.65	40.84	1	7	18	40	960
Lifetime Total Spending	106296	8576.14	15610.92	2	1467	4107.65	10161.91	2433147.07
Average Daily Regular Firm Outage Exposure	106296	0.37	0.21	0	0.19	0.44	0.53	1
Conditional on Any Transactions in a Day								
Average Daily Transactions	106296	1.1	0.16	1	1	1.06	1.14	6
Average Daily Spending	106296	334.83	456.54	2	145	236.39	387.86	27072.5
Average Daily Spending Share at Above-Median Firms	106296	0.87	0.18	0	0.83	0.93	1	1
Average Daily Spending Share at Below-Median Firms	106296	0.13	0.18	0	0	0.07	0.17	1

Note: This table presents summary statistics of the sample of debit and credit cards that we observe as having at least 2 identified regular firms within an industry.

TABLE C.4. Effect of outages on firm performance: Outage days only

	Daily Sales			Daily Transactons		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-8.320	-95.73***	-91.27***	-0.0192	-0.2909***	-0.2736***
	(5.226)	(18.53)	(17.75)	(0.0221)	(0.0814)	(0.0751)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		178.5***			0.5548***	
		(34.37)			(0.1504)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			167.5***			0.5138***
			(35.28)			(0.1424)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,568.7	1,568.7	1,568.7	5.8354	5.8354	5.8354
R^2	0.47544	0.47557	0.47555	0.59935	0.59942	0.59941
Observations	4,697,226	4,697,226	4,697,226	4,697,226	4,697,226	4,697,226

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on daily sales (panel A) and daily transactions (panel B), restricting to only days with an electricity outage. The coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage in columns 1 and 2 of panels A and B. In columns 3–6, the coefficient on $\mathbb{1}$(Outage) represents the effect of an exposure to an electricity outage for below-median firms and the coefficient on $\mathbb{1}$(Outage) interacted with either $\mathbb{1}$(Above Median) or $\mathbb{1}$(Above Median in Industry $\times$ Block) represents the differential effect of an outage for above-median firms relative to below-median firms. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.5. First Stage and Reduced form

Panel A: First Stage

	$\mathbb{1}$(Outage)		$\mathbb{1}$(Outage) × $\mathbb{1}$(A.M.)	$\mathbb{1}$(Outage)	$\mathbb{1}$(Outage) × $\mathbb{1}$(A.M Within)	$\mathbb{1}$(Outage)	$\mathbb{1}$(Outage) × $\mathbb{1}$(A.M.)	$\mathbb{1}$(Outage) × $\mathbb{1}$(A.M. Within)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Scheduled Outage)	0.9752***	0.9750***	-0.0090***	0.9753***	-0.0093***	0.9752***	-0.0089***	-0.0094***
	(0.0021)	(0.0021)	(0.0009)	(0.0021)	(0.0009)	(0.0021)	(0.0009)	(0.0009)
$\mathbb{1}$(Scheduled Outage) × $\mathbb{1}$(Above Median)		0.0004**	0.9942***			0.0017***	0.9949***	0.0008**
		(0.0002)	(0.0005)			(0.0005)	(0.0005)	(0.0003)
$\mathbb{1}$(Scheduled Outage) ×				-4.52×10^{-5}	0.9939***	-0.0015***	-0.0008***	0.9932***
$\mathbb{1}$(Above Median in Industry × Block)				(0.0001)	(0.0005)	(0.0004)	(0.0002)	(0.0006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.45348	0.45348	0.22412	0.45348	0.22391	0.45348	0.22412	0.22391
R^2	0.99026	0.99026	0.99306	0.99026	0.99279	0.99026	0.99306	0.99279
Observations	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049

Panel B: Reduced Form

	Daily Sales				Daily Transactions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\mathbb{1}$(Scheduled Outage)	-6.373	-155.9***	-150.2***	-164.9***	-0.0169	-0.4051***	-0.3706***	-0.4172***
	(4.367)	(20.93)	(19.37)	(22.89)	(0.0212)	(0.0944)	(0.0780)	(0.0959)
$\mathbb{1}$(Scheduled Outage) × $\mathbb{1}$(Above Median)		305.1***		208.9***		0.7921***		0.6627***
		(35.28)		(23.31)		(0.1739)		(0.2002)
$\mathbb{1}$(Scheduled Outage) × $\mathbb{1}$(Above Median in Industry × Block)			290.5***	113.5***			0.7142***	0.1525
			(37.18)	(35.46)			(0.1476)	(0.1199)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,470.7	1,470.7	1,470.7	1,470.7	5.4899	5.4899	5.4899	5.4899
R^2	0.44834	0.44888	0.44883	0.44890	0.57052	0.57073	0.57069	0.57073
Observations	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049	7,969,049

Note: This table presents the first-stage results using scheduled outage as an instrument for observed outage in Panel A. Panel B shows the reduced-form results. The IV results are presented in Table 4. We augment with the additional instruments in the respective specifications in Table 4 by interacting scheduled outage with indicators for above median. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.6. Card Substitution: Extensive and Intensive Margins

Panel A: Card-Day Level						
	$\mathbb{1}$(Transacted)		Below-Median Merchant Spending		Above-Median Merchant Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\leq$P50 Regular Firm Outage)	-0.0008***		-3.535***		1.932***	
	(0.0003)		(0.7324)		(0.3491)	
$\mathbb{1}(>$P50 Regular Firm Outage)		-0.0005**		0.4737		-0.6003*
		(0.0002)		(0.8045)		(0.3365)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Card FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.07299	0.07299	34.008	34.008	154.81	154.81
R^2	0.07396	0.07396	0.10406	0.10405	0.26751	0.26750
Observations	40,787,210	40,787,210	2,976,935	2,976,935	2,976,935	2,976,935

Panel B: Card-Industry-Day Level						
	$\mathbb{1}$(Transacted)		Below-Median Merchant Spending		Above-Median Merchant Spending	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}(\leq$P50 Regular Firm Outage)	-0.0008***		-2.589***		1.198***	
	(0.0003)		(0.4483)		(0.1798)	
$\mathbb{1}(>$P50 Regular Firm Outage)		-0.0002		0.6320*		-0.0487
		(0.0002)		(0.3642)		(0.1490)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Card-industry_l1 FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.07788	0.07788	12.089	12.089	57.249	57.249
R^2	0.07763	0.07763	0.11630	0.11628	0.26836	0.26834
Observations	45,951,631	45,951,631	3,578,566	3,578,566	3,578,566	3,578,566

Note: This table presents separate estimates of card substitution by the extensive (columns 1–2) and intensive margins (columns 3–6). Panel A estimates Equation 4 at the card-day level and Panel B estimates Equation 5 at the card-industry-day level. Standard errors are clustered at the card level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.7. Effect of outages on firm performance: Announcement outages sample

	Daily Sales			Daily Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-10.27	-97.27***	-91.72***	-0.0173	-0.2076**	-0.1794**
	(13.55)	(20.03)	(18.71)	(0.0653)	(0.0940)	(0.0801)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		177.3***			0.3879***	
		(21.27)			(0.0901)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			164.8***			0.3279***
			(21.71)			(0.0715)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,373.7	1,373.7	1,373.7	5.1294	5.1294	5.1294
R^2	0.43894	0.43904	0.43903	0.56491	0.56494	0.56493
Observations	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on daily sales (columns 1–3) and daily transactions (columns 4–6). We restrict the sample of outages we examine to electricity outages we are able to link to an Eskom announcement. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.8. Alternative outage definitions

	Daily Sales		Daily Transactons	
	(1)	(2)	(3)	(4)
Number of Outages	-55.15***		-0.1295***	
	(6.776)		(0.0256)	
Number of Outages × $\mathbb{1}$(Above Median in Industry × Block)	114.7***		0.2884***	
	(15.43)		(0.0626)	
Outage Duration		-24.97***		-0.0586***
		(3.144)		(0.0119)
Outage Duration × $\mathbb{1}$(Above Median in Industry × Block)		51.93***		0.1301***
		(6.946)		(0.0281)
Firm FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,470.7	1,470.7	5.4899	5.4899
R^2	0.44884	0.44883	0.57070	0.57070
Observations	7,969,049	7,969,049	7,969,049	7,969,049

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on daily sales (columns 1–3) and daily transactions (columns 4–6). We consider alternative definitions of outage exposure: number of outages per day and hours of outage per day. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.9. Aggregate spending: Market-day regressions

	Market Daily Sales	Market Daily Transactions
	(1)	(2)
$\mathbb{1}$(Outage)	-332.1	-2.577
	(541.4)	(1.983)
Market (Industry $\times$ Block) FE	Yes	Yes
Date FE	Yes	Yes
Dep. Var. Mean	81,526.0	287.15
R^2	0.87480	0.88592
Observations	155,311	155,311

Note: This table presents estimates from Equations 2 at the market (industry by load shedding block) level. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.10. Effect of frequent outages on firm performance

Panel A: Firm-Week Level

	Weekly Sales			Weekly Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Outage Duration	24.77	-374.5***	-358.3***	0.1845	-0.9194**	-0.8182**
	(47.12)	(85.69)	(81.27)	(0.1982)	(0.3749)	(0.3287)
Log Outage Duration × $\mathbb{1}$(Above Median)		825.7***			2.283***	
		(102.1)			(0.5519)	
Log Outage Duration × $\mathbb{1}$(Above Median in Industry × Block)			775.4***			2.030***
			(105.6)			(0.4628)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	10,626.8	10,626.8	10,626.8	39.722	39.722	39.722
R^2	0.70053	0.70161	0.70148	0.76699	0.76739	0.76731
Observations	1,134,050	1,134,050	1,134,050	1,134,050	1,134,050	1,134,050

Panel B: Firm-Month Level

	Monthly Sales			Monthly Transactions		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Outage Duration	-1,386.7	-3,131.7***	-3,338.0**	-1.367	-6.369	-6.692
	(1,105.3)	(1,165.7)	(1,279.2)	(5.822)	(6.352)	(6.432)
Log Outage Duration × $\mathbb{1}$(Above Median)		4,302.9***			12.33***	
		(528.6)			(2.750)	
Log Outage Duration × $\mathbb{1}$(Above Median in Industry × Block)			4,034.5***			11.01***
			(544.2)			(2.268)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	46,579.7	46,579.7	46,579.7	173.83	173.83	173.83
R^2	0.78265	0.78448	0.78426	0.81902	0.81970	0.81956
Observations	256,597	256,597	256,597	256,597	256,597	256,597

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on weekly sales and transactions (panel A) and monthly sales and transactions (panel B). We drop a firm's first and last week or month from the data to ensure that we only capture total revenue over a full week or month. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE C.11. Effect of outages on firm performance: Cash-reporting firms

	Cash Revenue Share			Cash Transactions Share		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	0.0010	-0.0115*	-0.0123**	0.0017	-0.0073	-0.0081
	(0.0017)	(0.0063)	(0.0054)	(0.0016)	(0.0062)	(0.0054)
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median)		0.0192**			0.0138	
		(0.0090)			(0.0089)	
$\mathbb{1}$(Outage) $\times$ $\mathbb{1}$(Above Median in Industry $\times$ Block)			0.0220***			0.0163*
			(0.0083)			(0.0082)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.30939	0.30939	0.30939	0.35273	0.35273	0.35273
R^2	0.38760	0.38778	0.38786	0.42679	0.42688	0.42692
Observations	431,422	431,422	431,422	431,464	431,464	431,464

Note: This table presents estimates from Equations 2 and 3 on the average treatment effect of exposure to an electricity outage on the daily cash share of revenue (columns 1–3) and transactions (columns 4–6), conditional on any transactions. We restrict the sample of firms to 1,184 unique firms whose lifetime cash share of revenue exceeds 10%. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.12. Controlling for selection of announcements

Panel A: Load Shedding Stage Controls						
	Daily Sales			Daily Transactons		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}$(Outage)	-76.98*	57.64	58.27	-0.1576	0.2509	0.2272
	(43.51)	(36.92)	(37.21)	(0.1809)	(0.1527)	(0.1525)
$\mathbb{1}$(Outage) × Days of Notice	18.99	-36.78*	-36.52*	0.0265	-0.0709	-0.0601
	(20.03)	(21.84)	(21.66)	(0.0651)	(0.0660)	(0.0741)
$\mathbb{1}$(Outage) × Stage	31.22	21.52	21.00	0.0716	0.0091	0.0055
	(21.98)	(21.49)	(21.73)	(0.1026)	(0.1059)	(0.1053)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median)		-280.7***			-0.8515***	
		(33.19)			(0.1527)	
Days of Notice × $\mathbb{1}$(Above Median)		58.23***			0.2456***	
		(18.82)			(0.0821)	
$\mathbb{1}$(Above Median) × Stage		89.55***			0.1630***	
		(11.29)			(0.0413)	
$\mathbb{1}$(Outage) × Days of Notice × $\mathbb{1}$(Above Median)		112.9***			0.1945***	
		(22.00)			(0.0586)	
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median) × Stage		23.17			0.1392**	
		(16.38)			(0.0584)	
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block)			-273.4***			-0.7771***
			(36.38)			(0.1461)
Days of Notice × $\mathbb{1}$(Above Median in Industry × Block)			54.63***			0.2332***
			(18.33)			(0.0807)
$\mathbb{1}$(Above Median in Industry × Block) × Stage			86.65***			0.1295***
			(10.92)			(0.0370)
$\mathbb{1}$(Outage) × Days of Notice × $\mathbb{1}$(Above Median in Industry × Block)			111.5***			0.1729**
			(19.93)			(0.0693)
$\mathbb{1}$(Outage) × $\mathbb{1}$(Above Median in Industry × Block) × Stage			20.62			0.1333**
			(16.04)			(0.0623)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,373.7	1,373.7	1,373.7	5.1294	5.1294	5.1294
R^2	0.43894	0.43937	0.43933	0.56491	0.56506	0.56503
Observations	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137

TABLE C.13. Controlling for selection of announcements

Panel B: Load Shedding Severity and Outage Duration Controls

	Daily Sales			Daily Transactons		
	(1)	(2)	(3)	(4)	(5)	(6)
𝟙(Outage)	-136.3	349.3***	329.5***	-0.3821	1.196***	1.031***
	(111.5)	(80.68)	(79.09)	(0.5659)	(0.3044)	(0.3425)
Log Outage Duration	12.32	-65.85***	-61.15***	0.0466	-0.2139***	-0.1818***
	(20.79)	(17.87)	(17.30)	(0.1052)	(0.0615)	(0.0678)
𝟙(Outage) × Days of Notice	18.76	-40.30*	-39.47*	0.0256	-0.0828	-0.0694
	(19.91)	(21.05)	(21.03)	(0.0639)	(0.0620)	(0.0709)
𝟙(Outage) × Stage	30.59	49.11**	46.36**	0.0692	0.1009	0.0839
	(22.21)	(21.67)	(21.67)	(0.1042)	(0.1040)	(0.1027)
𝟙(Outage) × 𝟙(Above Median)		-1,010.3***			-3.289***	
		(227.8)			(0.8377)	
Days of Notice × 𝟙(Above Median)		58.16***			0.2454***	
		(18.81)			(0.0820)	
𝟙(Above Median) × Stage		89.73***			0.1636***	
		(11.29)			(0.0413)	
𝟙(Above Median) × Log Outage Duration		162.1***			0.5414***	
		(45.58)			(0.1588)	
𝟙(Outage) × Days of Notice × 𝟙(Above Median)		119.1***			0.2150***	
		(21.37)			(0.0564)	
𝟙(Outage) × 𝟙(Above Median) × Stage		-34.03**			-0.0519	
		(14.63)			(0.0467)	
𝟙(Outage) × 𝟙(Above Median in Industry × Block)			-944.4***			-2.862***
			(230.2)			(0.7170)
Days of Notice × 𝟙(Above Median in Industry × Block)			54.58***			0.2331***
			(18.32)			(0.0807)
𝟙(Above Median in Industry × Block) × Stage			86.81***			0.1300***
			(10.92)			(0.0370)
𝟙(Above Median in Industry × Block) × Log Outage Duration			149.1***			0.4633***
			(45.61)			(0.1351)
𝟙(Outage) × Days of Notice × 𝟙(Above Median in Industry × Block)			117.1***			0.1903***
			(19.46)			(0.0673)
𝟙(Outage) × 𝟙(Above Median in Industry × Block) × Stage			-32.03**			-0.0303
			(14.36)			(0.0500)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1,373.7	1,373.7	1,373.7	5.1294	5.1294	5.1294
R^2	0.43894	0.43938	0.43934	0.56491	0.56507	0.56503
Observations	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137	4,919,137

Note: This table presents estimates from an augmented Equation 7 where we include additional controls in the following manner: $y_{it} = \beta_1 \text{Outage}_{it} + \beta_2 \text{Outage}_{it} \times \text{Days of Notice}_t + \beta_3 X_i \times \text{Days of Notice}_t + \beta_4 \text{Outage}_{it} \times X_i + \beta_5 \text{Outage}_{it} \times X_i \times \text{Days of Notice}_t + \beta_6 \text{Outage}_{it} \times \text{Control}_{it} + \beta_7 X_i \times \text{Control}_{it} + \beta_8 \text{Outage}_{it} \times X_i \times \text{Control}_{it} + \delta_t + \gamma_i + \varepsilon_{it}$. That is, we include the full set of interactions of outage and above-median with the controls as well. Panel A allow for differential effects of outages by the stage of load shedding (e.g. severity) that differ between below- and above-median firms. Panel B adds also allows for the differential effects of outages by the duration of the outage, included in the same manner as specified above. Standard errors are clustered at the industry by load shedding block level. ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.14. Platform usage by firm performance: Survey Evidence

	All Firms		Platform Users	
Revenue Bin	N	Mean Platforms	N	Mean Alt. Platforms
R5,001–R10,000	44	1.23	9	0.67
R10,001–R30,000	52	1.35	11	1.00
R30,001–R75,000	28	1.57	8	1.38
R75,001–R150,000	32	1.78	9	1.67
R150,001–R300,000	47	1.64	13	1.38
R300,001+	56	1.98	12	2.08
Spearman ρ	0.251		0.346	
p-value	<0.001		0.006	
N	259		62	

Note: All Firms columns report the mean number of digital payment platforms. Platform Users columns restrict to firms reporting use of the Platform and count alternative platforms only. Revenue bins below R5,001/month excluded for consistency with the main estimation sample. Spearman rank correlations test the association between ordinal revenue rank and platform counts.